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Operational Planning of Active Distribution Networks - Convex Relaxation under Uncertainty

Bhargav Prasanna Swaminathan

▶ To cite this version:

Bhargav Prasanna Swaminathan. Operational Planning of Active Distribution Networks - Convex Relaxation under Uncertainty. Electric power. Université Grenoble Alpes, 2017. English. NNT : 2017GREAT039 . tel-01690509

HAL Id: tel-01690509
https://theses.hal.science/tel-01690509

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Communauté
UNIVERSITÉ Grenoble Alpes

THÈSE

Pour obtenir le grade de

DOCTEUR DE LA COMMUNAUTE UNIVERSITE GRENOBLE ALPES

Spécialité : **Génie Electrique**

Arrêté ministériel : 25 mai 2016

Présentée par

Bhargav Prasanna SWAMINATHAN

Thèse dirigée par **Raphaël CAIRE** et
codirigée par **Vincent DEBUSSCHERE**

préparée au sein du **Laboratoire de Génie Électrique de Grenoble (G2Elab)**
dans **l'Ecole Doctorale Électronique, Électrotechnique, Automatique et Traitement du Signal (EEATS)**

Gestion prévisionnelle des réseaux actifs de distribution – relaxation convexe sous incertitude

Thèse soutenue publiquement le **22 septembre 2017**,
devant le jury composé de :

Monsieur Nouredine HADJSAID Professeur, Grenoble INP	Président
Monsieur Johan DRIESEN Professeur, K.U. Leuven	Rapporteur
Monsieur Andrew KEANE Professeur associé, University College Dublin	Rapporteur
Monsieur Christian CRISTOFARI Professeur, Université de Corse	Examinateur
Monsieur Raphaël CAIRE Maître de conférences, Grenoble INP	Directeur
Monsieur Vincent DEBUSSCHERE Maître de conférences, Grenoble INP	Co-directeur

Communauté UNIVERSITÉ Grenoble Alpes

THESIS

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Presented by

Bhargav Prasanna SWAMINATHAN

Thesis supervised by **Raphaël CAIRE** and
co-supervised by **Vincent DEBUSSCHERE**

prepared at the **Laboratoire de Génie Électrique de Grenoble (G2Elab)**
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Operational Planning of Active Distribution Networks – Convex Relaxation under Uncertainty

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Mr. Andrew KEANE Associate Professor, University College Dublin	Reporter
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Operational Planning of Active Distribution Networks

Convex Reformulations under Uncertainty

Thesis by Bhargav Prasanna Swaminathan

Public Dissertation on 22 September 2017

Supervised by:
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This thesis was typeset using the LaTeX typesetting system originally developed by Leslie Lamport, which is based on Donald Kruth's TeX. The template used is based on Eivind Uggedal's *Uiothesis* class.

The body text is set to 11/14.5pt on a 35pc measure with the *Latin Modern* Fonts package derived from Donald Knuth's Computer Modern family. The *kpfonts* package with old-style numbering is used for math.

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Also, 42.

Acknowledgements / Remerciements

To the esteemed members of the jury before whom I defended my thesis, I would like to thank you from the bottom of my heart for your contributions to making this thesis better. It has been a pleasure to defend my work in front of you, and your feedback on my work is of great value to me.

I would like to express my profound gratitude to my thesis supervisors Raphaël Caire and Vincent Debusschere. Since 2014, their continued guidance has been one of the cornerstones of this thesis. Their patience, enthusiasm, and suggestions have helped me immensely. Raph, thank you for all the ideas, suggestions, the discussions we had about work and otherwise, your constructive criticism, your ability to make time for me with your tightly packed schedule, the car rides from Genève, and many other things I surely will remember for a long time. Vincent, thank you for always making time for me, and providing valuable professional and personal insights every single time I walked through the door to your office. You have been a wonderful co-supervisor.

A big thank you to my parents, who have guided me my entire life, and are *literally* the reason I am here today. Thanks are also in order to all the colleagues I worked with in the laboratory, the evolvDSO project, the CIRED working group, and otherwise: Andreas, Daan, Damien, Daniele, Egor, Fred, Helena, Jef, Marie-Cécile, Martin, Matthieu, Paolo, Pedro, Philippe, Roberto, Yann, and several others I have surely forgotten to mention here but remember fondly nevertheless.

Côté amis, une mention très spéciale pour *Les French Rainbow Unicorns* (Aurel, Julien et Stéphane) pour les blagues nulles, les escape game, les matchs de badminton et de squash et surtout aussi pour tout ce que vous m'avez appris à propos de la culture française (une décision que vous regrettez bien évidemment). Et je sais que le combat n'est pas fini pour Aurel, je vais te voir quasiment tous les jours au boulot ! Stéphane, j'espère que tu vas continuer à entretenir le mur d'honneur en y ajoutant plein d'autres affiches dans l'avenir. Merci aussi pour les *geoguessr* (t'en as pas encore gagné un seul) en compagnie de Felix, Nikolas et Kevin. Je voudrais également remercier les autres amis / doctorants du laboratoire : Audrey, Barnabé, Catalin, Emmanuelle, Geoffrey, Jean-Nicolas, Kalle, Karla, Mahana, Olivier, Oussama, Sellé, Victor et plein d'autres gens dont le prénoms ne figurent pas ici. Merci pour les bons moments.

Sarah, last but not least, tu mérites une mention séparée. Les années passées avec toi sont parmi les meilleures que je connais. Tu es là pour moi quand j'en ai besoin, toujours à l'écoute et avec tes conseils magnifques. On a vécu plein de belles histoires ensemble, et je ne compte pas arrêter. Merci d'être là et merci d'être toi !

Grenoble, I'm going to miss you! Over the last five years, you have seen me grow professionaly and personally. I have seen, done and experienced so many things while I was here. But like all good things in life, my stay here must also come to an end. I hope this is not a goodbye, but more like a *see you later*. In the meantime, Paris, here I come!

List of Acronyms

ADN Active Distribution Network

ANM Active Network Management

B&C Branch-and-Cut

BFM Branch Flow Model

BIM Bus Injection Model

BRP Balancing Responsible Party

CDF Cumulative Distribution Function

CF Central Forecast

DC-OPF DC Optimal Power Flow

DSO Distribution System Operator

ED Economic Dispatch

ENTSO-E European Network of Transmission System Operators for Electricity

FIT Feed-in Tariff

GAMS General Algebraic Modeling System

GED Générateur d'énergie distribué (see **DRES**)

IGDT Information-Gap Decision Theory

KCL Kirchoff's Current Law

LB Lower Bound

LP Linear Programming

LV Low Voltage

MCP Marginal Clearing Price

MCS Monte-Carlo Simulation

MILP Mixed Integer Linear Programming

MIP Mixed Integer Programming

MISOCP Mixed-Integer Second-Order Cone Programming

MKT Market Domain

MV Medium Voltage

NLP Non-Linear Programming

NP Network Planning & Connection

OLTC On-Load Tap Changer

O&M Operation & Maintenance

OP Operational Planning

OPF Optimal Power Flow

PDF Probability Density Function

PMF Probability Mass Function

P-OPF Probabilistic OPF

PV Photovoltaic

Q-Compensation Reactive Power Compensation

QoS Quality of Supply

SCUC Security Constrained Unit Commitment

SLP Sequential Linear Programming

SOCP Second-Order Cone Programming

TDC TSO-DSO Cooperation Domain

TSO Transmission System Operator

UB Upper Bound

UC Unit Commitment

X/R Reactance to Resistance Ratio

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Equations – Nomenclature

SETS

Ω	Set of all the transformers and power lines
$\Omega!$	Set of all the transformers and power lines with current violations
κ	Set of all the transformers
ξ	Set of non-manoeuvrable transformers and power lines
Γ	Set of all nodes
$\Gamma!$	Set of all nodes with voltage violations
$\Gamma_{mod}, \Gamma_{act}$	Set of all nodes for load curtailment without and with rebound
Γ_{bat}	Set of all nodes with battery systems
Γ_g	Set of all nodes with DRES
Γ_i^u, Γ_i^d	Set of upstream / downstream nodes directly connected to i
C	Set of elementary loops in the network
K	Set of transformation ratios of an OLTC
Ψ_{ij}	Set of indices with each tap of OLTC
S	Set of scenarios for uncertain variables
T	Set of day-ahead time periods
H	Set of hour-ahead time periods

INDICES

i, j, k	Indices for nodes
ij, jk, ik	Indices for lines / transformers
q	Index for an OLTC Tap
t	Day-ahead time period index
h	Hour-ahead time period index
c	Index for Load
f	Index for Flexibility
g	Index for Generator (DRES)
G	Index for Slack node
bat	Index for battery
s	Index for a given scenario of an uncertain variable
cf	Index for the central forecast in interval formulations
ub, lb	Indices for upper and lower bounds in interval formulations
da, ha	Index for day-ahead and hour-ahead

VARIABLES

θ_{it}	Phase angle for node i at time period t
a_{it}^{aon}	Variable indicating activation of regular block order (all-or-nothing)
a_{it}^{act}	Variable indicating activation of capacity based load modulation
I_{ijt}, l_{ijt}	Current and square of current
V_{it}, v_{it}	Voltage and square of voltage
P_{ijt}, Q_{ijt}	Active and Reactive Power flow
P_{it}, Q_{it}	Active and Reactive Power injection
e_{ijt}	Binary variable for line connection status
k_{ijt}	Discrete variable for transformation ratio of OLTC
k_{qijt}	Bi-valued variable for the transformation ratio of tap q of OLTC
w_{qijt}	Binary variables for OLTC tap status
δ_{qijt}	Linearised variable for product between l_{ijt} and w_{qijt}
γ_{qijt}	Linearised variable for product between v_{it} and w_{qijt}

PARAMETERS

SU^g, SD^g	Start-up and shut-down costs of generator g
ρ_t^{da}	Day-ahead spot market electricity price
ρ^l	Cost of Losses
$\rho_1^{oltc}, \rho_2^{oltc}$	Cost coefficients for operation of OLTCs
$\rho_1^{rec}, \rho_2^{rec}$	Cost coefficients for reconfiguration
ρ_t^{ch}, ρ_t^{dc}	Cost of charging and discharging a battery system per MWh
ρ_t^{cur}	Cost/MWh of DRES curtailment
ρ^{lcup}, ρ^{lcdn}	Cost/MWh for load decrease and increase
ρ^{act}	Cost/MW for load activation with rebound
ρ^{end}	Cost/MW for Energy Not Distributed (END)
ρ^{org}	DSO expenditures without optimisation
ρ^{inv}	Investment (Capital) Cost
ρ^{dep}	Depreciation Cost
ρ^{deg}	Degradation Cost
ρ^{op}	Operation Cost
ρ_m^{tot}	Total Maintenance Cost
P_{it}^{cap}	Reserved capacity for load modulation with rebound (MW)
e_{ij}^0	Initial (original) status of lines and transformers in the network
n_N	Number of nodes in the network
n_G	Number of slack nodes in the network

n_C	Number of lines in each elementary loop
n_m	Number of operations before maintenance
E_t^{soc}	State of Charge of the Battery at time t
E^{dod}	Depth of Discharge (DoD) of the Battery
K_a	Actualisation Cost Factor
K_i	Depreciation Cost Factor
r_{ij}, x_{ij}	Per-unit component resistance and reactance
$tan(\phi)_i$	Ratio between reactive and active power
α_i	Max. no. of activations of capacity based load modulation
d_{qij}	Transformation ratio of tap q
ϵ	Infinitesimal value (very close to zero)
M	Large Value
π_s	Probability of occurrence of a particular scenario s

ARBITRARIES

$\overline{var}, \underline{var}$	Upper and lower bounds of an arbitrary variable var
Δvar	Register for the change of an arbitrary variable var
$v\tilde{a}r$	Arbitrary uncertain variable var
$f(), g()$	Arbitrary functions of variables
x_0 & x_1	Arbitrary variables that are independent, and dependent on uncertainty
$\zeta(var)$	Rate of change (with respect to the time period) of arbitrary variable var

1 General Introduction / Overview of the Thesis

« The only thing that is constant is change. / Change is the only constant. »
- Anonymous (wrongly attributed to Heraclitus)

There are two major challenges facing electric power systems today. The first is human-induced climate modifications, arguably the root cause for record increases in worldwide temperatures. It has set the wheels of political establishments all over the world in motion to create policies that will help contain these record increases. International accords such as the Kyoto protocol [Nat98], the Doha amendment to the protocol, and the recent the negotiations at the United Nations Conference on Climate Change [Fra16] in Paris have strived to maintain worldwide temperatures to a certain limit above pre-industrial levels. They aim to achieve this mainly through the reduction of CO2 and other greenhouse gases.

The production of electricity through large fossil-fuel based generation is one of the largest contributors to greenhouse gas emissions, with some studies pointing out that electricity production (including cogeneration) contributes to 25 % of all greenhouse gas emissions [ORY+14]. This makes it a prime target for the aforementioned efforts, and is giving rise to a fundamental change in the way electricity is produced. In Europe, policies like the 2001 directive on promotion of electricity generation from renewable energy sources [Eur01], and more recently 20/20/20 directive [Eur12] have been implemented. The rising shares of Distributed Renewable Energy Sources (DRES) in power systems as a result of these policies attest to a change, away from bulk and polluting generation technologies towards dispersed, renewable, and clean generation technologies.

The second challenge comes from new actors and services in deregulated electric power systems. Traditionally speaking, power systems present a very good case for natural monopolies. The collective infrastructure, built for public good, was financed by governments. They invested in large generation facilities, and ensured the transmission and distribution of this via a power system. However, electricity production is becoming more and more decentralised, with the rising shares of DRES. The deregulation of the electricity industry will necessitate a change in the way these systems are built, operated, and maintained.

In Europe, the European Commission directive of 1996 for deregulation of the internal electricity market [Eur96], among the first of many other directives issued to the effect of deregulation, energy efficiency, and electricity access, initiated the dismantling of these monopolies. The new actors created have fostered higher competition and an increased complexity of the entire power system.

1.1 PROBLEM STATEMENT

These changes affect the electric power system across the board – in production, transmission, and distribution. In terms of production, the rising share of intermittent DRES will continue to change the power generation mix, and force investors to rethink investment strategies. In terms of the power transmission and distribution, a new system equilibrium will have to be found, and system operators will have no choice but to tackle these changes through a systematic evolution of their planning, operation, and maintenance practices. Distribution networks and its operators (DSOs) in particular, are at the front-line of these changes.

Traditionally, electric power flowed from bulk generation, via transmission networks, to distribution networks and then to end-customers. This allowed DSOs to size their networks based on a set of rules that considered only the most critical scenarios. This resulted in networks that required little or no short-term (days to hours before real-time) decisions, since they were designed to accommodate loads at large. This fit-and-forget approach will however cease to be effective in a situation where more DRES are introduced by the day. The critical scenario formulation either provides an oversized network, resulting in higher DSO expenditures, or networks with technical constraints, incapable of accommodating DRES. The intermittence of DRES, the main reason behind this, can also provoke power flows towards the transmission network in certain cases.

Active Distribution Networks (ADN), and Active Network Management (ANM), both revolving around the concept of flexibility in distribution networks, have been touted as a solution towards intelligent management of distribution networks [Eur13a]. By adopting this solution, DSOs potentially stand to benefit, as they streamline investment and operational decisions, creating a cost-effective framework of operations. However, such a change necessitates a large and concerted effort. DSOs will have to evolve and take up new roles. A specific emphasis should be laid on their capability to contract and use flexibility, and to manage their networks in the short-term using intelligent optimisation algorithms (operational planning). This will also necessitate a change in regulation, without which DSOs will find themselves unable to take up these roles.

Considering a scenario where national regulation does allow DSOs to take up these new roles, the different types of flexibilities that they will be able to contract and use will have to be characterised. An unbiased trade-off between flexibilities owned by the DSO[1] and those offered by external parties will have to be struck. Finally, optimisation algorithms for operational planning (OP) will have to be developed in order for these flexibilities to be used effectively. These algorithms have to take into account: (1) the differences in modelling with respect to nature (discrete or continuous) of the different flexibilities, (2) the temporal aspect of the constraints specific to some these flexibilities, (3) the physical features of distribution networks like their low reactance-to-resistance (X/R) ratio, and (4) the uncertainty in some of the input parameters to the optimisation.

A lot of research has recently been done in operational planning thanks to advancements in techniques for modelling and operation of power systems. However, most of this research has drawbacks, including but not limited to the unsuitability of the research in a practical context and the quality of the mathematical modelling of these methods which translate to the quality of the solutions obtained among others.

[1] See Chapter 2, Section 2.4.3 for more information.

1.2 CONTRIBUTIONS OF THIS THESIS

The contributions of this thesis towards operational planning of distribution networks are presented here. Part of this thesis is a result of the work done in the evolvDSO European project [evo14] and in two working groups on losses and flexibilities respectively. The context and the necessity for these contributions are outlined later in the thesis, in Chapter 2.

1.2.1 *Flexibility – Modelling and Economic Analysis*

In the modelling and economic analysis of flexibility in distribution networks, the contributions of this thesis are as follows:

C1 The development of technical models of endogenous and exogenous network flexibilities. These exact models accurately / practically capture the behaviour of the flexibility, conforming to literature or to practically applied DSO methodologies.

C2 The economic analysis of these flexibilities in the short-term context, with an emphasis on achieving an unbiased trade-off between indogenous and exogenous flexibilities in terms of utilisation costs. The derivation of these utilisation costs for flexibilities for a particular test case, to be utilised in a techno-economic optimisation.

1.2.2 *Operational Planning – Framework and Convex Optimisation*

In the context of operational planning of distribution networks, this thesis advances the formulation of operational planning models. The contributions in this field are:

C3 The reformulation of flexibility models developed via contributions C1 – C2 to achieve exact linearisations. These exact linearisations can then be used in a convex optimisation problem.

C4 The development of a novel operational planning (OP) formulation for active distribution networks using the Second-Order Cone Programming (SOCP) relaxation of the Optimal Power Flow (OPF) problem. This formulation integrates the linear flexibility models from contribution C3, and solves the OP problem with global optimality.

C5 Tests of the novel OP formulation with networks, for varying levels of DRES integration, and for different levels of flexibility utilisation.

C6 The development of a dichotomic search heuristic that recovers a globally optimal solution to the OP problem in the event of the failure of the SOCP relaxation. This convergence to the globally optimal solution is proved experimentally.

C7 A discussion of the use of flexibility in operational planning, and the effects on the solution characteristics of the problem.

1.2.3 *Analysis of Uncertainty in Operational Planning*

Since most practical optimisation problems contain parameters that are uncertain, they have to be explicitly accounted for. In the case of the novel OP formulation, forecasts for intermittent DRES are the main source of uncertainty. In this context, this thesis contributes as follows:

C8 An analysis of different approaches to operational planning under uncertainty for distribution networks to identify the approaches that offer the best compromise between five different factors.

C9 The development of an exact two-stage optimal deterministic operational planning formulation to counter uncertainties. This formulation optimises the distribution network in the day-ahead, and hour-ahead stages, treating the additional information on uncertainty in the second stage.

C10 The development of an exact two-stage optimal stochastic operational planning formulation to counter uncertainties. This formulation optimises the distribution network under uncertainty based on the scenario characterisation of uncertainty.

C11 The development of an exact optimal interval operational planning formulation to counter uncertainty. This formulation treats uncertainty in the form of bounds and optimises a deterministic forecast, while ensuring feasibility across the bounds.

C12 Tests on the different formulations developed for operational planning under uncertainty. A comparison and analysis for the performance of the different formulations for different realisations of uncertainty.

The optimisation algorithm for operational planning is therefore extended to include different approaches to managing uncertainty in power forecasts in the short-term. A specific emphasis is provided to decision-making under lack of information with respect to the uncertainty. Parallels are drawn between uncertainty handling in the unit commitment problem for transmission networks and the operational planning for distribution networks. Three different approaches to handling uncertainties are explored and an analysis of the best way to handle uncertainties in the context of distribution networks – taking into account the characteristics of flexibility – is performed.

1.3 ORGANISATION OF THIS THESIS

This thesis is organised in five parts, composed of 8 chapters (including this general introduction; plus annexes) in total. Part I of this thesis, consisting of Chapters 2 and 3 deals with the detailed aspects of the evolution of distribution networks and DSOs. To this effect, Chapter 2 presents the analysis of the current technical and regulatory contexts with respect to distribution network operation and the challenges facing them. The concept of Active Distribution Networks (ADN) is then introduced. The new potential roles that DSOs will have to take up are elaborated, and a brief introduction to the various tools that they will need is done. In Chapter 3 flexibility in distribution networks is described and characterised. An economic analysis that determines the cost of use of a broad range of endogenous (DSO-owned) and exogenous flexibilities is then presented. As mentioned earlier, this analysis strives to achieve an unbiased trade-off between the different types of flexibilities.

One of the tools defined in Chapter 2 lays the basis for Part II of this thesis, consisting of Chapters 4 and 5. This part deals with the development and testing of a methodology for short-term technical and economic optimisation of distribution networks. The problems associated with optimal power flow (OPF) and operational planning (OP) formulations for distribution networks are first discussed in Chapter 4. This highlights the shortcomings of current research in the field, and outlines the requirements of an ideal operational planning formulation. Subsequently, an exact operational planning formulation for distribution networks employing the second-order cone programming (SOCP) relaxation of the optimal power flow and integrating the flexibility models is developed. This model provides globally optimal solutions to the problem. A contingency formulation to obtain a global optimum is also developed, to be used when the SOCP relaxation fails. In Chapter 5, the exact OP formulation and the contingency formulation are tested on two test distribution networks, and the results obtained are presented.

In Part III, consisting of Chapters 6 and 7, the exact OP formulation is extended to incorporate decision making under uncertainty. Chapter 6 deals with an introduction to uncertainty in short-term operations and discusses the various approaches to handling and mitigating the effects of uncertainty. In the same chapter, three methods developed to treat uncertainties in the OP formulation are presented. A framework to compare the performance of these methods is also developed. Chapter 7 presents additional results through tests of these methods. A large number of tests using the comparison framework show the advantages and drawbacks of each of the formulations.

Part IV consists of the following: (1) the general conclusions of the work done in this thesis and perspectives for future work are presented in Chapter 8, (2) references cited in the thesis, and (3) a brief summary in French. Finally, appendices and additional information to complement the work done as a part of this thesis are presented in Part V.

1.4 GENERAL NOTES

The following points may be noted by the reader in order avoid any ambiguity when consulting this thesis:

1 We abuse notation in this thesis with respect to the term 'losses'. Where it is used, and unless otherwise specified, the term losses referes to the active power (ohmic / copper) losses in the network.

2 The term endogenous flexibility refers to the flexibilities of Reconfiguration and On-Load Tap Changers (OLTC). These elements are inherent to the network. The term exogenous flexibility refers to the other flexibilties that the DSO does not own (and therefore external to the network).

3 The relaxation error of the Second Order Cone Programming (SOCP) problem is expressed in VA^2 (volt-ampere squared). This precision is made in case the superscript is mistaken for a footnote.

4 Unless otherwise specified, all the equations in the thesis use the nomenclature presented in Page xvii of this thesis.

PART I

ACTIVE DISTRIBUTION NETWORKS & FLEXIBILITY

The Evolution from Passive to Active Distribution Networks

2

« The measure of intelligence is the ability to change. »
- Albert Einstein

2.1 introduction

2.1.1 Context

The basic goal of a power system is to connect electricity production and consumption in a robust, efficient, and reliable manner. By production, on the one hand, we refer to the multitude of electric power generation apparatus capable of injecting power into a power system. On the other hand, by consumption, we refer to the multitude of apparatus connected to this power system capable of consuming the injected power. The history of the electrical power system dates back to the late 19th century, when the first electrical networks were built. These networks were simple and small in size, with the production and consumption located near each other. They were usually owned by the city or municipality, which could allow private companies to operate them.

Fast forward in time, and the power system grew more and more complex. Inventions like that of the transformer, combined with the growing economies of countries required the construction of large and centralised power generation, usually running on fossil fuels, hydro-power, or nuclear material. This power was transmitted over increasingly longer distances as generation sites and load centres were increasingly further apart from each other. A large portion of the power systems in developed countries was designed and (re)constructed after the Second World War, when many economies boomed. The generation, transmission, and distribution of power were ensured by the state, with state-owned monopolies undertaking the responsibility of constructing, operating, and maintaining these large infrastructures.

In France, the evolution of the ownership of power systems was a rather difficult one, as the nationalisation of the power sector was viewed as a threat [Abd15]. However, in 1946, after the Second World War, a vertically and horizontally integrated company, EDF (*Electricité de France*) was created.

The earliest investments by EDF in production from the 1950s to the 1970s were in large hydroelectric and thermal production units. The development of high-voltage power networks accompanied these investments. French political policy during the oil crisis of the 1970s pushed EDF to nuclear power, to ensure the energetic independence of France. Lately, its investments in renewable energy have increased, due to factors described further in this section. The evolution of electricity production in France from different sources of energy over time is illustrated in Fig. 2.1. Today, the largest proportion of electricity generated in France comes from 58 nuclear reactors in 19 different generation sites across the country.

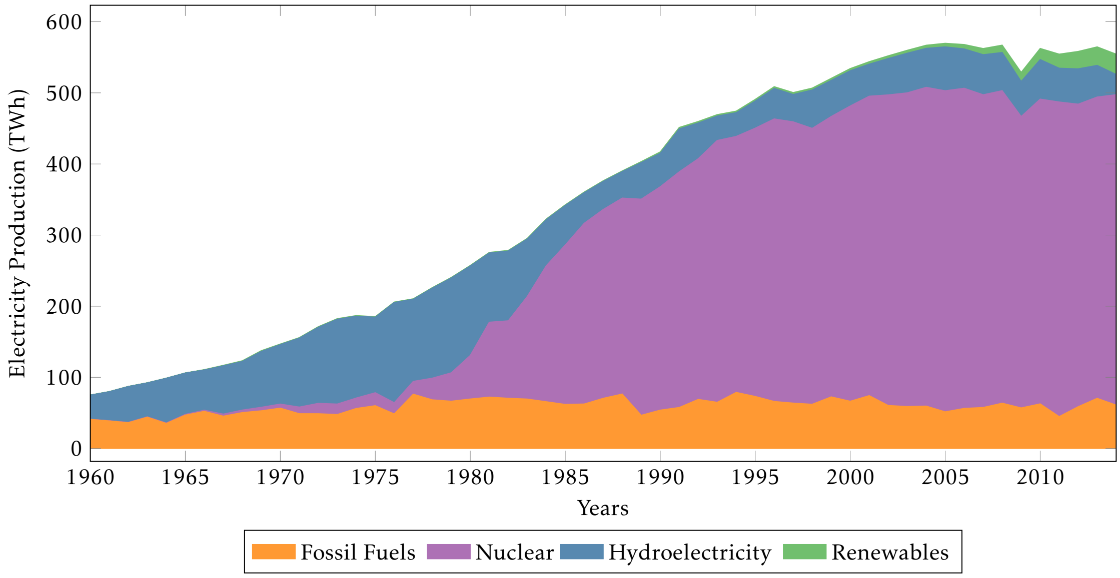


Figure 2.1: Evolution of Electricity Production in France (Source: World Bank / IEA)

The '90s saw two landmark changes that would shape the future of European and in-turn French power systems. These changes were brought about in the context of climate change and the monopoly of power system operations.

Man-made climate change, brought on by the industrial revolution and the unsustainable exploitation of fossil fuel resources had grown steadily leading up to the '90s. The signature of the Kyoto protocol [Nat98] in 1998 signalled the beginning of international cooperation in the fight against climate change. These efforts, including the recent negotiations at the *COP21* [Fra16] in Paris have continued to put pressure on governments to create policies that would decrease their dependence on fossil fuels, and in-turn decrease emissions of CO2 as well as other greenhouse gases.

A large portion of the electricity in the world is generated through polluting sources of primary energy like fossil fuels. This contributes directly to man-made climate change. In fact, studies such as reference [ORY+14] have shown that electricity generation (including cogeneration) are the largest contributors to greenhouse gas emissions, with a share of a quarter of all CO2 emissions worldwide (see Fig. 2.2).

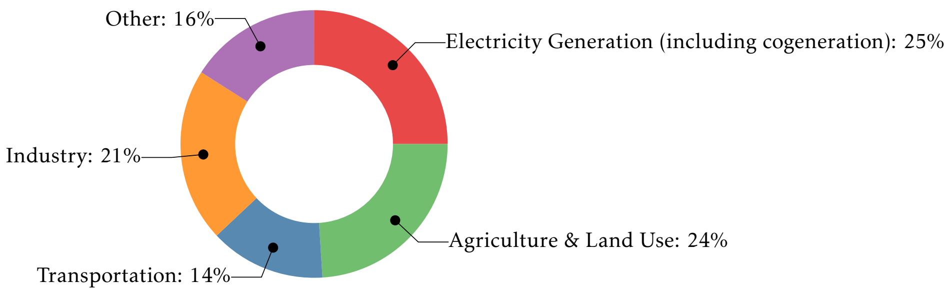


Figure 2.2: Worldwide CO2 Emissions by Sector (2010)

The efforts to decrease greenhouse gas emissions have therefore influenced power systems to a great deal. In Fig. 2.1, one can see that the share of renewable energies in the French production mix have been growing steadily from the turn of the century. The French case however is peculiar, as the French energy mix is low on greenhouse gas emissions, largely due to the presence of nuclear and hydroelectric power. Nevertheless, the reduction of these emissions is one of the many factors that contribute to the share of renewable energies. In other countries like the USA, efforts to increase the share of renewable energies are a direct effect of the efforts to reduce these emissions. National policy in many countries has promoted investments in renewable energy sources through Feed-in Tariffs (FIT), premiums and tax credits among others. For example, the concept of FITs was explored as early as 1993 in Denmark, as a part of its third energy plan (*Energi 2000*) [IRE12].

FITs were developed later-on in other countries to support small-scale investments in distributed renewable energy sources (DRES). They allowed for the power produced by DRES to be sold at a fixed price, borne by an electricity utility. These tariffs are high enough to render investments in DRES profitable, but low enough to limit the share of costs that end users of electricity had to pay. This delicate scheme and the actual price has been the subject of a lot of discussions and laws, with several modifications over short periods of time in countries like France.

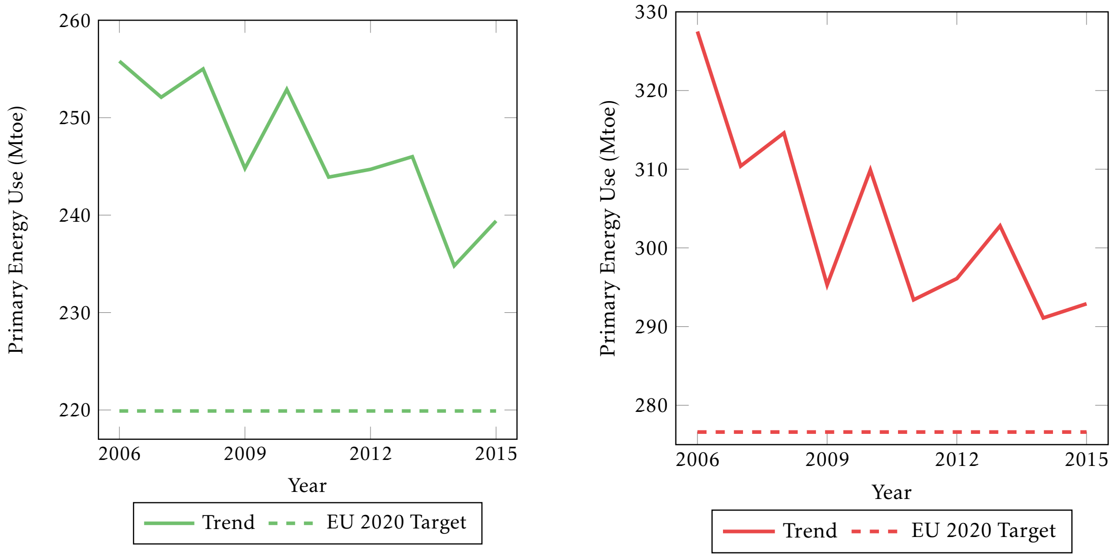
As we will see in Section 2.4.1 of this chapter, these incentive mechanisms have kick-started a rapid integration of DRES in power systems. This is the first challenge that power systems face today.

The second landmark change in European power systems was the adoption of the European directive 96/92/EC [Eur96]. This directive paved the way for deregulation in power systems and the creation of electricity markets. It opened up competition between actors in the European power sector by mandating the unbundling of the activities of state-owned electricity companies into generation, transmission, and distribution. The economy of power systems was now market-based, with several new actors involved in the generation and trade of electricity (see Section 2.4.3 for more).

The directive was enacted as law in France in 2000, and progressively, the French power system was liberalised. Today, the French power system can be considered nominally liberalised, mainly owing to the lack of competition in the power sector. This is however changing slowly, with mechanisms like ARENH (*Accès régulé à l'électricité nucléaire historique*) being put in place, and should lead to a complete liberalisation of the French power system in the years to come.

Other European directives like the energy efficiency directive [Eur12] have set targets for reduction in primary energy consumption and renewable energy integration. The reduction in primary energy consumption in France and Germany between 2006 and 2015 are shown in Fig. 2.3. The global trend of the consumption in both countries shows a decrease. It is to be noted that this trend has not been controlled for climatic aspects that change every year. Both these countries are behind the EU targets in terms of energy efficiency. Both these countries are behind the EU targets in terms of energy efficiency.

These targets have naturally affected network operators, who have had to work on integration of DRES and the Quality of Service (QoS) among others. Roll-outs of smart meters and other communicating devices have helped increase the 'smartness' of the power system, but has also forced new responsibilities on network operators. All this has contributed to the second challenge that power systems face: the changing environment in which they function today.



(a) France (b) Germany

Figure 2.3: Evolution of Primary Energy Consumption (Source: Eurostat)

Both these changes affect the operators of transmission and distribution networks. Distribution networks and their operators (DSO) are in particular at the front-lines of this change. This is because (1) a majority of the DRES connected to the network is connected to distribution networks, and (2) DSOs have historically planned and operated their networks in a passive manner. Further information on this is presented in this chapter. What this means that they currently do not have the means to face these complex challenges.

DSOs will have to evolve in order to meet them. This entails the adoption of new roles, the utilisation of new services, new interactions, and the use of new and intelligent tools and methods to plan and operate their networks. The concept of Active Distribution Networks (ADN) encompasses all these new evolutions in distribution networks. One of the intelligent tools that the DSOs will need in this context relates to the short-term optimisation (operational planning) of their networks. This tool relies on new services and interactions, and is the main focus of this thesis.

In this chapter, serving as an introduction to this thesis, the main focus is on the new roles, services and interactions in the ADN context that will enable DSOs perform operational planning on distribution networks. The organisation of this chapter with respect to these concepts is presented in the next section.

2.1.2 *Organisation of this Chapter*

In this chapter, we first introduce a traditional electric power system and its structure in Section 2.2. We describe the various parts of this complex system and outline each of their major functions. Next, the current state of electrical distribution networks in the French / European context is described in Section 2.3.

This throws light on the responsibilities of the operators of these networks: Transmission and Distribution System Operators (TSO & DSO). We focus particularly on the case of DSOs, and introduce the current network planning and operation practices of DSOs.

The two landmark changes and the associated problems facing distribution networks – DRES integration and deregulation – are then discussed in Section 2.4. Here, European and French numbers for the DRES integration are first outlined and illustrated. The effects of DRES integration on distribution network operation are subsequently described. The changes brought about by deregulation: the creation of the electricity market, new actors, and new services is then briefly described. The concept of flexibility is discussed, and the various sources of flexibility in distribution networks are identified. The problems and opportunities posed by these changes for DSOs are finally elaborated.

The concept of Active Distribution Networks (ADN) is then described in detail in Section 2.5. The new responsibilities that DSOs have to undertake in this context are then outlined, with a specific emphasis on the roles needed to effectively adopt novel operational planning practices. This naturally leads to the contextualisation of the contributions of this thesis listed in Chapter 1. The concluding remarks for the chapter are then made in Section 2.6.

2.2 GENERALISED STRUCTURE OF A POWER SYSTEM

As explained earlier in the chapter, large, centralised generation sources are usually located away from consumption centres, and this means that the power generated by these sources has to be transmitted over long distances before being supplied to consumers. In order to do so, the power systems of the 20$^{\text{th}}$ century were built in a specific way. A generalised structure of such a power system is illustrated in Fig. 2.4. An explanation on this structure follows. In the figure, four main network types can be seen. They are: the transmission network, the sub-transmission network, the MV distribution network, and the LV distribution network. Each of these networks has its own functions, and is built and operated using different rules and criteria. We describe these network types briefly in the sections below.

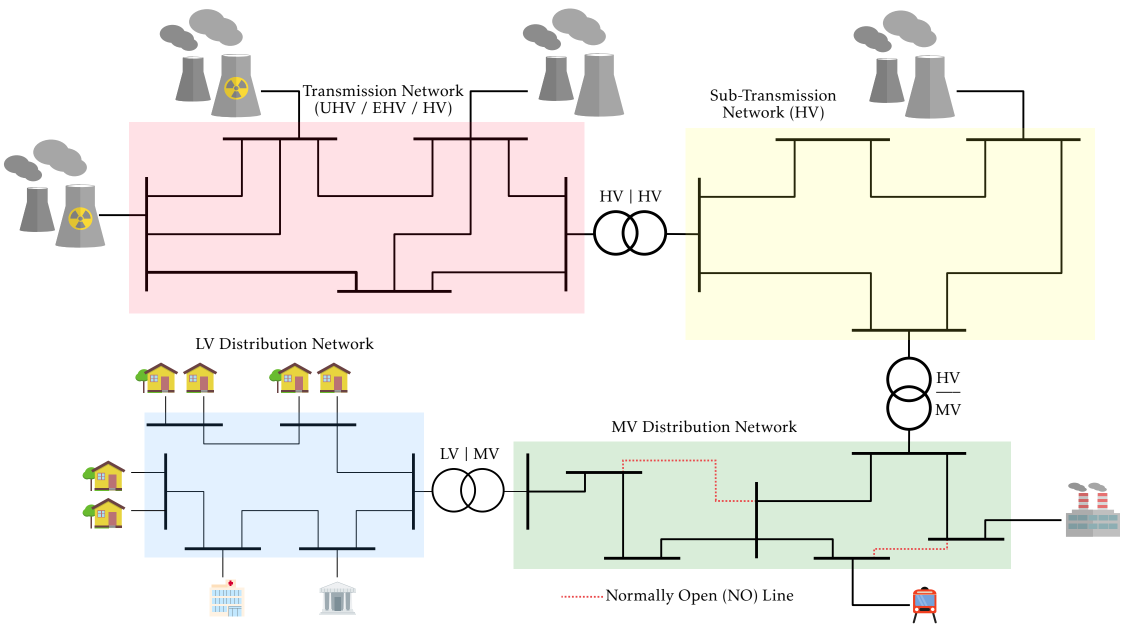


Figure 2.4: Generalised Structure of a Power System

2.2.1 *Transmission and Sub-Transmission Networks*

Transmission networks are extra or ultra high-voltage networks that serve to gather and transport the power generated by the centralised sources of power. The generated power is transported at high voltages to reduce Ohmic losses. In Europe, transmission network voltages are 225 or 400 kV (see Fig. 2.5). The choice of these voltages depends largely on the distance over which power has to be transported. In countries like China and India, these networks reach voltages of up to 765 kV or even 1.2 MV. Step-up transformers are therefore used to increase the voltage level of the power generated by the centralised generators. Certain large industries are also directly connected to the transmission network. In France, for example, 258 industries are connected to the transmission network[1].

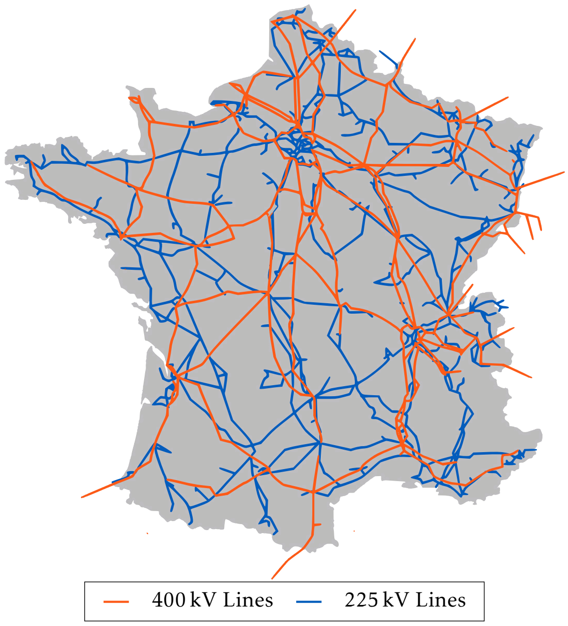


Figure 2.5: The French Transmission Network in 2013 (Source: RTE / EDF)

Transmission networks are complex, meshed, and interconnected systems. They are built, operated and maintained by Transmission System Operators (TSO). In Europe, there is a tight interconnection between the transmission networks in different countries. This allows the exchange of power between neighbouring countries, and contributes to better stability. At the European level, the cooperation between TSOs and their activities is ensured by the association called ENTSO-E (European Network of Transmission System Operators for Electricity).

Sub-transmission networks act as an interface between the transmission networks and distribution networks. In some countries, these networks do not exist. Where they do exist, these networks are high-voltage networks, and can also be used to gather power generated by smaller centralised generators. In France, these networks are operated at a voltage of 63 or 90 kV. In other countries like Japan, these networks work at 66 or 77 kV.

In the year 2015, the total amount of energy transported by the transmission networks in 31 countries whose operators belong to ENTSO-E was around 3 278 TWh [ENT15].

[1] See http://lemag.rte-et-vous.com/dossiers/258-entreprises-directement-connectees-au-reseau-rte-des-enjeux-xxl (in French)

The French TSO RTE, which had 105 448 km of transmission and sub-transmission networks in 2015, transported about 476 TWh [RTE16] during this period.

2.2.2 *Distribution Networks*

Distribution Networks are usually medium and low voltage networks that serve to distribute the energy from (sub-)transmission networks to consumers. In some countries, some high voltage networks may also be included in this classification, as they come under the purview of DSOs. The EU Directive 2009/72/EC [Eur09b] defines electricity distribution as "the transport of electricity on high-voltage, medium-voltage and low-voltage distribution systems with a view to its delivery to customers." The electricity from transmission networks is supplied to distribution networks via primary sub-stations, where step-down transformers decrease the voltage level of the electrical energy. The planning, construction, operation, and maintenance of distribution networks are usually done by Distribution System Operators (DSO).

MV distribution networks function at voltages between 11 and 33 kV. In France, a majority of the MV distribution networks are operated at a voltage of 20 kV. Some other networks are operated at 15 kV, while in rare occasions, networks operating at 5.5 kV (like the network in Grenoble) can also be found. The main functions of MV distribution networks are to supply the customers directly connected to the network, while also ensuring that secondary sub-stations, which form the interface between MV and LV distribution networks, are supplied with energy.

LV distribution networks are the final component in the power system. These are the networks where loads are predominantly connected. They usually operate at 400 V, with some other voltage levels like 750 V also employed in practice. Secondary sub-stations have step-down transformers as well, allowing for this change in voltage.

Distribution networks cover a much larger area than transmission networks, given the *last mile* nature of their functions. The line lengths of distribution networks therefore far exceed those of transmission networks. Based on the data provided by ENTSO-E [ENT13] and Eurelectric [Eur13b], the proportion of power line lengths for transmission and distribution networks is presented in Fig. 2.6.

Among the countries for which data is available, distribution networks constitute more than 97 % of lines constructed on an average. In France, the largest DSO, Enedis, responsible for 95 % of the country's distribution networks, had around 1.29 million km of power lines in operation in 2015. Not all of these lines are necessarily used though, as networks are built with redundant power lines (which are still live, but open). They can be operated in a meshed manner, just like transmission networks, but are usually radial, for simplicity.

In fact, simplicity has been one of the cornerstones of the technological choices of DSOs in their networks for a very long time. Such choices may be related to the voltage levels, earthing, cable dimensions and redundancy among others. This is partially because of the sheer size of these networks, and also because of the traditional role that these networks played as a liaison between transmission networks and customers. In the next section, we describe the current practices of most DSOs in planning and operation of their networks, and the various responsibilities they undertake today.

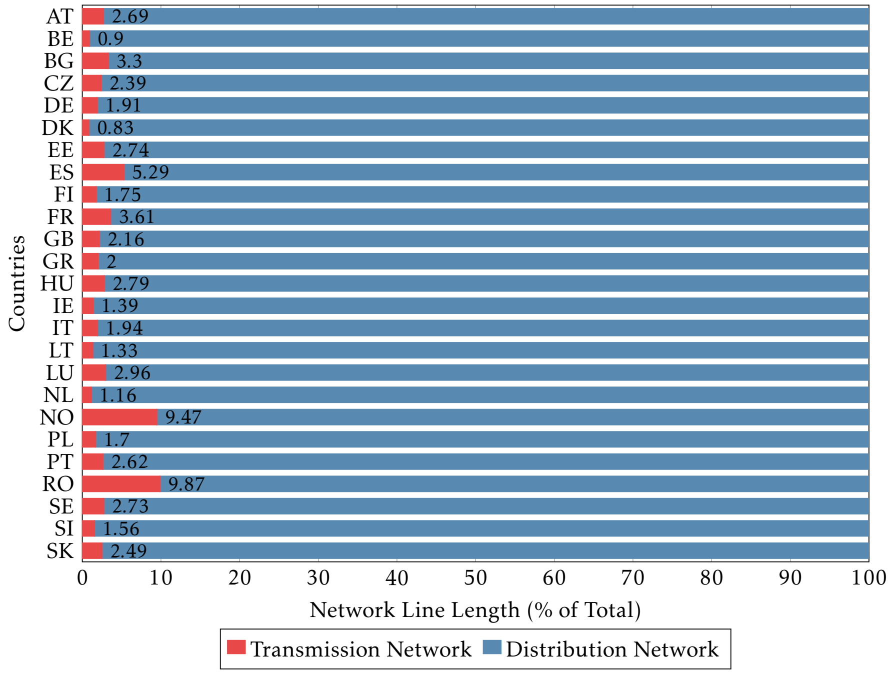


Figure 2.6: Comparison of Transmission and Distribution Network Line Lengths by Country (Europe)

2.3 PASSIVE DISTRIBUTION NETWORKS – THE STATUS QUO

Historically, most DSOs have planned, constructed, and operated their networks in a passive manner, with a "networks follow (predicted) demand" approach [EDA+14]. In such an approach, the evolution of network demand dictates their actions. Section 2.3.1 first outlines the responsibilities that DSOs have to fulfil. The current procedures adopted by the DSOs for planning and operating these networks are then outlined in Section 2.3.2.

2.3.1 *Responsibilities of the DSO*

In order to ensure a safe, reliable, and efficient supply of power to customers, DSOs must respect certain conditions. They are outlined in this section. It is to be noted that the strictness of these conditions varies from country to country. In general, developed economies have stricter conditions imposed on DSOs. In France for example, the law 803 of 2004 [Leg04] defines these responsibilities. These responsibilities are categorised into two: connection and access to the network and quality of supply.

2.3.1.1 Connection and Access to the Network

DSOs are required by regulation / law to ensure that consumers and producers of electricity have access to the public distribution network. This access has to be indiscriminate, within the capacity of the distribution network. In order to provide this access, DSOs are allowed to charge a fee. This fee can be broadly split into two: a connection fee and a utilisation fee [AED14].

The connection fee is, as the name suggests, charged to the user in order to be connected to the network. Countries like Denmark charge a hefty connection fee for large consumers. This fee includes all or part of the cost for network reinforcement necessitated by the connection request (direct connection costs) and the costs of the transformers in the network (indirect connection costs). Other countries like Belgium and Portugal charge users only the direct connection costs to the network.

The utilisation fee is, as the name suggests, charged to the user in order to use the network. It can be calculated either in terms of the energy injected / consumed, or on the capacity of the connection. Countries like France have an advanced system for charging the utilisation fee. This system, called TURPE (*Tarif d'Utilisation des Réseaux Publics d'Electricité* or Tariffs for Use of Public Electricity Networks) consists of several components, with different users charged for different components, based on the voltage levels and the subscribed energy among others. Countries like Ireland charge this fee irrespective of these criteria, while other countries like Portugal, Belgium and Germany do not charge any utilisation fee.

2.3.1.2 Quality of Supply

The Quality of Supply (QoS) defines the continuity of supply, the quality of power supplied, and the customer support provided by the DSOs. National regulation in countries often mandate strict performance requirements with respect to these criteria. In Europe, the duration of interruptions across all networks in the power system is considered low, with durations between 15 and 400 minutes of outages a year [Eur13b]. Indices like SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index) are used for performance metrics with respect to the continuity of supply. In France, a hypothetical penalty of 10 000 €/MWh is often associated to the *énergie non-distribuée* or energy not supplied in power system studies.

The quality of power supplied refers to the voltage deviations, the quality of the power (harmonics, distortions), and the deviations in supply frequency. In Europe, the voltage deviations allowed for MV distribution networks are fixed at ± 5 % by the European DSOs in order to be able to restrict voltage deviations to ± 10 % for the LV end-customer, as fixed by the standard EN 50160 [CEN99]. In normal operation, European operators are required to keep the frequency deviation within ± 1 % of its nominal value of 50 Hz. Among limits that exist for the different harmonics, depending on the voltage level, the standard EN 50160 stipulates that the total harmonic distortion of the power waveform should be below 8 %.

The regulation in more than half of the EU countries promotes adherence to these performance criteria, by linking DSO revenues to their performance on these criteria [AED14]. Austria and Belgium are examples of countries where QoS is monitored but not linked to DSO revenues.

2.3.2 *Distribution Network Planning and Operation*

The "networks follow (predicted) demand" approach, also called the "fit and forget" approach to planning and operation of distribution networks, involves the resolution of potential problems that may occur in distribution networks at the planning stage. In this approach, the choice of the construction of new power lines and infrastructure, and reinforcement of existing power lines is done with the current loads connected to the network, and the future loads that can be connected to the network in mind.

The definition of these extreme conditions differs from country to country. The French DSO Enedis considers that its MV distribution networks should function without violations of the voltage or current limits in the stable-state for two conditions: (1) minimum production & maximum consumption, and (2) maximum production & minimum consumption. The minimum production is considered to be equal to zero. The maximum production is attained when all the generators connected to the network generate power at their rated capacity. The maximum consumption in each feeder is not equal to the connected load. It is decided every year through the measurement of the power flows in primary sub-station feeders [ENE08].The minimum consumption in each feeder is defined as minimum the consumption measured in every feeder, or 20 % of the maximum consumption [Gar16] in the feeder. The MV distribution network is then designed to meet these criteria.

During the operational stage, DSOs then decide on the topological configuration of the network. This configuration chooses the open and closed lines in the network, and takes into account the seasonal variations in the load and the power lines under maintenance among other things. The general structure of a radial MV distribution network [Coi13] is shown in Fig. 2.7. This general structure can evolve depending on the location, size and function of the network.

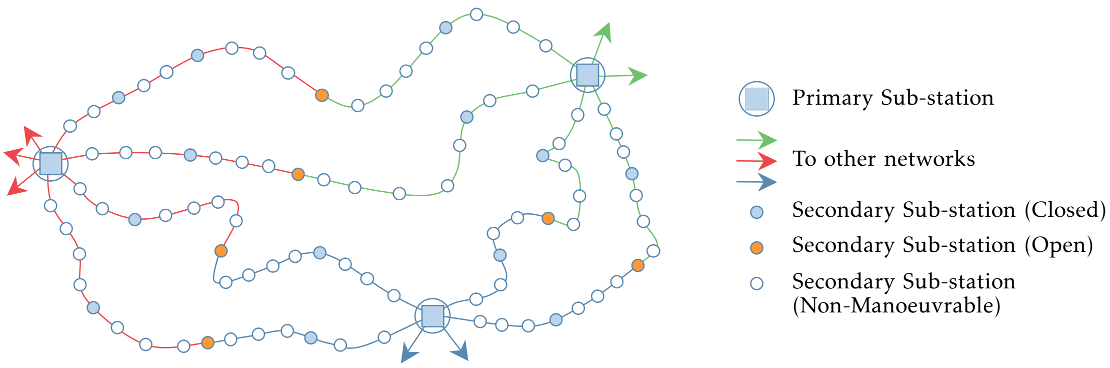


Figure 2.7: Structure of a MV Distribution Network

In the figure, three distinct radial distribution networks (red, blue & green) are shown. The primary subIn the figure, three distinct radial distribution networks (red, blue & green) are shown. The primary sub-stations and the secondary sub-stations are also indicated. The topological configuration of these networks is chosen by opening or closing the switches present in the manoeuvrable sub-stations (closed & open).

Closer to real-time operations, On-Load Tap Changers (OLTC) are used to regulate the voltage in distribution network nodes. The operating principle of OLTCs consists of changing taps that modify the transformation ratio of the power transformer they are a part of. This changes the voltage at the secondary of the transformer, and thus its output voltage. This operation depends on a set-point and is chosen based on one of the two following strategies. In the first strategy, the set-point is chosen to be the voltage at the primary of the transformer with the OLTC. The second, preferred strategy consists of comparing the primary voltage to $U - Z \cdot I$. Here, U and I are measured at the output of the transformer, and Z is the equivalent impedance of the network as seen from the secondary. The tap adjustment then raises or lowers the voltage of the secondary, thereby influencing all the downstream voltages. Note that in both the strategies, the tap changes are done without any visibility of the actual network conditions.

To illustrate how the OLTC works to solve voltage issues in the network, we present a simple example in Fig. 2.8. In the figure, we consider a network with one OLTC transformer and two feeders. The node O of the network is the secondary of the transformer. The graph on the right shows node voltages as a function of the distance (1 – 3) from node O.

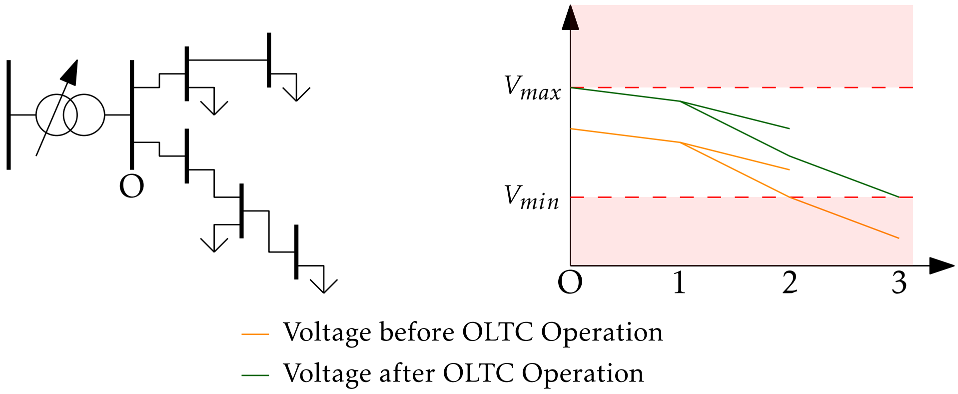


Figure 2.8: OLTC Operation

In Fig. 2.8, the voltage profile before the OLTC operation is shown in orange. There is an under-voltage violation in one of the nodes. Based on the set-point calculated in either of the strategies mentioned above, the OLTC usually acts to increase the secondary voltage. After this operation, the new voltage profile in the network (shown in green) indicates that there are no voltage violations. Other traditional operational actions like capacitor banks for reactive power consumption and injection are also used by many DSOs in their networks.

Even with the automatic voltage correction in the OLTCs, this mode of planning and operating distribution networks can be termed 'passive'. This is because the network problems in both planning and operation of the distribution network are solved as they occur, in a reactive manner. With potentially oversized networks in planning, many DSOs have been able to operate their networks reactively with seasonal reconfiguration and real-time OLTC operation, given that the network voltages have always decreased downstream. However, this may have to change very soon. In the next section, the predicament that DSOs and distribution networks find themselves in is elaborated.

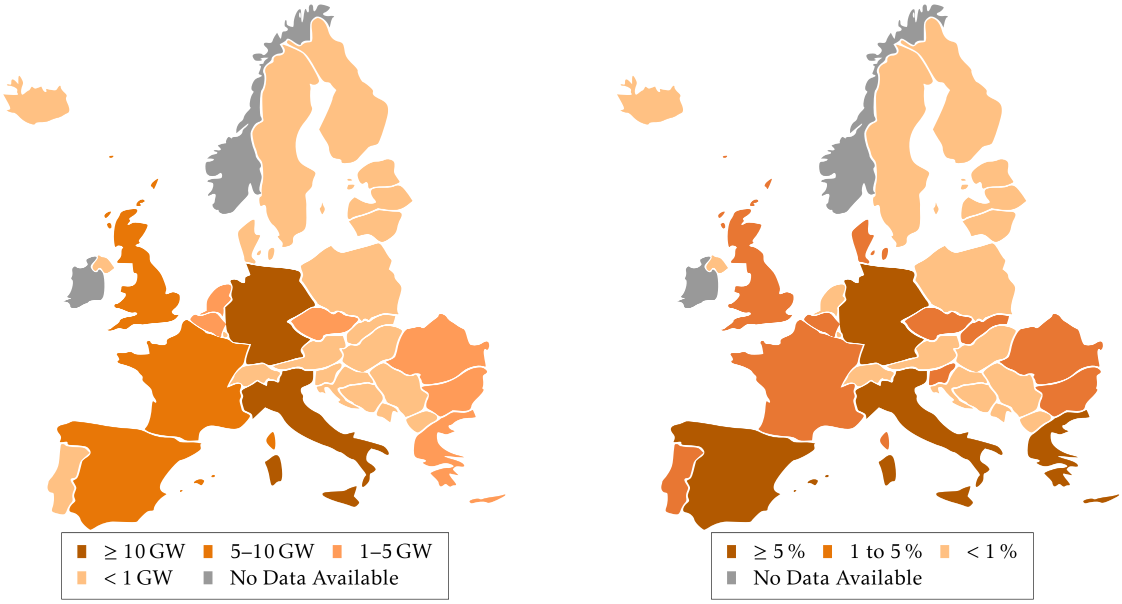
2.4 DRES & DEREGULATION – THE PREDICAMENT

The current practices of many DSOs in planning and especially operation of their networks works in a traditional, regulated set-up. However, as mentioned in Chapter 1, there are two major issues facing distribution networks. These issues adversely affect the current operational practices of these DSOs. In this section, these two problems – integration of intermittent DRES and deregulation – are described. The effects of the two problems on the DSO practices are also explained.

2.4.1 *The Rising Shares of Intermittent DRES*

The EU 20/20/20 targets [Eur12] have contributed to a notable increase in the share of intermittent DRES (PV and wind power) in the energy mix of the European power system. As a result, around 137 GW of wind power and 95 GW of PV power had been installed in power systems in the EU-28 countries at the end of 2015. To illustrate the scenario of intermittent DRES at the European level, we first present a panorama of

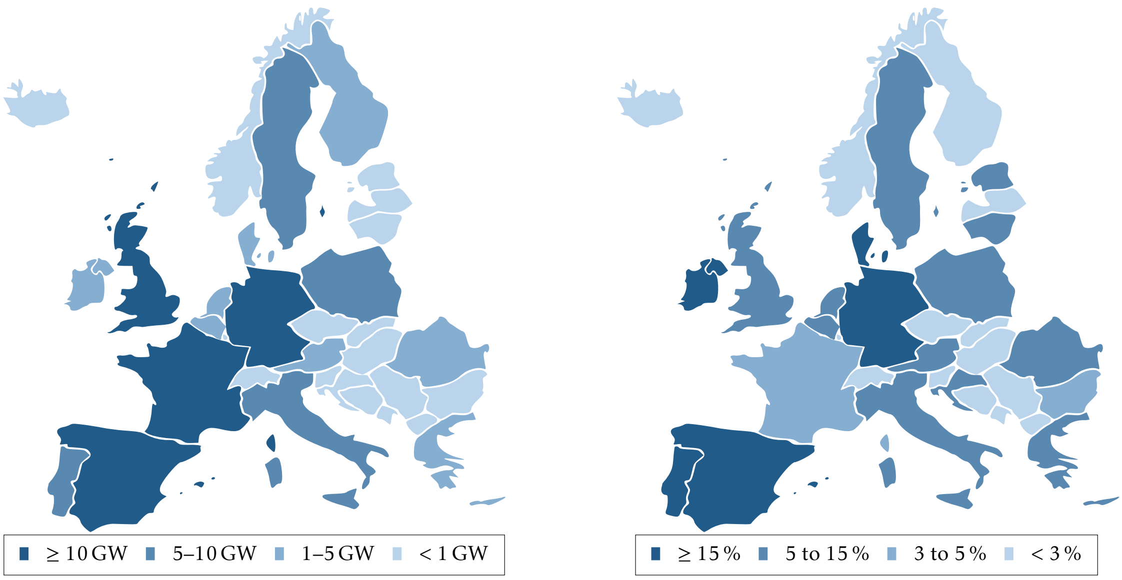
PV installations is illustrated in Fig. 2.9 as installed capacities and energy produced in percentage of the annual consumption.



(a) Installed Capacity (b) Production as % of Consumption

Figure 2.9: Solar Photovoltaic Power in Europe (2015)

The countries with the highest installed capacities of PV systems were Germany (39.7 GW) and Italy (18.89 GW). The installed capacities of Germany, Italy, Spain and France represented 80 % of the total installed PV in Europe. During the period between July 2014 and June 2015, solar PV power supplied 2.86 % of the total European electricity consumption, with a maximum of 7.7 % attained in Italy. A similar panorama of wind power installations in terms of installed capacities and energy produced in percentage of annual consumption is illustrated in Fig. 2.10.



(a) Installed Capacity (b) Production as % of Consumption

Figure 2.10: Wind Power in Europe (2015)

The countries with the highest installed capacities of wind power were Germany (44.67 GW) and Spain (23 GW). In all, 7.9 % of European energy consumption was procured from wind power, with Denmark attaining a high score of 39.9 %. This information was sourced from ENTSO-E, Eurostat, and from references [SER15] and [SER16]. As for the French case, at the end of 2015, the country was 4$^{\text{th}}$ at the European level in terms of the installed capacity of intermittent DRES, with 6.19 GW and 10.3 GW of PV and wind power respectively.

Solar PV installations have grown steadily in France over the past few years, as illustrated by Fig. 2.11. The figure shows the yearly installations of PV DRES connected to transmission and distribution networks[2], and the total installed power in the country at the end of the year. The average yearly rate of growth between 2011 and 2015 was a whopping 58.77 %. PV installations grew at a rapid pace between 2010 and 2012, primarily owing to the attractive Feed-in Tariffs (FIT). Since the FIT was replaced with tender-based projects, PV installations have grown at about 18.4 % every year.

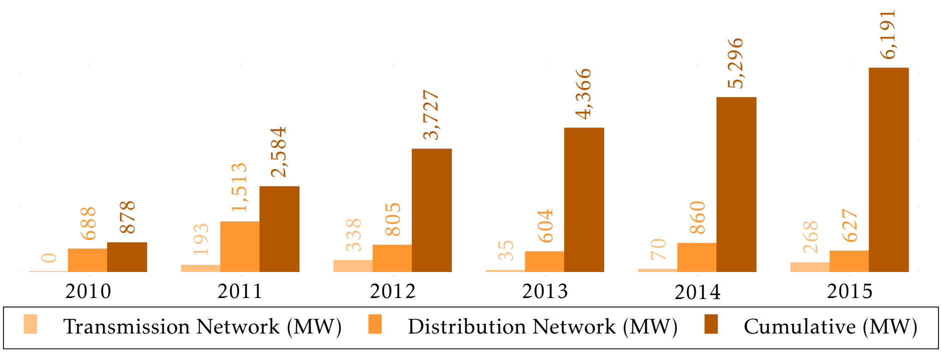


Figure 2.11: Installed Capacity in France 2010-2015 – PV Power

Wind power installations have also grown steadily in the period between 2010 and 2015, as illustrated in Fig. 2.12. This figure shows the yearly installations of wind DRES connected to transmission and distribution networks, and the total installed power in the country at the end of the year. New installed power in France grew at an average of 12.4 % between 2010 and 2015.

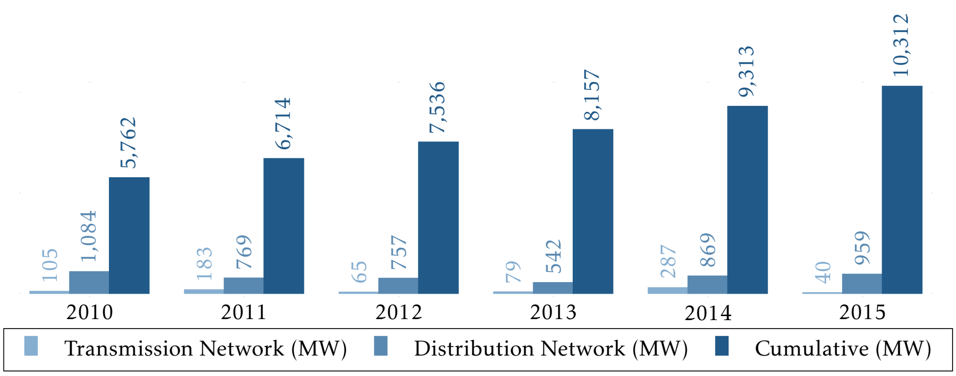


Figure 2.12: Installed Capacity in France 2010-2015 – Wind Power

One can infer an important fact from the figures. A large share of the new installations of both PV and wind DRES were connected to distribution networks during this

[2] Data available for networks managed by Enedis, serving 95 % of the territory.

period. In fact, among the 6.19 GW of installed PV power, only 565 MW (or 9.12 %) is connected to the transmission network. The rest is connected to the various distribution networks in France, and to the island network in Corsica. It is a similar story with wind power, where only 585 MW (or 5.67 %) of the installed wind power is connected to the transmission network. This means that distribution networks are at the forefront of this integration of DRES. Any ill-effects of a massive integration of DRES will therefore be directly felt by distribution networks.

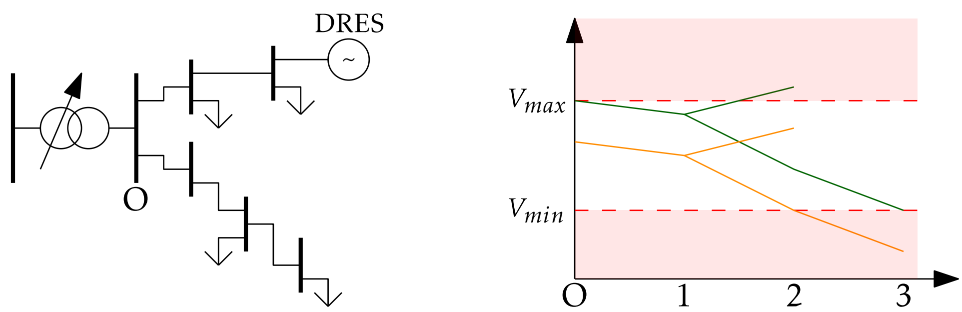
2.4.2 *Effects on Distribution Network Operation*

With a large integration of DRES, distribution networks, which were planned and are operated in a passive manner, will face several problems. Some of these problems are not immediately apparent, as the initial integration of DRES tends to improve certain network conditions. The effects of this integration, and in essence, the problems they pose to distribution networks, are presented here.

2.4.2.1 Effect No. 1 – OLTC Operation

The operation of OLTCs with and without compounding can be adversely affected by the integration of intermittent DRES. We recall that the automatic voltage regulation of OLTCs is done based on the measurement of the voltage at its secondary (without compounding) or based on the voltage $U - Z \cdot I$ (with compounding). With DRES integration, the taps chosen automatically may provoke voltage violations in the network. This is illustrated with the case below.

Let us take the example of the OLTC voltage control achieved in Fig. 2.8. Now, we add a DRES to the network, as shown in Fig. 2.13. The power injection from the DRES causes an increase in voltage at the node where it is connected. We recall that the operating principle for OLTCs considers that the voltages in the network decrease as we move further away from the sub-station. This cannot account for an increase in voltage downstream.



— Voltage before OLTC Operation
— Voltage after OLTC Operation

Figure 2.13: OLTC Operation with DRES

In this case, if the OLTC were to operate and choose a tap setting that increases the voltage, the under-voltage issue would be solved. However, the node with the DRES would exhibit an over-voltage violation, as shown in the voltage profile after the OLTC operation. In such a case, the OLTC is unable to maintain network voltages within the specified limits. This means that the principles of OLTC operation must be rethought, with a need for additional mechanisms for voltage regulation.

2.4.2.2 Effect No. 2 – Reverse Power Flows

The second effect of a high integration of DRES is reverse power flows. In MV distribution network, when production exceeds consumption, power flows from these networks to the transmission network. This phenomenon fundamentally affects the design criteria of distribution networks. In the case of protection for example, unidirectional trip relays will no longer suffice. This will necessitate additional investments in these networks. This will also require extensive system-wide operational changes and the implementation of additional control measures [SWE15].

2.4.2.3 Effect No. 3 – Losses

The third effect of a high integration of DRES is the change in active power losses. Depending on the location and the amount of power generated by the DRES connected to a distribution network, the active power losses may either increase or decrease. When DRES generation is close to consumption, the power generated transits through smaller distances. This decreases the losses in the network. Conversely, when the DRES is connected further away, losses increase. Losses also increase during the night when the demand is low and high power is generated from wind DRES generators. Generally, the trend is for the losses to decrease initially with low DRES integration, and then increase at higher integration rates, as illustrated in Fig. 2.14.

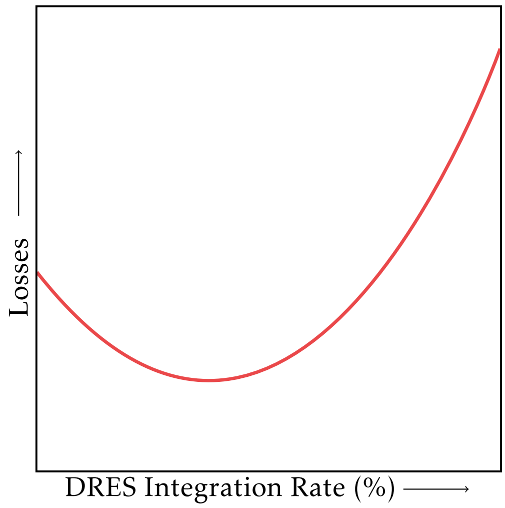


Figure 2.14: Losses with DRES

National regulation in many European countries promotes energy efficiency, and in countries like France obliges DSOs to take responsibility for distribution network losses [AED14]. This means that DSOs in these countries must buy electricity in the market to cover their losses, and usually negotiate long-term contracts to this effect. An increase in losses adversely affects the DSOs and their energy efficiency. This will force DSOs to find other ways to decrease losses, either in planning or during operation.

2.4.3 *Deregulation and The Creation of New Actors & Services*

The European directive 96/92/EC [Eur96] mandated the liberalisation of the energy sector and led to the creation of an internal European energy market. Competition between different actors in the electricity sector was subsequently encouraged, and the unbundling of production, transmission and distribution companies ensued. Today, this liberalisation has created several new avenues for actors – traditional and new – in the electricity value chain. Electricity markets, where electricity is traded from a long time to a few minutes before operation of electricity networks, are playing a vital role in this transformation. These markets and their actors are outlined in this section.

2.4.3.1 Electricity Markets

An electricity market, like any other market, is a place where electricity (commodity) is traded. This trade can take different forms, and can be done for different periods of time. An overview of the various electricity markets with the associated time-frames is presented in Fig. 2.15.

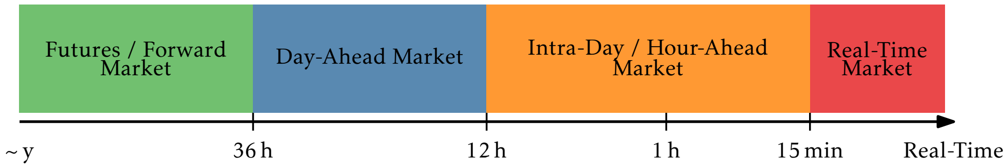


Figure 2.15: Overview of Electricity Market Time-Frames

The futures / forward market is where electricity is traded between several years to several days in advance. In this market, long-term electricity supply contracts are negotiated. The main reason for trading electricity in these markets is to hedge against the risk of price fluctuations. The prices in these markets tend to fluctuate less.

The day-ahead markets are where electricity is traded from 36 hours to 12 hours before real-time. In these markets, electricity is traded in blocks of half or one hour. The pricing in this market works on the Marginal Clearing Price (MCP) system [Nou09] where the highest price selected based on a merit order of supply contracts is paid to all selected supply offers. The largest day-ahead markets in Europe are NordPool and EPEX Spot.

The hour-ahead / intra-day market serves to adjust the power flows up to 45 minutes before the actual real-time, based on updated load and DRES forecasts. The pricing in this market is also decided based on the MCP, and generally tends to be higher than that of the day-ahead market. The day-ahead market and the hour-ahead market are sometimes referred to as spot markets.

The balancing or adjustment market (real-time) functions a bit differently from the rest of the markets. The main motivation of this market is to provide balancing and ancillary services to ensure system reliability.

2.4.3.2 New Actors in the Deregulated Environment

Before deregulation, only two major actors were present in the electricity value chain. The first one was the electricity company. This company was usually state-owned and constituted a monopoly. Its responsibility was to produce, transport, and distribute electricity. The other actor was the consumer who purchased electricity from the electricity company for consumption.

With deregulation, one of the first entities to be subject to unbundling was the electricity company. Unbundling refers to the separation of the activities of a company. This meant that in place of the electricity company, three actors were created: the electricity supplier, the transmission system operator (TSO), and the distribution system operator (DSO). This unbundling has been achieved to varying degrees in the countries in Europe. Belgium and Denmark have achieved complete unbundling of these activities, whereas other countries like France are still bundled in terms of the ownership. The French government has the controlling stake in the largest electricity supplier – EDF, the TSO – RTE, and the largest DSO – Enedis, and other DSOs like ESR (Strasbourg). A brief description of these actors along with the other new actors follows.

Grid users: Electricity suppliers and consumers are together called grid users, as they access the power system to inject or consume electricity. An electricity supplier, also called producer, is obliged to contribute to the voltage and reactive power control of the network they inject power into under certain conditions. A consumer is either a wholesaler or final customer of electricity. Wholesalers buy large blocks of electricity in markets to sell them to final customers. The difference in pricing constitutes their business model. France had more than 5 suppliers representing 95 % of the national electricity generation at the end of 2015. The Netherlands and Italy had around 650 suppliers, while Denmark topped the list with around 1300 suppliers of electricity.

System Operators – TSO & DSO: System operators are responsible for the planning, design, construction, operation, and maintenance of power systems. As explained in Section 2.2, the TSO is responsible for the transmission network, while the DSO is responsible for the distribution network. France has 1 TSO and 158 DSOs, while Germany has 4 TSOs and 880 DSOs.

Regulator: TSOs and DSOs are still regulated entities in the deregulated environment, due to the geographic nature of their activities. They cannot discriminate between different suppliers and must act in an unbiased manner during electricity trades in the market. The responsibility of ensuring that this discrimination does not occur lies in the hands of Regulators, which are independent public authorities.

Aggregator: An aggregator or flexibility operator is a new actor that aggregates and offers flexibility (see Section 2.4.3.3) in electricity markets or via bilateral contracts to system operators. The aggregator contracts flexibility from consumers and producers for a price, and sells it in the market for a higher price. Their business model lies in the difference in pricing.

Balancing Responsible Party (BRP): BRPs are actors who have a portfolio of generation and consumption within a physical perimeter. Their responsibility is to guarantee financial settlements for all imbalances recorded between injections and extractions within this perimeter to the System Operator. This is primarily done because the electricity supplied and consumed in a power system should be the balanced at all times for its proper functioning. Suppliers can either take this responsibility themselves, becoming BRPs, or contract a third-party to ensure this role.

2.4.3.3 Flexibility – A New Service

A service can be defined as a business transaction between two or more parties to achieve a particular goal. Aggregators, one of the new actors in a deregulated environment, offer flexibility in markets. This flexibility is a new service in the deregulated environment. Its goal is to help system operators manage constraint violations in their networks. But what is a flexibility, or how can one define flexibility? The answer to this question may come from a largely agreed-upon definition in reference [Eur14b], where flexibility is defined as follows:

Definition 2.1. *Flexibility is the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system.*

However, this definition may be restrictive in terms of what can or cannot be considered flexibility. This is because it restricts flexibility to generation and consumption in the network. In the context of this thesis we broaden the scope of flexibilities. We therefore redefine flexibility as follows:

Definition 2.2. *Flexibility is the modification of the state of an element in the network in reaction to an activation signal in order to improve network conditions.*

The justification for this new definition of flexibility is simple. We would like to call any modification to the status of distribution networks during operation as brought about by flexibility. This allows us to include OLTCs and reconfiguration, two traditional network operations, as a part of flexibility. In a competitive, deregulated environment, the DSO's aim is to be cost-effective in the utilisation of flexibility. Endogenous flexibilities like OLTCs and reconfiguration cannot be considered as free flexibilities, even though their utilisation entails no actual costs. The investements done by DSOs on these flexibilities have to be taken into consideration in this operation, and a utilisation cost must be computed. Their integration under the umbrella of flexibility allows the DSO to be cost-effective in their utilisation, as an unbiased comparison of the cost incurred to use each of these flexibilities can be facilitated (see Chapter 3). Based on this definition, a non-exhaustive list of different types of flexibilities in distribution networks is presented in Table 2.1.

Table 2.1: List of Flexibilities in Distribution Networks

Flexibility	Acts on
DRES Curtailment	Active Power Injection
DRES Q-Compensation	Reactive Power Consumption / Injection
Load Modulation	Active Power Consumption
Batteries	Active Power Consumption / Injection
OLTC	Tap Changer in Sub-station Transformers
Reconfiguration	Topology of Power Lines

We briefly describe the flexibilities listed in Table 2.1 below. Chapter 3 of this thesis revolves around this concept of flexibility and its cost-effective use in ADN. It also describes their technical and economic aspects in detail.

DRES Curtailment refers to the reduction in the active power output of DRES for a particular period of time. Some researchers also prefer to call it dispatch-down of DRES generation. At the outset, this flexibility may seem detrimental to the very concept of integration of DRES, and is a widely debated topic. However, in certain situations, research has shown that this is beneficial to the cost-efficient operation of networks [KJS12]. When network constraints are violated, this curtailment is shown to be acceptable.

DRES Reactive Power Compensation refers to the injection or consumption of reactive power in the network through the power electronic interface equipment. Reactive power compensation, also called *Q-compensation* is already widely used by some DSOs today to improve network conditions, especially voltages. Some DSOs like Enedis already require DRES connected to MV distribution networks to provide between -35 % and +40 % of the active power injected as reactive power compensation [ENE17]. In some cases, a reactive power compensation of up to -50 % may also be demanded.

Load Modulation or demand-side Flexibility refers to the modification of consumption in networks. Unlike generation-side flexibility, the physics of demand-side flexibility sometimes requires the restoration of the energy decreased. For example, if there is a reduction in the consumption of industrial processes, this needs to be restored, as these processes need a fixed amount of energy. Demand-side flexibility is therefore a reduction or a shift in the demand.

Batteries and other storage devices can be charged or discharged for a change in active power in the network. They work by storing and releasing energy through electrochemical reactions. Batteries have a rated capacity that cannot be surpassed and other restrictions on the charging and discharging rates that have to be met in order to use them as flexibility.

OLTCs, as already explained earlier in this chapter, work by changing the transformation ratio of the power transformer, and can be used to regulate the voltage downstream in the distribution network. When used as a flexibility, the way in which the taps are changed will have to be rethought. The drawback of automatic tap changes has been illustrated in Section 2.4.2. Taps have to be chosen during the operational planning to ensure coordinated control and to overcome the drawbacks of automatic tap changes.

Reconfiguration, as already explained earlier in this chapter, refers to the topology of a radial distribution network. It takes advantage of the redundant power lines in the network and modifies the paths through which the power flows. While reconfiguring the network, one has to ensure that there is no islanding. One should also ensure that there are no loops in the network, as such loops would provoke problems with protection equipment.

2.4.3.4 DSOs in a Deregulated Environment

Deregulation poses problems as well as opportunities for DSOs. To ensure the proper functioning of a distribution network in a deregulated environment, DSOs have to interact directly or indirectly with all the actors in electricity value chain. These interactions will not just be limited to electricity flows, but also information and financial flows. To effectively interact with these new actors, DSOs will have to undertake the following tasks.

DSOs will first have to be capable of observing[3] and controlling their networks. Investments in modernising distribution networks and their operation will therefore be necessary. The three major investment areas as identified by European DSOs are network automation and communication, smart metering, and demand-side management [Eur14a]. Communication devices and smart meters will help DSOs better understand the state of their network, and forecast production & consumption. Automation devices will help them control the state of their network based on these forecasts. Demand-side management and other flexibilities will help them achieve better control over congestions and voltage problems in their networks.

When DSOs can observe and control their networks, they will have to perform certain roles in order to interact with the other actors. As a part of these roles, they will have to obtain and offer certain services. Services that they can avail of, like that of flexibility, cannot be used as such. Since DSOs would have to spend money to avail of flexibility,

[3] A power system is said to be observable if its state variables (voltages, currents, and angles) can be measured, or uniquely estimated based on the available measurements.

decisions regarding its use must be streamlined. The cost of flexibility must first be evaluated, and it must then be used in an optimised manner.

In a deregulated environment, DSOs will therefore have to evolve, as these interactions will affect the way they build, operate, and maintain their networks. The new roles and services of DSOs in such an environment, along with the changes in operational practices necessitated by the integration of DRES are discussed in the next section on Active Distribution Networks.

2.5 ACTIVE DISTRIBUTION NETWORKS – THE SOLUTION?

The problems posed by the integration of intermittent DRES and the new responsibilities that DSOs have to take up in a deregulated environment underline the need to rethink the planning and operation of distribution networks. Active Distribution Networks (ADN) and the associated Active Network Management (ANM) are touted to be a means to solve these issues for DSOs. But what is an active distribution network, and how is it different from distribution networks today? In reference [CCS+11], active distribution networks are defined as follows:

Definition 2.3. *Active distribution networks are networks that have systems in place to control a combination of distributed energy resources (DERs), defined as generators, loads and storage. Distribution system operators (DSOs) have the possibility of managing the electricity flows using a flexible network topology. DERs take some degree of responsibility for system support, which will depend on a suitable regulatory environment and connection agreement.*

This definition focuses solely on the operation of distribution networks. In general, ADN is an umbrella term that encompasses all intelligent management of distribution networks, be it in planning, operation, or maintenance. The approach to managing ADNs is Active Network Management (ANM). In this approach, the DSO performs coordinated and optimised actions across different time-frames and domains [Eur13a]. Time-frames range from as early as several years before real-time operation of their networks, to the real-time operation and beyond. The domains that DSOs will work with in active distribution networks as identified in [EDA+14] are listed in Table 2.2.

Table 2.2: Domains in Active Distribution Networks

Domain	Description
NP	Network Planning & Connection
OP	Operational Planning
O&M	Operation & Maintenance
TDC	TSO-DSO Cooperation
MKT	Market

In the network planning domain (NP), DSOs will to take into account the totality of DRES connection requests instead of allowing access on a first-come first-served basis. A coordinated grid connection request process like the case of “evacuation boards” in Spain could be adopted. DSOs would also coordinate with TSOs and ensure that the planned network integration of DRES does not saturate transmission networks upstream. Network reinforcement decisions from DSOs would be coupled with flexibility in order to intelligently invest in planning and avoid over-sizing of their networks for worst-case network conditions.

In the operational planning domain (OP), DSOs would be able to create schedules for a coordinated control of their networks. As a part of these schedules, flexibilities that are present in the network and those that have been contracted or bought on the market could be activated, and be used to solve network constraint violations. These schedules would be created in an optimised manner, with an objective to decrease expenditures.

In the operation & maintenance domain (O&M), DSOs would be able to optimise their asset management and renewal processes, and take into account the operational requirements while creating schedules for these processes. In the TSO-DSO cooperation domain (TDC), DSOs would be able to communicate and manage TSO requests for flexibility activation, and intimate the changes in their own networks to the TSOs. In the market domain (MKT), DSOs would be able to first operate a market where flexibilities can be traded for their distribution networks. Such markets could be coupled with electricity markets for better access.

In all these domains, DSOs would work to offer services to new actors in the deregulated environment. These services and the new roles that DSOs will have to take up in order to offer them are discussed below.

2.5.1 *DSO Services & Roles*

The interactions between DSOs and other actors in the deregulated environment are done through services. Fig. 2.16 shows the various services that DSOs can offer in the context of ADN across time-frames and domains [EDA+14].

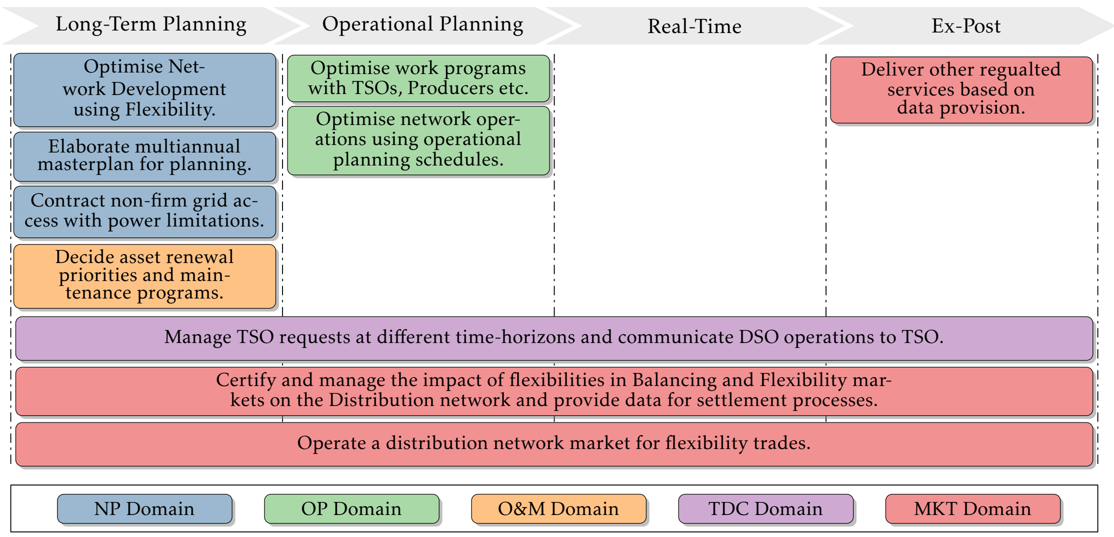


Figure 2.16: Services Provided by the DSO in Active Distribution Networks (Source: evolvDSO)

Three services are identified in the NP domain, all performed during the long-term planning time-frame. The two services in the OP domain are performed in the operational planning time-frame. The service in the TDC domain is performed across all time-frames. Two of the three services in the MKT domain are performed across all time-frames as well. The other service is performed in the ex-post time frame (after real-time). All these services are linked to responsibilities that DSOs must shoulder.

These responsibilities, called roles, and are illustrated in Fig. 2.17. Some of these roles are already being performed by DSOs and are shown in the figure as *low innovation* or *extended* roles. A majority of these roles are being studied by DSOs today and are shown as *medium innovation* or *evolving* roles. Other roles are completely new to DSOs and are shown as *high innovation* or new roles.

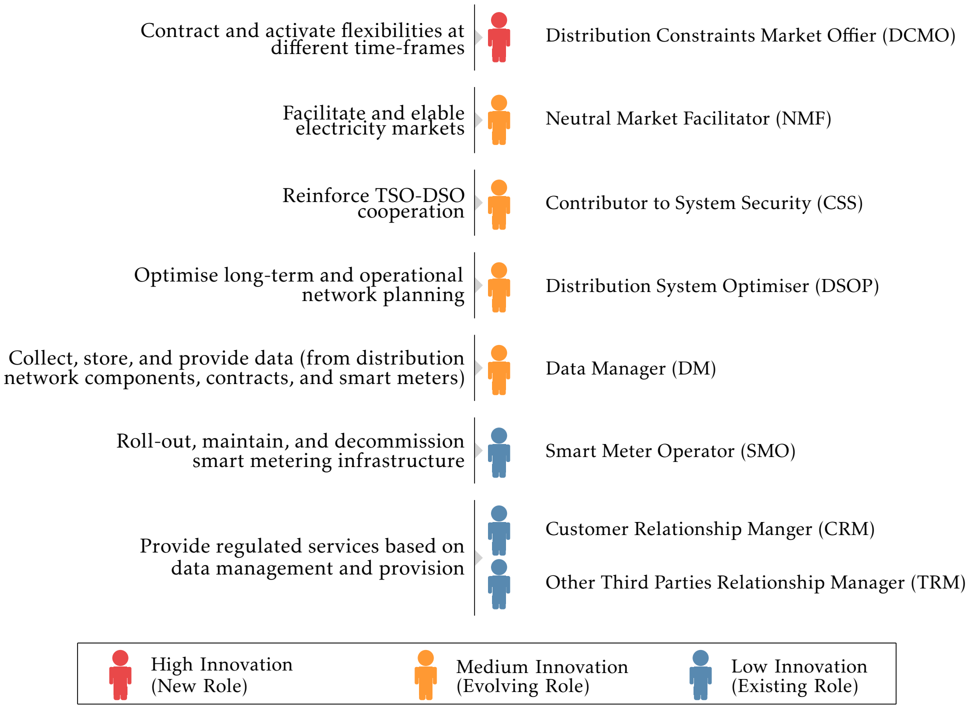


Figure 2.17: DSO Roles in Active Distribution Networks (Source: evolvDSO)

In the context of this thesis, the service we are particularly interested in is the optimisation of network operations using operational planning schedules. A part of the work leading to this thesis was applied to the development of a preliminary solution for operational planning of distribution networks in the evolvDSO project (see Appendix A). This work relied on this service, and the schedules created as a part of it enable the DSO to solve network constraint violations through the use of flexibility.

The DSO interacts with aggregators, the grid users, and the TSO as a part of this service. The main role that the DSOs need to perform in order to effectively optimise their networks in operational planning is the *Distribution System Optimiser* (DSOP) role. In this role, the DSO is tasked with improving the development, operation, and maintenance of distribution networks by managing network constraint violations in a cost-efficient and non-discriminatory manner.

One of the core responsibilities of DSOs is to ensure the safe operation of distribution networks. In a changing environment, the adoption of this role is rather logical, as it would permit DSOs to optimally use resources such as flexibilities in order to safely operate distribution networks. The adoption of such a role would not be a leap forward in terms of DSO responsibilities, but an evolution that would allow them to continue undertaking this core responsibility in this changing environment [Eur13a], [RPAS+13].

The other roles that the DSO would have to perform as a part of this service are those of the *Distribution Constraints Market Operator (DCMO)* and the *Data Manager (DM)*. In the DCMO role, the DSO would be able to select, contract and activate flexibilities in a dedicated market. In the DM role, the DSO would be able to collect, store, and analyse data pertaining to the distribution network and the components connected to it, like the state of the network elements, the generation, and the consumption. This role allows DSOs the improved observability of their networks that is necessary in ADN. A conceptual model of the interactions and roles in this service is presented in Fig. 2.18.

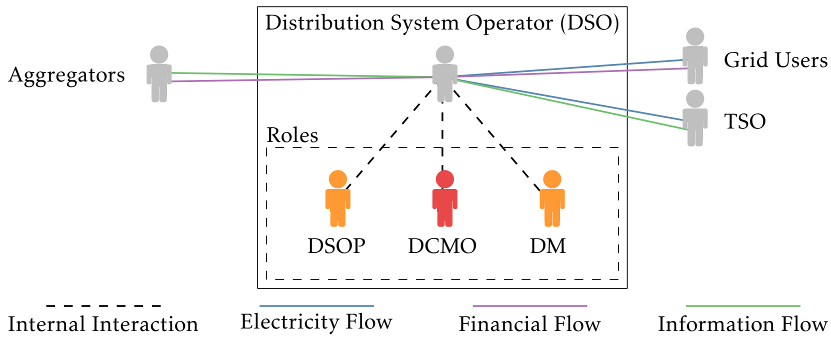


Figure 2.18: Conceptual Model of Roles and Interactions in the Operational Planning Service

The interactions in the figure are explained as follows. Four main types of interactions constitute the service. Internal interactions are those that concern the DSO and its capacity to perform the three main roles discussed previously in this section. Electricity flows exist between the DSO and grid users, as electricity is distributed to them via distribution networks. They also exist between the TSO and DSO. Information is exchanged by the DSO with the TSO (regarding network status among other) and aggregators (for flexibility use), while financial flows (flow of cash) exist between the DSO and Grid users (who pay for electricity, in the case where the DSO is a retailer) and aggregators (for flexibility use).

In practice, this service translates to a techno-economic short-term optimisation of flexibilities in the distribution network, to maintain network conditions within the prescribed limits. In the next section, the physical implementation of the service – operational planning in active distribution networks – is described.

2.5.2 *Operational Planning in Active Distribution Networks*

Operational Planning (OP) involves the creation of short-term schedules for distribution networks. These schedules are usually made for one day, on a day-ahead basis. This is natural, as a day represents an elementary cycle of time that repeats itself. Operational planning can also be done for a few days or a week at a time. In these schedules, set-points for the different flexibilities that the DSO is able to use are provided. Their use solves constraint violations in these networks.

As discussed in the previous section, three DSO roles intervene in order to make the operational planning process possible. These roles are the DCMO, the DM and the DSOP. A typical framework for operational planning is illustrated in Fig. 2.19.

In the Fig. 2.19, the market interface, and the flexibility block, shown in blue have the following functions. The exogenous flexibilities available on the market & through bilateral contracts, and those present endogenously (OLTC, reconfiguration and battery systems) are evaluated here. The evaluation has to be done in an unbiased manner, as the choice of using the flexibility has to be made without any preferential treatment. This evaluation and interface is the responsibility of the DCMO role.

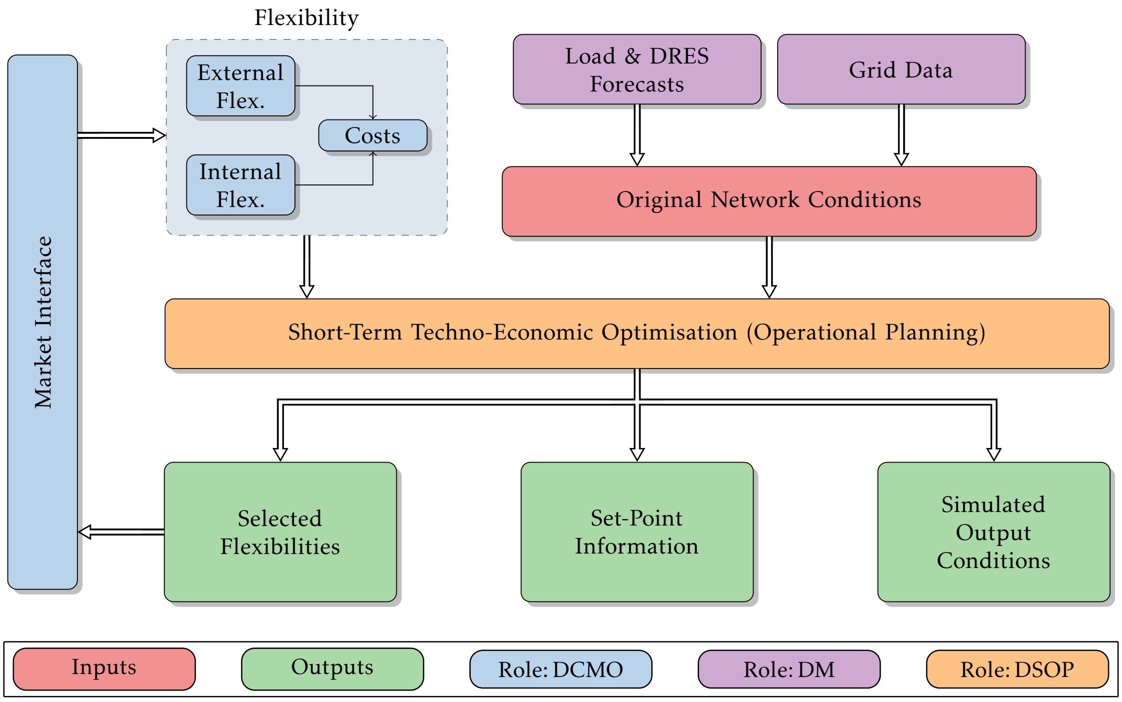


Figure 2.19: Typical Framework for Operational Planning in ADN

The forecasts for loads and DRES connected to the network, as well as the details of the network (*Grid Data*) are the responsibility of the DM role. The forecasts for loads can be generated based on the data from smart-meters. This data allows for the simulation of the conditions in the network, and allows the DSO to identify the time and location of network constraint violations.

The DSO, in the DSOP role, is then able to perform an optimal selection of flexibilities through the *Short-Term Techno-Economic Optimisation*. This optimisation should take into account the following points:

1 The cost of flexibility use must be minimised. We recall that the DSOP role is to be performed in a cost-effective manner. This means that the objective of the techno-economic optimisation should be to minimise costs.

2 The losses in the network (or the expenditures on losses) have to be minimised as well. This is necessary to mitigate the increase in losses due to DRES integration and its adverse effects on DSO revenues and energy efficiency targets.

3 The specificities of each of the flexibilities have to be accurately modelled in the optimisation. Some flexibilities like load modulation require energy restoration, while other flexibilities like OLTC are intricate in nature. The accuracy of modelling these flexibilities directly affects the solution to the optimisation, and therefore the DSO expenditures.

Finally, the output of the operational planning, shown in green, allows for the information of the selected flexibilities to be displayed and communicated to the market interface and for the simulation of the new network conditions. This can be directly interfaced to DSO control or operation centres to control the selected flexibilities.

In the next section, the contributions of this thesis are presented in the context of DRES integration in a deregulated environment. The need for these contributions and the improvements they bring for DSOs over the current scenario in are also outlined.

2.5.3 Contributions of the Thesis in Context

This thesis consists of 12 contributions numbered from C1-12, and presented in Chapter 1. These contributions are divided into three major themes: the modelling and economics of flexibility, the development of a convex optimisation formulation for operational planning of distribution networks, and the analysis of uncertainty in operational planning of distribution networks.

Contribution C1 of this thesis consists of analysing the technical characteristics of the flexibility that DSOs can use in operational planning. Through this contribution, a first step is made towards accurately modelling the technical characteristics of flexibilities. Where not possible, these models are made based on practically applied DSO methodologies. This contribution is necessary as some of the flexibilities have underlying physical constraints that have to be captured. We recall the example of load modulation with energy restoration.

Through contribution C2, economic models of these flexibilities are formulated for short-term operational planning. The necessity of this economic modelling stems from the need for DSOs to manage their expenditures and be cost-effective. An unbiased trade-off for flexibilities is particularly necessary in this context, and to avoid any preferential treatment afforded to a flexibility. This contributes to the overall economic optimality of the flexibility choices made by the DSO.

For example, OLTCs and reconfiguration switches are network assets owned by DSOs. The investment on these assets are considered as sunk costs in economics. In such a scenario, the utilisation of these assets may entail lower costs for DSOs than that for externally procured flexibilities. This may lead to overuse of these flexibilities, and higher DSO expenditures. In order to avoid this, the economic modelling of these flexibilities should integrate the investment cost as well.

Contributions C3 to C7 are towards the development of a convex optimisation formulation for operational planning. In operational planning, DSOs aim to minimise expenditures on flexibility. This means that any optimisation actions to choose these flexibilities must provide a choice of flexibilities that entail the least possible expenditures. Any simplifications in the underlying optimisation model may increase these expenditures, and decrease the cost-effectiveness of the DSOs in the long-term. The hindrance to this optimality comes from the non-linear and non-convex nature of the models for distribution networks and flexibilities. Solutions to such models cannot be guaranteed to be globally optimal, and may therefore not be the best in terms of DSO expenditures.

Through these contributions, the flexibilities and the network model are first convexified, and a formulation capable of providing a globally optimal choice of flexibilities is then developed. Tests on different distribution networks are then conducted with this formulation to show its effectiveness. A discussion on the effective use of these flexibilities is also presented based on the results obtained.

The optimality, or even the feasibility of the solutions provided by the convex formulation depends on the accuracy of the input parameters. In practice, parameters like DRES forecasts tend to change over time. While such forecasts are more accurate for short-term operational planning than for other long-term studies, their variability may decrease the quality of this formulation, or even render it infeasible.

In order to avoid this problem with solution quality and feasibility, the formulation developed and tested in contributions C3 to C7 has to take this variability into account. This is done through contributions C8 to C12. Through these contributions, the uncertainty in DRES is first analysed, and three different formulations that integrate uncertainty are developed, tested, and compared.

2.6 CONCLUSIONS

In this chapter, the generalised structure of power systems was first presented. This structure outlined the four major parts in power systems: transmission networks, subtransmission networks, MV distribution networks, and LV distribution networks. Each of these parts and its functions were briefly described.

Next, the status quo in distribution networks was presented. The core responsibilities of DSOs were first discussed. The current practices of DSOs with regards to planning and operating their networks were then outlined. These practices are prevalent in what can be called *Passive Distribution Networks*, where DSOs oversize networks in planning and then perform minimal and reactive network operations to handle network constraint violations.

The two major problems that face passive distribution networks were then presented. The first problem, the massive integration of DRES and its effects on distribution networks, was first discussed. The rising shares of DRES in European countries including France were illustrated with the latest publicly available data. The three adverse effects of this DRES integration on distribution networks – on OLTC operation, on reverse power flows, and on losses – were then discussed.

The second problem, deregulation and the creation of new actors and services, was then outlined. The new actors created due to deregulation of power systems were introduced. Flexibility as a service in the deregulated environment was also briefly described. An introduction on the different types of flexibilities present in distribution networks was done as a part of this description. The need for DSOs to evolve in light of the new threats and opportunities posed by deregulation and related political decisions was stressed upon.

These two problems underlined the need to rethink the current DSO practices. The concept of Active Distribution Networks (ADN) was presented as a solution to these problems. As a part of ADNs, DSOs would take up new responsibilities, called roles, and offer new services, in order to interact with all the actors in a deregulated environment.

One of the services related to operational planning of distribution networks, the main theme of this thesis, was then elaborated. The interactions and roles that this service necessitated were then described. The practical implementation of this service was then elaborated, and this lead to the contextualisation of the contributions of this thesis. This contextualisation explained the necessity and the role of each of the contributions with respect to the information presented in this chapter.

In Chapter 3 of this thesis, the concept of flexibility in operational planning is discussed. The technical and short-term economic models of the flexibilities identified in this chapter are developed, and the utilisation costs of these flexibilities for a test case are calculated from these models.

3 Flexibility in Operational Planning

« Develop flexibility and you will be firm; cultivate yielding and you will be strong. »
- Lie Yukou (Liezi, ca. 400 BCE)

3.1 Introduction

3.1.1 Context

Flexibility has existed in power systems for a long time, even if it was limited to the domains of power generation and the management of transmission networks. In this traditional context, flexibility essentially referred to generation reserves. In distribution networks, elements like reconfiguration and OLTCs existed and were used to manage network constraints. However, they were not called flexibility, as the name implies activation through external stimuli (signals) and an inherent optimal decision making behind their use. Reserves in transmission networks were used in optimised dispatch, where both activation signals and optimal decision making existed. In distribution networks, OLTCs were used in a reactive manner, responding to changes in downstream voltages. For its part, reconfiguration was in most cases used to change the network topology seasonally, or after a fault. These elements could therefore not be called flexibility in a traditional context.

However, with a rapid integration of intermittent DRES and in a deregulated environment, the context in which power systems operate is changing. Distribution networks are at the front-lines of these changes. A passive management of these networks with OLTCs and reconfiguration may not suffice in this new context. The effects of this new context on the operation of distribution networks, and the insufficiency of OLTCs for instance, were detailed in Section 2.4.2 of Chapter 2.

Active Distribution Networks (ADN) are shown to be a potential solution to these ill-effects, and flexibility in distribution networks is one of their main components. Flexibility is, as defined in Chapter 2, "the modification of the state of an element in the network in reaction to an activation signal in order to improve network conditions." Sources of flexibility in distribution networks were also identified and outlined in the same chapter. When reconfiguration and OLTCs are activated through external signals in an optimised manner, they can also be considered as flexibilities. This is typically the case in ADN.

Flexibility is arguably the key to integrating intermittent DRES in active distribution networks. In long-term planning, we know that the integration of intermittent DRES is causing dimensioning problems in planning. By considering flexibility in planning, DSOs could potentially defer or avoid expensive oversizing of networks related to the construction and reinforcement of power lines and other infrastructure [THJ+15], [CE16].

With intermittent DRES, the traditional critical operating points will see a very low probability of occurrence. In operational planning (OP), flexibility has been shown to be useful in solving distribution network constraint violations, and improving the quality of supply [DGR+15].

However, the use of flexibility in ADNs entails certain requirements. In this context, to integrate flexibility in operational planning, the following points have to be considered:

1 The effects of flexibility use on distribution networks have to be ascertained. This means that flexibilities have to be modelled, and their operational limits have to be assessed. Also, flexibility is a service in active distribution networks. A service is a business transaction, and the DSO, in a deregulated environment, is in competition with other actors. Any use of flexibility must therefore come at a cost to the DSO.

2 In operational planning, the DSO's aim is to be cost-effective in using flexibilities to solve network constraint violations. Since the use of flexibility entails DSO capital and operational expenditures, its integration into operational planning must be done only after these expenditures can be evaluated. To do so, models to determine utilisation costs of flexibilities have to be developed.

3 Since DSO-owned flexibilities like reconfiguration and OLTCs are also considered as flexibilities, their economic models have to be developed in an unbiased manner, considering the real cost of utilising these flexibilities. This would not allow a preferential choice of these flexibilities and would actually result in the use of the cheapest overall flexibilities in operational planning.

Conforming to the considerations listed above, in this chapter, the technical and economic models for flexibilities in distribution networks are developed. The major contributions of this chapter are listed below. The numbering is consistent with the list in Chapter 1.

C1 The development of technical models of endogenous and exogenous network flexibilities. These exact models accurately / practically capture the behaviour of the flexibility, conforming to literature or to practically applied DSO methodologies.

C2 The economic analysis of these flexibilities in the short-term context, with an emphasis on achieving an unbiased trade-off between endogenous and exogenous flexibilities in terms of utilisation costs. The derivation of these utilisation costs for flexibilities for a particular test case, to be utilised in a techno-economic optimisation.

3.1.2 Organisation of this Chapter

This chapter is organised as follows. The current scenario for flexibility use in operational planning in the case of five European DSOs is subsequently presented in Section 3.2. The information presented is the result of a survey conducted as a part of this thesis and presented in [Pau16]. The survey outlines the capabilities and barriers of the DSOs with respect to the use of flexibilities. The impediments to the use of flexibility are also discussed, along with the potential solutions that active distribution networks can bring to them in the near future.

The development of models for flexibilities in distribution networks is the focus of Section 3.3. In this section, a discussion on the real utilisation cost of DSO-owned flexibility in the short-term is first presented. This discussion deals with the issue of ascertaining the actual cost incurred by DSOs when they use endogenous flexibilities like reconfiguration, OLTCs, and battery systems. It aims to facilitate the development of unbiased economic models for endogenous flexibilities, as outlined in one of the considerations presented in the introduction. Subsequently, the technical and economic models of different flexibilities in distribution networks are developed. The technical models developed aim to accurately depict the working of these flexibilities. Where this is not possible, the models actually used by DSOs in practice are considered. The economic models strive to provide a means to analyse the cost of use of each of the flexibilities.

This is followed by the calculation of utilisation costs for these flexibilities for a particular test case, and is presented in Section 3.4. These utilisation costs are calculated in order to be used in a techno-economic operational planning formulation. The concluding remarks are finally presented in Section 3.5.

3.2 CURRENT SCENARIO – DSO AND FLEXIBILITY USE

As a part of the study on flexibility in electrical distribution networks, we conducted a survey with 5 major DSOs in Europe. In this section, the survey results are first presented. Then, a summary of the issues identified as a result of this survey with respect to the use of flexibility in operational planning is presented. The results of the survey have been published as a part of the evolvDSO project in reference [Pau16].

3.2.1 Survey Results

The survey conducted with 5 major European DSOs, with a total of around 98 million customers, consisted of questions related to the regulatory barriers for flexibility use, the availability of endogenous flexibility, their capability to use flexibility, and their current operational planning practices. An illustration of the responses is shown below in Fig. 3.1. Some of the responses in this section have been made anonymous at the request of all the DSOs.

The responses to the survey indicate the following situations with respect to flexibilities and DSOs. Regulatory barriers for the use of flexibility exist to some extent in all the countries surveyed. In Italy for example, the DSO is not allowed control flexibilities at all. In the other countries, regulation related to the control and exploitation of flexibilities is not yet clear. In France, trial projects where the DSO is able to use flexibility are ongoing, as indicated by the DSO.

All the surveyed DSOs indicate that their networks contain endogenous flexibility like OLTCs in primary sub-stations and reconfiguration. The DSOs also indicate that reconfiguration decisions are not made as a part of an optimisation routine. Three of the five surveyed DSOs indicate that they are able to control the active and reactive power flows in their networks through the use of flexibility.

As for the curtailment of DRES, the responses show that in most of the cases, DSOs are allowed to curtail active power from DRES, even if only under special circumstances.

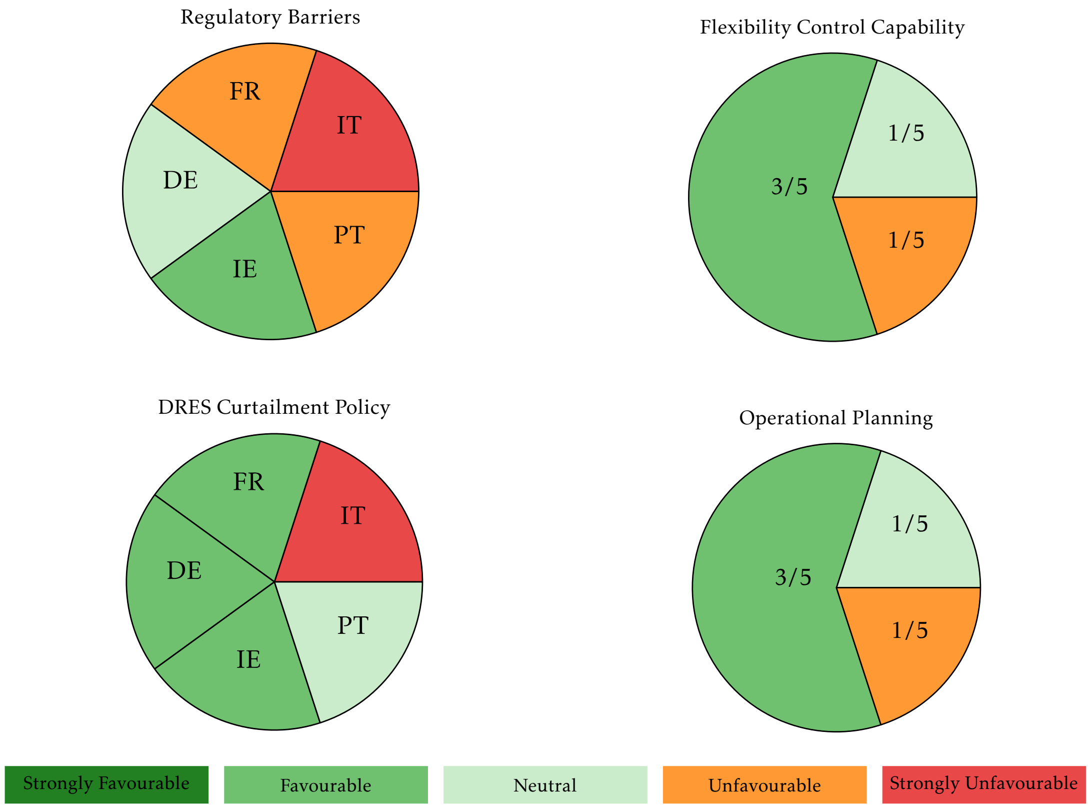


Figure 3.1: Survey Results on DSO Flexibility Use

In Italy, curtailment is not allowed in normal operation of distribution networks. In Portugal, wind DRES is for example allowed to inject up to 20 % above their contractual power. This power can, when needed, be curtailed for free. In France, the DSO can disconnect large DRES generation units over a limited number of hours per year for free. They have to pay penalties if other DRES units are disconnected or curtailed. In Germany, DSOs can curtail DRES if there is a problem with the amount of power injected. They have to pay for this curtailment. However, if the DRES affects N-1 contingency conditions (security conditions), they can curtail them for free.

Three out of the five surveyed DSOs showed interest in adopting operational planning formulations in their networks. However, only one of those DSOs actually uses operational planning in their networks. The other two DSOs are testing operational planning routines that take into consideration the forecasts for loads and DRES and impose inter-temporal constraints.

In the survey, the DSOs also identified principal temporary impediments to the use of flexibility and to operational planning in distribution networks. These impediments are discussed in the section below.

3.2.2 *Impediments to Flexibility use in Operational Planning*

Three main temporary impediments to the use of flexibility in operational planning were identified by the surveyed DSOs. These impediments, along with the potential solutions that Active Distribution Networks can bring are discussed herein.

The first impediment identified to the use of flexibility in operational planning is the observability of distribution networks. DSOs today do not have a complete picture of the state of their network, due to the lack of sensors in the network and of information about the different grid users. With a large-scale roll-out of smart meters and other communication devices, active distribution networks of the future promise to overcome this issue. By taking up the Data Manger role, DSOs, with the help of communication devices and control interfaces, should have sufficient observability of their networks.

The second impediment relates to the limited technical prowess access that DSOs have today with respect to flexibility, more so in the case of exogenous flexibility than endogenous flexibility. Pilot programs for flexibility use in distribution networks are few in number, and are mostly used for transmission network purposes. This decreases the possibilities for DSOs in operational planning. In the future, access to flexibility should increase, given that the DSOs will improve their technical ability to use flexibility through the use of optimised network planning and operational planning approaches.

The third impediment is that apart from the technical limitations to accessing flexibility, DSOs today do not have access to the market for flexibilities. This should however change if the proposals in the 2016 Clean Energy Package from the European Commission [Eur16b] are to be accepted. The proposals allow for DSO access to energy markets to contract and activate flexibility, including the procurement of standardised services from resources such as distributed generation, demand-side response, storage, and energy efficiency measures and from all market participants [Lin16].

In the future, it should therefore be possible for DSOs to contract and use flexibility in operational planning of their networks. In the next section, the technical and economic models of flexibilities envisaged to be used in operational planning are developed.

3.3 FLEXIBILITY IN OPERATIONAL PLANNING – MODELS

The flexibilities listed in Table 2.1 in Chapter 2 can be broadly classified into two categories. Endogenous flexibilities like reconfiguration, OLTCs and batteries are owned by the DSO. This means that investments for these flexibilities are made by the DSO themselves. Exogenous flexibilities, like load modulation and flexibility from DRES, are contracted flexibilities that are offered by other actors in the deregulated environment, like aggregators. One of the proposals in the 2016 Clean Energy Package [Eur16b] provides DSOs the ability to contract and use exogenous flexibility. However, citing the proposal, "since many DSOs are part of vertically integrated companies which are also active in the supply business, regulatory safeguards are necessary to guarantee the DSOs' neutrality in their new functions, e.g. in terms of data management and when using flexibility to manage local congestions."

In essence, the package allows DSOs to contract and use flexibility, but in an unbiased manner. This means that the DSOs should not show preference to using a specific type of flexibility, and will be held accountable by regulation to ensure that flexibilities are used based on their merit. An unbiased use of these flexibilities is especially important in a case where endogenous DSO flexibilities like reconfiguration and OLTCs will have to be used alongside exogenous flexibilities.

The equipment allowing DSOs to utilise endogenous flexibilities are already present in distribution networks. This means that for such equipment, investments have already been made. If these investments are considered as "sunk" costs, any economic model for their utilisation costs would not consider the investment, and would result in an underestimation. When subsequently, these costs are used in an optimisation for operational planning along with the costs for exogenous flexibilities, the results obtained may show a bias towards the utilisation of endogenous flexibilities, even though these flexibilities cost the DSO more. It is therefore necessary to consider a part of the investment costs in the economic model describing the utilisation costs of endogenous flexibilities.

In this section, we develop technical and economic models of endogenous and exogenous flexibilities. The economic models of endogenous flexibilities are developed by integrating investment costs, in order to avoid the underestimation and bias described above. The economic models of exogenous flexibilities are developed based on currently available information with respect to the use of these flexibilities.

3.3.1 Reconfiguration

MV distribution networks are generally built to be meshed, but operated in a radial fashion[1]. This means that there is a potential to modify the topological configuration of these networks by utilising the redundant lines in the network. The connection status of the power lines in the network is modified to change the topology of the network. This change is called network reconfiguration.

Traditionally, reconfiguration was a means used by DSOs to modify the network topology after a fault, during maintenance, or to balance loads across network feeders during seasonal changes in consumption patterns. The number of reconfiguration actions performed in networks was therefore relatively low. This approach to reconfiguration was justified for the following reasons. Firstly, the switching devices in distribution networks were traditionally operated manually, in countries like Germany for example. This meant that someone had to be physically present on-site to perform the reconfiguration action. For actions containing many open / close operations across the network, a real coordination was therefore necessary. Secondly, this manual coordination created loops in the network, even if only for brief moments in time. This posed a problem related to protection schemes and high short circuit currents. Thirdly, frequent use of these switches in energised power lines resulted in rapid degradation of the material, as traditional switching elements were not rated for looped operations. In countries like France, where the switching elements were automatic, the issue with coordination did not exist. However, the relatively low use of these elements was due to a voluntary choice of the system operator.

In recent times, reconfiguration has become more interesting due to the following changes. Firstly, new switching devices in distribution networks can be operated remotely from control centres. This greatly improves coordination during reconfiguration. Secondly, this coordination makes it easier to maintain protection schemes, as the duration of momentary loops is reduced. Thirdly, switching devices are rated for between 100 and 1000 on-load (electrical) operations [Ena07]. Network reconfiguration is therefore an interesting flexibility to be considered in the operational planning of distribution networks. In this section, we develop a technical and economic model for this flexibility.

[1] A vast majority of distribution networks are radial. For simplicity, distribution networks are considered radial in the scope of this thesis.

3.3.1.1 Technical Model

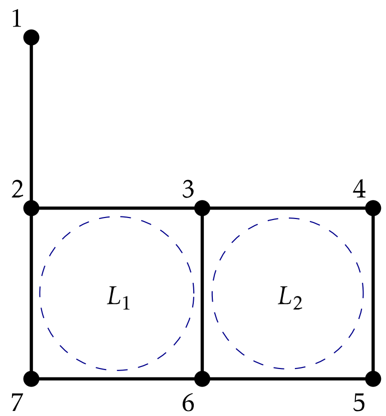
The purpose of reconfiguration is to find a new radial topology for the distribution network without disconnecting any consumption or production. This means that in general, loops and/or islanding of nodes cannot be accepted in the final topology. Reconfiguration can be integrated in operational planning by imposing certain constraints. We call these radiality constraints.

The constraint (3.1) is one such constraint used to ensure that the number of closed lines in the network, represented by a binary reconfiguration variable e_{ijt}, is equal to the difference between the number of nodes and the number of slack nodes in the network. The reconfiguration variable takes a value of 0 or 1 depending on whether the line ij it represents is connected or not. This status can change over time (index t). In steady-state operation of the power system, the status of reconfiguration changing over time can be used to accommodate for maintenance of power lines. Restoration of supply after faults can also be considered, while keeping in mind that this work considers only the steady-state modelling.

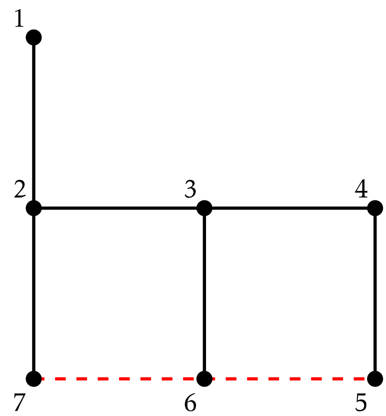
$$\sum_{ij\in\Omega} e_{ijt} = n_N - 1 \qquad \forall t \in T \tag{3.1}$$

This constraint should usually suffice when imposing radiality on a network. However, as some researchers have observed, under a high penetration of DRES (or any embedded generation for the matter), self-sufficient zones could be created wherein the local production could be high enough to feed all the loads. This potentially creates islands during reconfiguration, even if constraint (3.1) is satisfied. This is illustrated below.

A 7-node meshed network is shown in Fig. 3.2a, with two elementary loops L1 and L2. A permissible radial configuration, satisfying the constraint (3.1) is shown in Fig. 3.2b. In case a DRES is present in the network (Fig. 3.3) and if this DRES produces enough power to cater to local consumption, an island may be created as shown in Fig. 3.3b.



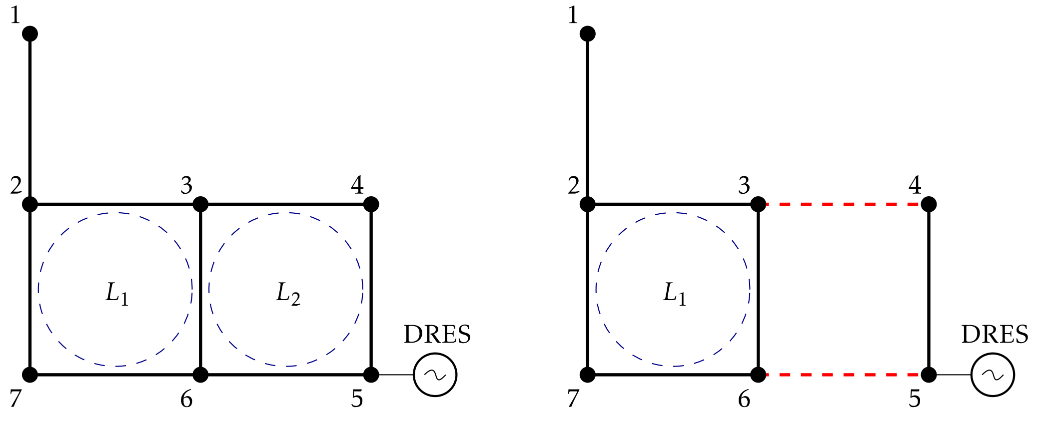
(a) Meshed Network with Loops L1 and L2



(b) A Radial Configuration

Figure 3.2: Concept of Elementary Loops - 1

Certain DSOs do not accept islanding in their networks. Therefore, to overcome this issue, path constraints were introduced in [RRRSR10]. However, the complexity



(a) Meshed Network with DRES (b) Islanded Nodes with DRES

Figure 3.3: Concept of Elementary Loops - 2

of these constraints increases exponentially with the number of loops and DRES. We use a method based on elementary loops, first presented in [LFRR12] and exploited in [Tou14] and [Van16]. In this method, a second radiality constraint (3.2) is added. This constraint imposes the number of closed lines in an elementary loop to be at most equal to one less than the number of lines in the loop. The advantage of this constraint is that its complexity increases linearly with the number of loops, and is independent of the number of DRES in the network.

$$\sum_{ij \in C} e_{ijt} \leq n_C - 1 \qquad \forall C, \forall t \in T \tag{3.2}$$

In combination with constraint (3.1), constraint (3.2) ensures radiality even in a case with a high penetration of DRES. The reader may consult references [LFRR12] and [Tou14] for proof of this method.

3.3.1.2 Economic Model

The economic model of reconfiguration aims to model the economics of the usage of reconfiguration switches. A change in the status of these switches is called a switching action. There are two components to the economic model of the switching action. The first component is related to the depreciation of the investment on the switch. This occurs whether or not the switch is in use. To model this depreciation cost ρ^{dep}, we express the following.

$$\rho_i^{dep} = \rho^{inv} \cdot K_i/n \qquad i = 1, \ldots, n \tag{3.3}$$

$$\rho_d^{dep} = \rho_i^{dep}/365 \tag{3.4}$$

Here, ρ_i^{dep} and ρ_d^{dep} are the yearly and daily depreciation, ρ^{inv} is the capital cost of the switching device, K_i is the depreciation factor of the switching device for each year, and n is the expected pay-back period for the switching device in years. The depreciation factor is a factor that represents the ageing of the device. This factor has to conform to the following constraint.

$$\sum_{i=1}^{n} K_i = n \tag{3.5}$$

This means that the relationship between ρ^{inv} and ρ_i^{dep} can also be expressed using the following equations.

$$\rho^{inv} = \sum_{i=1}^{n} \rho_i^{dep} = \sum_{i=1}^{n} \rho^{inv} \cdot K_i/n \tag{3.6}$$

At the end of the pay-back period n in years, the total depreciation cost of the switch should be equal to the investment cost. In other words, the value of the switching device should be equal to 0 at the end of the pay-back period. Considering a preventive maintenance approach after a set number of operations, the cost of maintenance per operation can be given by:

$$\rho_m^{op} = \frac{\rho_m^{tot}}{n_m} \tag{3.7}$$

Here, ρ_m^{op}, ρ_m^{tot}, and n_m are the cost per operation, total maintenance cost, and number of operations before preventive maintenance respectively. The final cost of operation of each switching device is represented by the two parameters ρ_1^{rec} and ρ_2^{rec}. They are expressed as follows.

$$\rho_1^{rec} = \rho_d^{dep} \tag{3.8}$$

$$\rho_2^{rec} = \rho_m^{op} \tag{3.9}$$

In this thesis, the operational planning for distribution networks considers a time horizon of one day. This is the reason for the calculation of the daily depreciation cost. It is to be noted that among the two coefficients, ρ_1^{rec} is "incurred" by the DSO even when there are no switching actions performed. We recall that these costs are not actually incurred during every day in the operational planning, but are added to the utilisation cost in order to reflect the real operational cost of flexibilities owned by the DSO.

3.3.2 On-Load Tap Changers

An On-Load Tap Changer (OLTC) is a mechanism in a transformer that changes the transformation ratio of the transformer in discrete steps. Each of these steps, associated with a particular transformation ratio, is called a *tap*. By switching the taps, and thereby modifying the transformation ratio, the OLTC is able to change the voltage at the secondary of the transformer.

OLTCs differ from Off-Load or No-Load Tap Changers in the sense that the switching of taps can be done without de-energising the transformer. This is especially useful when loads are connected to the network downstream of the transformer. In traditional, mechanical tap changers, this switching action is achieved through the use of tap selectors and diverter switches. This is illustrated in Figs. 3.4a to 3.4e, where the tap changes from tap 2 to tap 3.

Other, newer generation OLTCs use hybrid power electronic switches to ensure continuity of the on-load current when the tap change occurs. Some other OLTCs have such switches to also change the taps, in addition to ensuring the continuity of current. The advantage of these OLTCs is that there is no arcing during tap changes and higher reliability, while the disadvantage is that auxiliary circuits are necessary to control these switches, making the OLTCs more expensive.

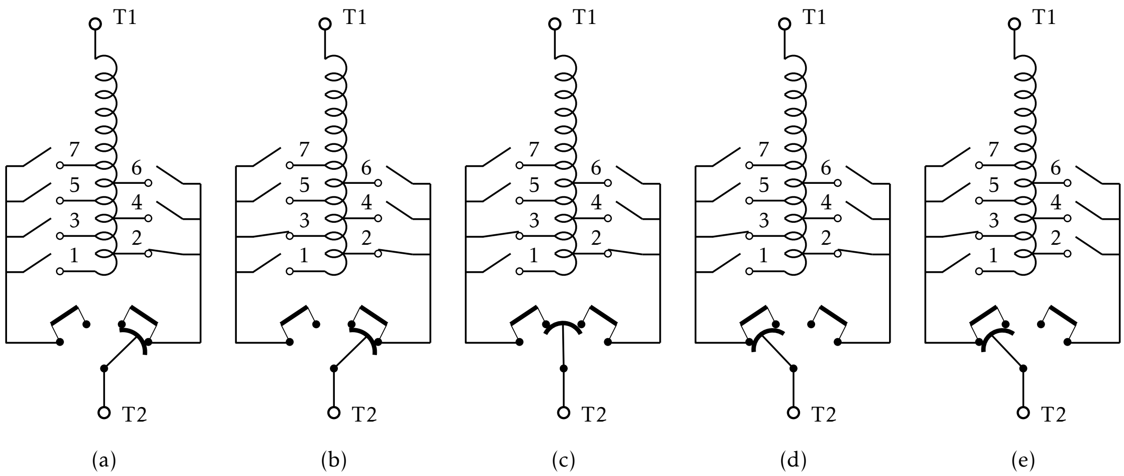


Figure 3.4: Tap Changing in a Mechanical OLTC

3.3.2.1 Technical Model

We model the OLTC and the transformer as a power line ij with a ratio k_{ij} that represents the transformation ratio [Pra94]. Since the taps in the OLTC are discrete, the values that k can take are also discrete in nature, and constant for each tap. By choosing one of the possible values that k_{ij} can take, the functioning of the OLTC which modifies the transformation ratio can be simulated. OLTCs usually have 17 to 25 taps, although others with 9 or 5 taps have also been studied and used in practice [Rau16].

Fig. 3.5 shows the equivalent circuit of a transformer with an OLTC. In this figure, Y_0 represents the no-load losses of the transformer referred to the secondary. The Ohmic losses and other leakages are modelled using Z_{ij}. The value of k_{ij} is chosen depending on the tap chosen by the OLTC, and acts on the impedance Z_{ij}. This model has already been adopted in [Tou14].

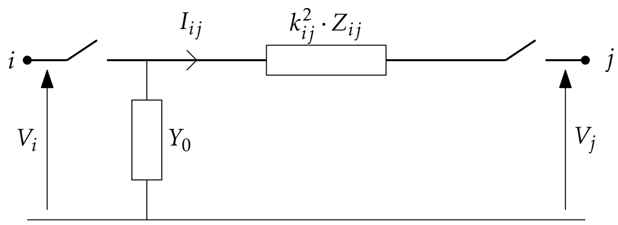


Figure 3.5: Model of the OLTC with a Transformer

The voltage at the secondary of the transformer V_j is a function of the voltage of the primary of the transformer V_i, its impedance referred to the secondary Z_{ij}, the transformation ratio as set by the OLTC k_{ij}, and the current flowing through the main circuit of the transformer I_{ij}. This relation is described below.

$$V_j = V_i - I_{ij} \cdot k_{ij}^2 \cdot Z_{ij} \tag{3.10}$$

3.3.2.2 Economic Model

The economic model of an OLTC aims to model the economics of the usage of the OLTC, when the current transits through it, and when tap changes are made. Two different methods can be used to develop the model for OLTCs. In the first, integral method, the cost of each operation depends on the number of available operations before a periodic maintenance operation. The OLTC can thus be used more frequently at the beginning, when a high number of operations are available, and less when the maintenance is imminent. The second method uses a fixed function that does not depend on the how imminent the maintenance is, and instead focuses on using the OLTC independently. In this method, the cost of each OLTC tap change is fixed, and a portion of this cost is comprised by the cost of periodic maintenance. An example of the first method can be found in [ZR05]. The second methodology, described here, has been developed as a part of this thesis and presented in [JJR+15].

This economic model in this method is similar to the model developed for reconfiguration. We first calculate the annual depreciation ρ_i^{dep} of the OLTC as follows:

$$\rho_i^{dep} = \rho^{inv} \cdot K_i/n \qquad i = 1, ..., n \tag{3.11}$$

$$\rho_d^{dep} = \rho_i^{dep}/365 \tag{3.12}$$

Here, ρ_i^{dep} and ρ_d^{dep} are the yearly and daily depreciation, ρ^{inv} is the capital cost of the OTLC, K_i is the depreciation factor of the OLTC for each year, and n is the expected payback period for the OLTC in years. The following conditions related to the depreciation and investment have to be respected, like in the case of reconfiguration:

$$\sum_{i=1}^{n} K_i = n \tag{3.13}$$

$$\rho^{inv} = \sum_{i=1}^{n} \rho_i^{dep} = \sum_{i=1}^{n} \rho^{inv} \cdot K_i/n \tag{3.14}$$

For the maintenance costs of the OLTC, given that there is a preventive maintenance approach followed between every set number of operations, the cost can be given by:

$$\rho_m^{op} = \frac{\rho_m^{tot}}{n_m} \tag{3.15}$$

Here, ρ_m^{op}, ρ_m^{tot}, and n_m are the cost per operation, total maintenance cost, and number of operations before preventive maintenance respectively. The two cost components of the OLTC, ρ_1^{oltc} and ρ_2^{oltc} are respectively the depreciation cost during the period considered for the operational planning and the maintenance cost per operation.

$$\rho_1^{oltc} = \rho_d^{dep} \tag{3.16}$$

$$\rho_2^{oltc} = \rho_m^{op} \tag{3.17}$$

Similar to the case for reconfiguration, the first component is related to the daily depreciation, and is "incurred" whether or not the OLTC is used. This corresponds to the actual cost of utilsation that factors the investment cost of the transformer and the OLTC. Only the cost ρ_2^{oltc} is incurred in reality as a part of daily OLTC operations.

3.3.3 *Battery Systems*

Battery systems consist of power electronic and electrochemical equipment to convert and store energy respectively. Their use in distribution network applications has been studied for quite sometime now. In Italy for example, the largest DSO *e-distribuzione* plans to install battery storage systems in 40 primary sub-stations in its network [HJT14]. However, to date, this has not been done. Apart from some planned large-scale pilot applications like the one in Italy, very few actual applications of these systems have been realised for batteries as distribution network flexibility. This is partly due to the high capital costs of these systems [SWE15]. With time, as some of the technologies behind battery systems mature, the capital costs will naturally decrease.

With a high integration of intermittent DRES, storage technologies like battery systems can be used to complement the variability of intermittent DRES. Their potential uses in operational planning of distribution networks find their roots in the ability of these systems to control power flows, regulate voltages, and smoothen the variable production from DRES in a fast and efficient manner. In this section, we develop technical and economic models for a generalised battery system.

3.3.3.1 Technical Model

A battery system can be described by the following parameters: the rated energy, the maximum power that the battery can store / discharge, the charging and discharging efficiency, the state of charge, the allowed depth of discharge, and the lifetime energy throughput.

The rated energy of the battery E^{bat} is expressed in MWh. It is the maximum theoretical energy that the battery can store. The maximum power that the battery can store or discharge $\overline{P^{bat}}$ depends on the power conversion capability of the battery and the power electronic interfacing equipment. The charging and discharging efficiency η^{in} and η^{out} are used to account for the inefficiency in the power conversion in the power electronic equipment and the battery. The state of charge E_t^{soc} provides an indication of the additional energy that the battery can store or produce. A lower limit on the state of charge is the depth of discharge (DoD) represented by the parameter E^{dod}.

The lifetime energy throughout E^{let} is a measure of the total energy the battery can produce in its lifetime. This can be further segregated into the expected lifetime n^{bat} in years, and the expected energy throughput E^{eet} in MWh/year.

In operational planning, a battery system can be modelled as follows. The first equation developed below describes the state of charge of the battery at a given hour as a function of the state of charge of the previous hour, and the power entering and exiting the battery for the given hour.

$$E_t^{soc} = E_{t-1}^{soc} + \eta^{in} \cdot P_{in,t}^{bat} - \eta^{out} \cdot P_{out,t}^{bat} \qquad \forall t \in T \tag{3.18}$$

The state of charge can be restricted to minimum and maximum limits, and the maximum ramp rate of charge and discharge can also be imposed using the following constraints. Models to calculate the upper and lower limits on the state of charge in terms of the age of the battery have been developed by researchers. In our case, given that the models are for use in operational planning, the limits on the state of charge can be considered constant.

$\forall t \in T$:

$$\underline{E^{soc}} \leq E_t^{soc} \leq \overline{E^{soc}} \tag{3.19}$$

$$P_{in,t}^{bat} \leq \overline{P^{bat}} \tag{3.20}$$

$$P_{out,t}^{bat} \leq \overline{P^{bat}} \tag{3.21}$$

3.3.3.2 Economic Model

The economic model of a battery system describes the cost of utilisation of the battery. This utilisation cost is expressed in €/MWh. Research studies have already worked on developing models for calculating the cost of utilisation [MSC+13]. Among these studies, we rely on the model proposed in [GTS+11] to further develop an economic model for the charging and discharging of battery systems in operational planning.

There are two components that make up the utilisation cost of the battery: (1) the depreciation cost that represents the depreciation of the battery for every unit of energy stored and consumed, and (2) the degradation cost that represents the degradation of the hardware material of the batter for every unit of energy stored and consumed.

We first calculate the cost for depreciation of the battery ρ^{dep}. This is a function of the investment cost ρ^{inv}, the expected pay-back period in years n^{bat}, and the expected energy throughput of the battery E^{eet} in MWh/year. This is expressed as follows.

$$\rho^{dep} = \frac{\rho^{inv}}{n^{bat} \cdot E^{eet}} \tag{3.22}$$

This establishes a linear depreciation of the battery for every MWh of power that the battery consumes or supplies. Next, we calculate the degradation cost of the battery ρ^{deg} as a function of the specific battery cost ρ^{bat}, the rated energy of the battery E^{bat}, the expected pay-back period in years n, the expected energy throughput E^{π}, and the input and output battery efficiencies η^{in} and η^{out}.

$$\rho^{deg} = \frac{\rho^{bat} \cdot E^{bat} \cdot \eta^{in} \cdot \eta^{out}}{n^{bat} \cdot E^{eet}} \tag{3.23}$$

The total cost for a cycle (charge / discharge) of 1 MWh of energy in the battery ρ^{tot} is therefore given by the sum of the two components.

$$\rho^{tot} = \rho^{dep} + \rho^{deg} \tag{3.24}$$

The minimum charge and discharge prices of the battery, which will translate to the minimum cost to the DSO for use of the battery, can therefore be expressed as a function of the day ahead market price ρ^{da}, and the total unit cycle cost ρ^{tot} of the battery.

$$\rho^{ch} = \frac{\rho^{tot}}{2} - \rho^{da} \tag{3.25}$$

$$\rho^{dc} = \frac{\rho^{tot}}{2} + \rho^{da} \tag{3.26}$$

The charge price is lower than the discharge price. This is done willingly, as the stored energy has a monetary value, and can be sold later on. The difference between the prices corresponds to the day-ahead price ρ^{da}, which is factored into the model. As a result, the total expenditure to the DSO for a unit cycle (charge and discharge) of the battery is equal to the total cycle cost ρ^{tot}.

3.3.4 *Flexibility from DRES*

In active distribution networks, the DRES connected to the network should participate in system support [Eur13a]. This support translates to the regulation of voltage and reactive power at the nodes where DRES is connected. The curtailment of DRES, though considered as detrimental to their integration, has been shown to be useful and even beneficial in certain conditions without remuneration.

In this section, we model two flexibilities from DRES: the reactive power compensation, and the active power reduction (curtailment). For both these flexibilities, we first illustrate technical models below.

3.3.4.1 Technical Model

Reactive power compensation from DRES involves the injection or consumption of reactive power by the power electronic interfacing equipment. DSOs usually require DRES to inject or consume reactive power as a function of the active power produced by the DRES. The model we adopt is based on the guidelines followed by Enedis [ENE17], in line with the ENTSO-E grid codes established by the European regulation 2016/631 [Eur16a]. According to these guidelines, the reactive power capability of DRES connected to MV distribution networks is between -35 % to +40 % of the active power injected by the DRES. In other words, a consumption capability of 35 %, and an injection capability of 40 % of the injected active power is demanded from all DRES units connected to the MV distribution network. In some cases, the consumption capability can go as high as 50 %.

Enedis requires that this reactive power compensation be automatic for new DRES units, based on a gradient and as a function of the voltage of the node at which the DRES injects power. This requirement is illustrated in Fig. 3.6. The figure shows the reactive power compensation required, as a percentage of the active power produced by the DRES, and as a function of the node voltage. Reactive power injection begins when the node voltage decreases below 0.9725 pu, and saturates at 40 % when the voltage reaches 0.96 pu. On the other side, reactive power consumption begins when the node voltage increases above 1.0375 pu, and saturates at between 35 and 50 % when the voltage reaches 1.05 pu.

Our technical model for DRES reactive power compensation is not automatic, meaning that the injection or consumption of reactive power is decided as a function of the voltage. as iIt is a decision variable in the OP formulation, meaning that its value can be chosen independent of the voltage, as long as the grid codes in reference [Eur16a] are respected. Hence, we consider the overall capability of the DRES in terms of reactive power compensation as the technical limits of the flexibility. This means that we allow

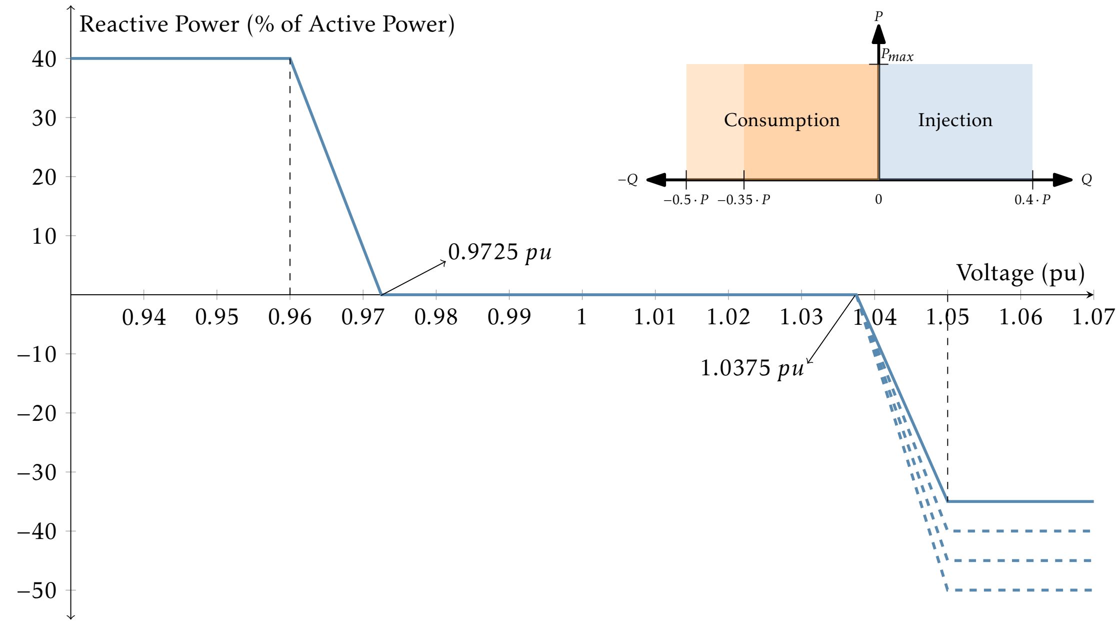


Figure 3.6: DRES Reactive Power Flexibility – Capability and Limits

up to 35 % consumption and 40 % injection of reactive power as the binding constraint, irrespective of the node voltage.

Active power curtailment from DRES is a widely debated topic. DRES generators receive priority dispatch in electrical networks, as mandated by the European directive 2009/28/EC [Eur09a]. This priority holds as long as system security is not affected. When the security of the system is under threat, curtailment of DRES can therefore be practised. Today, research shows that curtailment occurs both as a consequence of constraints in distribution and transmission networks and as a precautionary measure to secure stability of the power system [KJS12].

In this thesis, we consider a penalty cost for DRES curtailment. Since a penalty is paid, we can technically curtail or even completely disconnect DRES generation in our operational planning. This means that the limit for DRES curtailment that we consider is up to 100 %.

To model DRES curtailment and reactive power compensation mathematically, we consider a DRES generator connected to node i, producing active power P^g_{it} during time period t. The curtailment P^{fg}_{it} and the reactive power compensation Q^{fg}_{it} can be modelled as follows:

$$P^{fg}_{it} \leq P^g_{it} \tag{3.27}$$

$$\underline{Q^{fg}_{it}} \leq Q^{fg}_{it} \leq \overline{Q^{fg}_{it}} \tag{3.28}$$

$$\underline{Q^{fg}_{it}} \geq -0.35 \cdot (P^g_{it} - P^{fg}_{it}) \tag{3.29}$$

$$\overline{Q^{fg}_{it}} \leq 0.4 \cdot (P^g_{it} - P^{fg}_{it}) \tag{3.30}$$

3.3.4.2 Economic Model

DSOs like Enedis already use DRES reactive power compensation free of cost. They are able to do so because connection contracts for DRES in MV distribution networks clearly state that the DRES should be able to provide reactive power compensation. Hence, for this flexibility, we consider that there is no cost of use.

For DRES curtailment, a high penalty has to be paid by the DSOs in case they curtail DRES. This is because curtailment for any purpose other than security goes against the policy of DRES integration mandated by European directives and national laws. In a simple case, considering that the Feed-in Tariff is paid to the DRES for injecting power to the network, the lowest penalty on the DSO should be this tariff. However, the concept of Feed-in Tariff, and the costs associated with it change frequently. For example, in France, these tariffs were once as high as 601.76 €/MWh for PV systems as fixed by the law of 26 July 2006 [Min06], [Pho16]. However, they have since decreased substantially, and as of October 2015, are between 61.2 and 253.9 €.

In case the power produced from DRES is traded on the electricity market, the curtailment of this power will also entail penalties. The lowest imposed penalty on the curtailment action will therefore have to be the market price paid to the DRES. In both cases, the penalties paid will depend on the payment that DRES units receive [KJS12].

3.3.5 *Load Modulation*

Load modulation consists of controlling flexible loads in operational planning. This control primarily decreases or increases the power and energy consumption of a flexible load during a period of time. Load modulation is a useful method to control congestions in the network. By decreasing consumption at certain peak hours, system operators can

Before deregulation, electricity companies like EDF already used electricity tariffs as a means to indirectly control peaks in consumption and achieve smooth consumption curves. A few examples of such methods include the imposition of two electricity prices a day, introduced in 1965, or the definition of 22 critical days a year where electricity prices were prohibitively high in order to promote lower consumption. Today, EDF proposes a pricing scheme combining seasonal and peak tariffs [Bat15].

The French law 312 of 2013 allowed for the experimentation of load modulation for small consumers and households for aiding the management of power system constraints. Consequently, the development of technical and economic models for load modulation for small consumers is one of the challenges that researchers face today. In this section, we will develop three different models for load modulation. These models vary depending on how they are contracted, and what physical processes may be present behind these flexible loads.

3.3.5.1 Technical Model

We develop three different models for load modulation to be used in operational planning. The models for these three types – type-1, type-2, and type-3 load modulation – are described herein.

Type-1 Load Modulation: This type of load modulation is traded in fixed gate auction electricity markets. It corresponds to an all-or-nothing order, meaning that the flexibility energy block must either be utilised to the fullest or not utilised at all. This modulation is shown in Fig. 3.7. The region shaded in red show the modulated energy. This type of modulation is technically defined by two parameters: the energy of the block of flexibility and the time period of the activation of the flexibility.

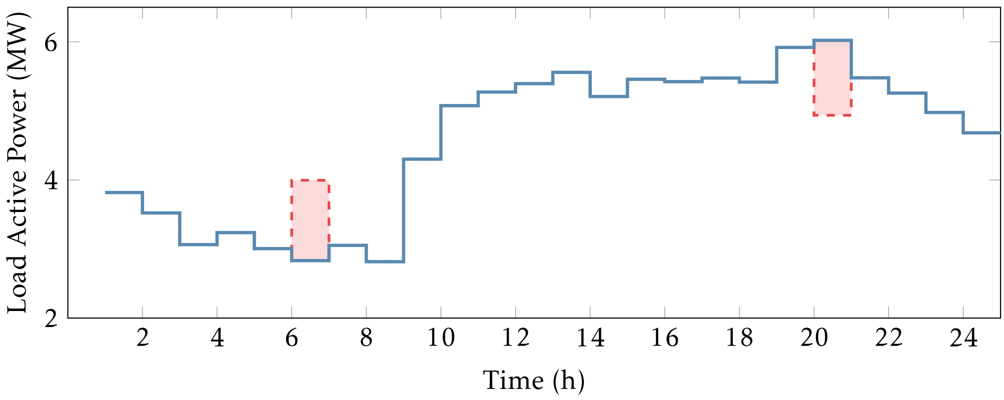


Figure 3.7: Type-1 Load Modulation (Modulated Load in Red)

Type-2 Load Modulation: This type of load modulation is also traded in fixed gate auction electricity markets. However, the block of flexibility traded can be matched to any proportion needed. This modulation is shown in Fig. 3.8. This type of modulation is technically defined by two parameters: the maximum energy of the block of flexibility and the time period of the activation of the flexibility.

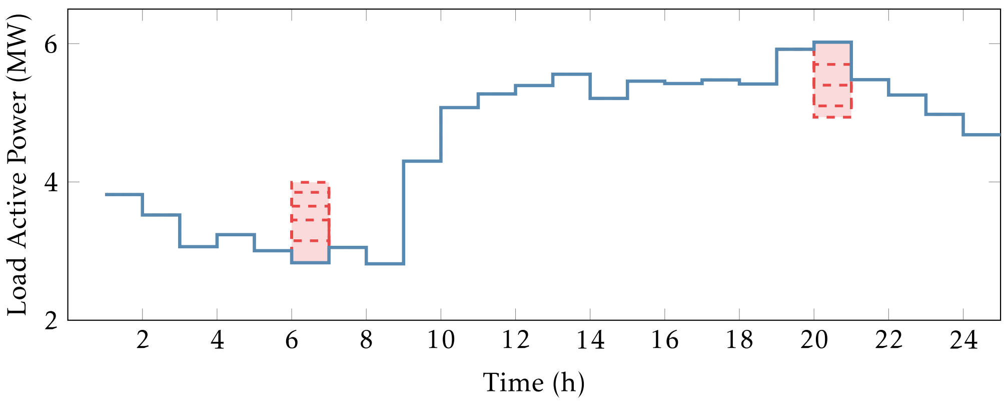


Figure 3.8: Type-2 Load Modulation (Modulated Load in Red)

Type-3 Load Modulation: This type of load modulation is obtained by the DSO through long-term contracts. It is based on the reservation of a modulation capacity as opposed to the purchase of modulation energy in types 1 and 2. The DSO can modulate the load up to the reserved capacity a certain number of times during a day. This type of modulation, based on the underlying physics of the load that is modulated, could require a rebound of the modulated energy. To this end, we model three different sub-categories of type-3 load modulation. Note that we only consider load decrease in type-3 load modulation, meaning that any rebound in energy translates to an increase in load.

In the first sub-category, there is no rebound required. This is termed as a type-0 rebound. In the second sub-category, the energy decreased has to be equalised over the time period considered for operational planning. This is termed as a type-1 rebound. In the third sub-category that we will call type-2 rebound, there are two components to the rebound [Bat15]. The first component is a rebound that must occur in the time period immediately after the activation of the flexibility. This component is called the power rebound and occurs as a result of the restarting of the physical devices in the loads that were switched off. The second component, called the energy rebound, can then occur at any time during the operational planning time horizon. We differ from the model adopted in [Bat15] in this second rebound component.

In our model, the difference is that the energy rebound can be made before (anticipation) as well as after the flexibility activation. Practical difficulties exist nevertheless with respect to anticipatory rebounds, and will have to be further explored in the future. The proportion of energy in each of these rebounds can vary. In this thesis, we use a power rebound for one hour corresponding to $1/3^{\text{rd}}$ of the decreased energy. The remaining $2/3^{\text{rd}}$ is allocated to the energy rebound. This is just one of the many potential proportions, and has been used in previous research [Des15]. Type-3 load modulation with rebound is illustrated in Fig. 3.9. It is characterised by the capacity, the maximum number of activations, and the type of rebound.

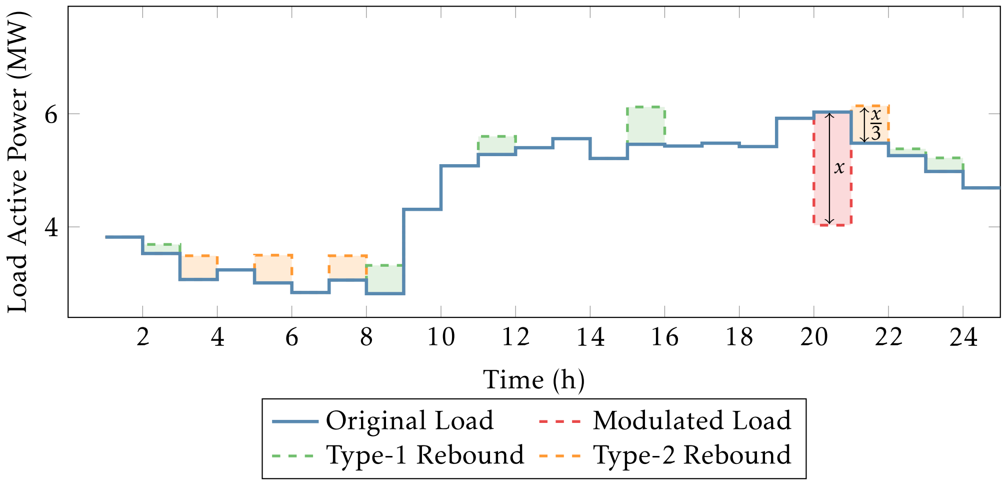


Figure 3.9: Type-3 Load Modulation with Type-1 and Type-2 Rebound

3.3.5.2 Economic Model

The economic model for the utilisation of type-1 and type-2 load modulation is straightforward. Since these types of load modulation are traded on the market, the marginal clearing price of the market is the final price that is paid by the DSO. The economic model of type-3 load modulation is developed below.

The price paid to contract type-3 load modulation consists of two components. The first component is a fixed fee that the DSO pays to reserve a particular capacity from a flexible load or aggregator. This fee can typically be expressed in €/MW/year. The second component is a variable fee component that may monetise the activations of this capacity. This fee is expressed in €/MWh.

In reference [JJR+15], an international benchmark on capacity based load flexibility products was done for more than 100 programs and for around a dozen countries. The results of this benchmark provide an insight into the ranges for prices that system operators paid for this load flexibility, and are listed in Table 3.1. For the economic model of type-3 load modulation, we consider the same costs.

Table 3.1: Type-3 Load Modulation – Cost of Reservation, Activation & Utilisation (Source: [JJR+15])

Max. Activations (Hours)		**Cost of Activation**	
Per Year	Per Day	Fixed Cost (€/MW/year)	Variable Cost (€/MWh)
1000	3	12000 – 24000	0
200	3	8000 – 15000	0
3000	12	40000 – 100000	0
20	5	5000 - 10000	200

3.4 UTILISATION COSTS FOR FLEXIBILITY – A TEST CASE

In the previous section, economic models for flexibility utilisation in operational planning were developed. In this section, we employ these models to ascertain utilisation costs for each of the flexibilities for a particular test case, with a view to integrate them in the operational planning formulation developed in Chapter 4. It is to be noted that in certain cases where data is unavailable, assumptions made to arrive at some of the costs. It is also to be noted that the costs obtained in this section are parameters to the operational planning (OP) of distribution networks, and that they can change depending on the input conditions to the models, and the models themselves.

3.4.1 *Reconfiguration*

To calculate the utilisation cost of a switching action, we first refer to the commonly available reconfiguration switches and their operational characteristics, as provided in [Ena07]. They are listed in Table 3.2.

Table 3.2: Switching Devices and their Characteristics

Company	**Product**	**Max. Current Opening (A)**	**Max. Current Closing (kA)**	**Electrical Endurance (CO)**
Novexia	IA 3T 2000 Auguste	400	31.5	100
Schneider Electric	RM6	630	50	100
ABB	NXA 24	630	40	400
Allias Electric	Pole Mounted Load Breaker	630	31.5	1000
Nulec	RL Series Load Breaker	630	31.5	600

The average electrical endurance among these devices is around 440 CO (close-open) cycles. We consider a capability of 500 CO cycles for the switching device for which the utilisation cost has to be calculated. Therefore, $n_m = 1000$. The pay-back period of the switching device n is assumed to be 20 years.We also consider that the capital investment ρ^{inv} = 15 000€ and the maintenance cost to be 30 % of the capital investment cost (ρ_m^{tot} = 4500 €). An actualisation cost K_a of 8 % year-on-year is used to calculate the depreciation factor K_i. We use the following formula.

$$K_i = \frac{n \cdot (K_a - 1)}{((K_a)^n - 1)}$$

The factor K_i takes a value of 0.437 for the first year, and 1.886 for the 20th year. The evolution of K_i along with the yearly decrease in the value of the switching device as a percentage of ρ^{inv} is shown in Fig. 3.10.

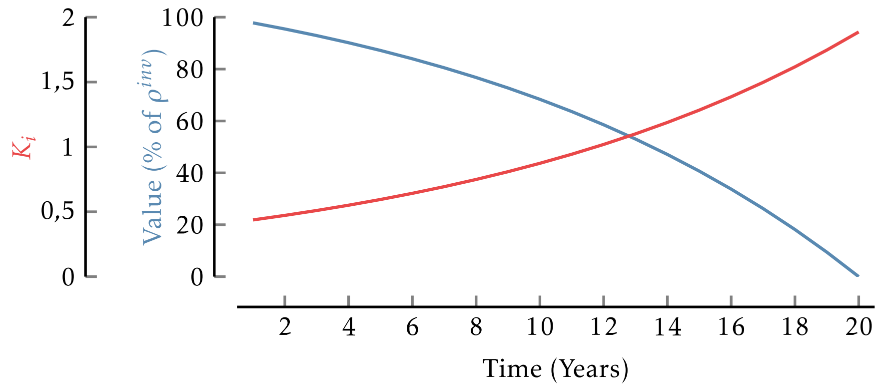


Figure 3.10: Evolution of K_i during the Pay-Back Period n

To calculate the depreciation cost of the switch, we consider that $K_i = 0.437$, which corresponds to the first year of installation of the switching device. Based on these parameters, we calculate the values of the cost coefficients for reconfiguration. They are listed in Table 3.3.

Table 3.3: Cost Coefficients – Reconfiguration

Coefficient	Value
ρ_1^{rec}	0.898 €
ρ_2^{rec}	4.5 € per Switching Action

3.4.2 *On-Load Tap Changer*

To calculate the utilisation costs of OLTC operation, we first define the technical and economic parameters of the OLTC. The parameters considered for this calculation are listed in Table 3.4.

Table 3.4: OLTC Cost Calculation Parameters

Parameter	Value
Transformer Rating	25 MVA
Unit Cost[2]	9 500 €/MVA
Actualisation Factor (K_a)	1.08 %
Operations before Maintenance (n_m)	10 000

[2]The unit cost is calculated based on confidential DSO data, and has been used previously in [JJR+15].

The total investment cost ρ^{inv} for the transformer and OLTC is therefore $9500 \cdot 25 = 237500$ €. The depreciation factor K_i is the same as that for reconfiguration switches, as the actualisation factor is the same. Considering a maintenance cost equal to 50 % of ρ^{inv}, we arrive at the cost of maintenance per operation $\rho_m^{op} = 11.875$ €. The depreciation cost per day ρ_d^{dep} is equal to 14.219 €. The final cost parameters for OLTC operation are listed in Table 3.5.

Table 3.5: Cost Coefficients – OLTC

Coefficient	Value
ρ_1^{oltc}	11.875 €
ρ_2^{oltc}	14.219 € per Tap Change

We remind the reader that the depreciation cost component ρ_1 for both the OLTC and reconfiguration is not actually incurred every day. This is a portion of the sunk cost of these devices, and is included in the utilisation cost only in order to provide a level playing field for all flexibilities.

3.4.3 Battery Systems

The minimum charge and discharge costs of battery systems depend on the Marginal Clearing Price (MCP) of the day-ahead market ρ^{da} and the parameters of the battery system including the investment cost and pay-back period. The MCP of the EPEX Spot Day-Ahead market for the 1st of July 2016 [EPE16] is considered for ρ^{da}. The parameters of the battery system are listed in Table 3.6. In this case, we consider a lead-acid battery system.

Table 3.6: Battery System Cost Calculation Parameters

Parameter	Value
Battery Rating	0.25 MWh
Unit Cost[3]	870 000 €/MWh
Pay-Back Period (n^{bat})	10 years
Lifetime Energy Throughput (E^{let})	362.5 MWh
Efficiencies (η^{in}, η^{out})	0.9

The lifetime energy throughput E^{let} is considered to be for 2900 cycles at 50 % depth of discharge. The expected energy throughput $E^{eet} = 36.25$ MWh/year. Given these parameters, the depreciation cost of the battery for a unit cycle ρ^{dep} is calculated to be 600 €/MWh. The hardware degradation cost for a unit cycle ρ^{deg} is calculated to be 486 €/MWh. The total unit cycle cost ρ^{tot} is therefore equal to 1086 €/MWh. Based on this, the minimum charge ρ^{ch} and discharge ρ^{dc} prices per MWh are can be calculated. These prices are listed in Table. 3.7.

The cost of the battery for this test case varies between 507.22 and 522.81 €/MWh for charging and between 563.19 and 578.78 €/MWh for discharging. This falls within the range of the levelised cost of usage of these batteries presented in [Laz16].

[3] The unit cost is based on the average cost of lead-acid battery systems for distribution network feeders found in reference [Laz16].

Table 3.7: Minimum Charge and Discharge Prices per MWh – Battery System

Hour	ρ^{ch}	ρ^{dc}	**Hour**	ρ^{ch}	ρ^{dc}	**Hour**	ρ^{ch}	ρ^{dc}
1	513.64	572.36	9	507.22	578.78	17	515.58	570.42
2	518.31	567.69	10	508.9	577.1	18	514.25	571.75
3	519.58	566.42	11	508.52	577.48	19	510.57	575.43
4	521.09	564.91	12	508.34	577.66	20	509.05	576.95
5	522.81	563.19	13	509.01	576.99	21	510.33	575.67
6	520.56	565.44	14	509.12	576.88	22	512.93	573.07
7	516.16	569.84	15	514.99	571.01	23	511.09	574.91
8	509.42	576.58	16	516.92	569.08	24	511.24	574.76

3.4.4 *DRES Curtailment*

In this test case, we consider the curtailment of DRES to be a flexibility traded on the day-ahead market. However, the price of DRES curtailment cannot be the MCP of market. Additional penalties have to be imposed on DSOs for using this flexibility. The current regulatory framework does not provide clear guidelines for these penalties. Therefore, to calculate these penalties, we assume the following.

First, we assume (pessimistically) that any curtailed DRES has to be replaced by the most polluting source of electricity – coal. The average CO2 emissions from coal amount to around 981.6 kg/MWh of electricity generated[4]. Second, we consider a factor of ten on the carbon credits for the penalties imposed. The minimum fair-trade price for carbon credits for renewable energy is 8.1 € per ton of CO2 emissions. The penalties thus calculated amount to around 80 €/MWh of DRES curtailed. For this test case, the final cost per MWh of DRES curtailment ρ^{cur} is presented in Table 3.8.

Table 3.8: Cost of DRES Curtailment per MWh

Hour	ρ^{cur}	**Hour**	ρ^{cur}	**Hour**	ρ^{cur}	**Hour**	ρ^{cur}
1	109.36	7	106.84	13	113.99	19	112.43
2	104.69	8	113.58	14	113.88	20	113.95
3	103.42	9	115.78	15	108.01	21	112.67
4	101.91	10	114.1	16	106.08	22	110.07
5	100.19	11	114.48	17	107.42	23	111.91
6	102.44	12	114.66	18	108.75	24	111.76

3.4.5 *Load Modulation*

Load modulation of types 1 and 2 are traded on the day-ahead market. Their price ρ^{lc} is therefore considered to be equal to the MCP of the day-ahead market. These prices are listed in Table 3.9.

For type-3 load modulation, we know from the benchmark conducted in [JJR+15] that the prices for type-3 load modulation change depending on the contract rules (see Section 3.3.5). To calculate the utilisation costs for each contract type, we consider the

[4]Data sourced and averaged from [OPE17]

Table 3.9: Cost per MWh of Load Modulation Types 1 & 2

Hour	ρ^{lc}	Hour	ρ^{lc}	Hour	ρ^{lc}	Hour	ρ^{lc}
1	29.36	7	26.84	13	33.99	19	32.43
2	24.69	8	33.58	14	33.88	20	33.95
3	23.42	9	35.78	15	28.01	21	32.67
4	21.91	2	34.1	16	26.08	22	12.07
5	20.19	3	34.48	17	27.42	23	31.91
6	22.44	12	34.66	18	28.75	24	31.76

average fixed cost of the contract. The calculated utilisation costs ρ^{act}, expressed in €/activation/MWh, are listed in Table 3.10.

Table 3.10: Utilisation Cost – Type-3 Load Modulation

Max. Activations (year/day)	**Utilisation Cost (ρ^{act}) (€/activation/MWh)**
1000/3	18
200/3	57.5
3000/12	70
20/5	575

The utilisation cost ranges from 18 € to 575 € for every activation and MWh of energy. This large range is primarily due to the difference in the contract rules. If the DSO is sure to use a reasonably high number of activations per year with a reasonably low number of activations per day, the flexibility is cheapest. If the DSO plans to use the flexibility for a high number of activations per day, but only for a few days in the year, it is expensive, even though the fixed cost is not that high. This is because of the high variable cost of this flexibility.

However, it turns out that a very high number of activations per day and a high number of activations per year makes the utilisation of the flexibility cheaper, even if the fixed cost is higher. For this test case, we consider the least expensive of the utilisation costs – 18 €/MWh. It is to be noted that the technical constraints associated with this pricing have to be imposed, notably the limit of a maximum of three activations per day.

We have therefore obtained utilisation costs for the endogenous and exogenous flexibilities present in distribution networks and considered in this thesis for the operational planning of distribution networks. To arrive at these costs, we use the models developed in Section 3.3 of this chapter, and make certain considerations, all of which are outlined for each flexibility. The input parameters that are used to obtain these costs can be varied, and the resulting costs will invariably be different. In this thesis, we consider a set of parameters, and we arrive at a set of corresponding utilisation costs.

3.5 CONCLUSIONS

The main focus of this chapter was the modelling the flexibilities for use in operational planning of active distribution networks. Towards this, the following items were developed, presented, and discussed in this chapter.

The results of a survey conducted as a part of this thesis (and the evolvDSO European project) and presented in this chapter showed the capabilities and limitations of five major European DSOs with respect to the use of flexibilities in their networks. The survey consisted of regulatory barriers, the current capability of DSOs to control flexibility, the ability to curtail DRES, and the status of operational planning in their networks. The major impediments to flexibility use from a DSO's point of view were then ascertained based on the responses. The potential solutions that active distribution networks could bring in the near future were also described as a part of the impediments. With the new roles and responsibilities that DSOs are willing to take up in the near future, they would be capable of better observing their networks and accessing flexibility in order to manage network constraints in an optimised manner. The regulatory aspects related to these changes should notably be addressed with the introduction of the 2016 Clean Energy Package [Eur16b].

With a view on the current DSO situation with respect to flexibility use, the development of technical and economic models of flexibilities in distribution networks was subsequently done. The flexibilities for which these models were developed have been listed in Chapter 2. Two types of flexibilities were identified. The first type, endogenous flexibilities, was understood to be flexibilities owned by the DSO. This included flexibilities like reconfiguration, OLTC, and in certain cases, battery systems. The second type, exogenous flexibilities, was understood to be flexibility that the DSOs contracted from other actors like aggregators.

One of the main considerations with respect to the development of these models was the need to develop unbiased models that reflected the real cost of usage of endogenous flexibilities. This real cost integrated the investment cost on the equipment that the DSOs invested in to avail of these endogenous flexibilities, and also the actual operational costs of such equipment. This was done in order to allow for an unbiased evaluation of the actual costs incurred by the DSOs in flexibility use. As for exogenous flexibilities, the economic models integrated publicly available information on these flexibilities, and in the case of type-3 load modulation, a benchmark of more than 100 capacity based load modulation programs.

Based on the economic models developed, the utilisation costs for these flexibilities was calculated for a test case. The assumptions behind the calculation of these costs were clearly outlined. This calculation was done with an ultimate aim of integrating these costs into a techno-economic optimisation formulation for operational planning of distribution networks. This leads to Part II of this thesis, where a novel techno-economic operational planning formulation that integrates these flexibilities and their utilisation costs is developed and presented.

PART II

A NOVEL FORMULATION FOR ACTIVE DISTRIBUTION NETWORK OPERATIONAL PLANNING

4 A Novel Operational Planning Formulation

« Tout objectif sans plan n'est qu'un souhait (A goal without a plan is just a wish). »
- Antoine de Saint-Exupéry

4.1 INTRODUCTION

4.1.1 *Context*

The two major changes affecting distribution networks, a high integration of DRES and deregulation, were discussed in Chapter 2 of this thesis. Active Distribution Networks (ADN) and the associated Active Network Management (ANM) practices were shown to help Distribution System Operators (DSO) counter the effects of these changes. This was essentially through the adoption of new roles, and the use of new services like that of flexibility. The technical and economic models for flexibility in distribution networks were developed in Chapter 3.

To efficiently utilise flexibility in operational planning (OP) of distribution networks, DSOs need to use new optimisation techniques. We call these techniques operational planning formulations. These formulations should not only integrate the physical features of distribution networks and flexibilities, but also the economics of distribution network operation and flexibilities. Furthermore, these formulations should ensure optimality, as they directly affect DSO expenditures on the operation of distribution networks.

To this end, the main theme of this chapter is the development of a novel operational planning formulation for operational planning of distribution networks. The main contributions of this chapter are (numbering consistent with Chapter 1):

C3 The reformulation of flexibility models developed via contributions C1 – C2 to achieve exact linearisations. These exact linearisations can then be used in a convex optimisation problem.

C4 The development of a novel operational planning (OP) formulation for active distribution networks using the Second-Order Cone Programming (SOCP) relaxation of the Optimal Power Flow (OPF) problem. This formulation integrates the linear flexibility models from contribution C3, and solves the OP problem with global optimality.

C5 The development of a dichotomic search heuristic that recovers a globally optimal solution to the OP problem in the event of the failure of the SOCP relaxation. This convergence to the globally optimal solution is proved experimentally.

The physical characteristics of flexibilities and distribution networks mean that the OP formulation is non-linear and non-convex. In essence, solutions to this formulation cannot be guaranteed to be globally optimal. The contributions in this chapter therefore focus on an OP formulation that can provide globally optimal solutions. The reformulation of the mathematical models of flexibilities and distribution networks is done with this optimality in mind. In the next section, the organisation of this chapter is outlined.

4.1.2 Organisation of this Chapter

This chapter is organised as follows. Mathematical concepts that underlie the OP problem: reformulations, unit commitment & economic dispatch, the optimal power flow, and the branch flow model are introduced in Section 4.2. This is followed by a review of the relevant state-of-the-art in the literature. This is presented in Section 4.3 and focuses on the mathematical nature of the optimisation techniques used in power system operational planning.

From this literature review, the best modelling and solution approaches to formulating OP problems are evaluated. This evaluation focuses on different criteria like the applicability to distribution networks, the accuracy and the optimality among others. It is presented in Section 4.4.

The novel operational planning formulation for distribution networks is then developed. This formulation uses the Second-Order Cone Programming (SOCP) relaxation of the Optimal Power Flow (OPF) problem, and integrates the reformulated models of flexibilities. This formulation, presented in Section 4.5, is therefore a direct result of contributions C3 and C4.

Subsequently, the dichotomic search heuristic that recovers globally optimal solutions is developed and presented in Section 4.6. This heuristic develops on the novel OP formulation, and works in the case of the failure of the SOCP relaxation. The optimality of the solutions recovered through this approach is proven experimentally later in this thesis, in Chapter 5. The concluding remarks are finally presented in Section 4.7.

4.2 UNDERLYING CONCEPTS

In order to better understand the OP formulation developed in this chapter, a definition of the techniques usually employed in short-term power system studies is important. To this end, we present an introduction of the main underlying concepts for mathematical modelling of short-term power system studies. This section consists of introductions to mathematical reformulations, the unit commitment & economic dispatch problems, the optimal power flow problems, and the branch flow model. Reformulations allow for the improvement of mathematical formulations, and are first presented below.

4.2.1 Mathematical Reformulations

Mathematical reformulations for optimisation problems have in general been explored for a very long time. The reasons for this are many. They may be in order to simplify the problem, to obtain a formulation that can be solved faster, or to adapt the problem to commercially available solvers. In essence, a reformulated problem is a problem that shares some or all properties with the original problem, but is ideally expected to perform better.

Optimisation problems can be classified into different categories based on the mathematical nature of their decision variables and equations, the type of constraints, on the physical structure of the problem, and the number of objective functions among others. Decision variables can either be discrete, continuous, or both, yielding discrete, continuous, and mixed optimisation problems respectively. The problems can be constrained (with constraints) or unconstrained (without constraints). The equations of the problem can be linear, convex, or non-linear non-convex, and the resulting problems are called the same way. The problem can also have one or multiple objectives.

A problem with continuous variables, imposed constraints, linear equations, and a single objective would be classified as a bounded Linear Programming (LP) problem. Problems in this classification are among the easiest to solve. On the other hand, a problem with both continuous and discrete variables, imposed constraints, non-linear equations, and a single objective would be called a Mixed-Integer Nonlinear Programming (MINLP) problem. Problems in this classification are among the hardest to solve, and are potential candidates for reformulations.

Several formal definitions of reformulations exist. Liberti et al. [LCT09], whose work we will rely on for our reformulations, define reformulations as follows:

Definition 4.1. *Any problem Q that is related to a given problem P by a computable formula* $f(Q,P) = 0$ *is called an auxiliary problem (or reformulation) with respect to P.*

Based on Definition 4.1, four different types of reformulations are presented in reference [Cos12]. These definitions are especially useful in understanding various approaches to reformulations presented in this chapter:

- *Exact reformulations*: These are reformulations of problems where the optima of the original problems are all preserved. This type of reformulation becomes really attractive if the reformulated problem becomes easier to solve. These reformulations are also called *opt-reformulations*.

- *Narrowings*: These are reformulations that eliminate certain optima, and for mixed integer problems conserve at least one global optimum.

- *Relaxations*: These are reformulations of problems that eliminate certain constraints and bounds or the discrete nature of variables. The optimal solution to a relaxed problem can be guaranteed to be optimal for its original problem under certain conditions that can be proven mathematically.

- *Approximations*: These are reformulations that fall in any of the above categories but are based on limiting the value of some parameters. There is no guarantee for the optimality of approximations.

Indeed, other types of reformulations may exist. In the context of this thesis, we are particularly interested in exact reformulations and relaxations. Formally, the two reformulations are defined as follows in the same reference:

Definition 4.2. *Q is an exact reformulation (or opt-reformulation) of P if each local optimum* $l \in L(P)$ *corresponds to a local optimum* $l' \in L(Q)$ *and each global optimum* $g \in G(P)$ *corresponds to a global optimum* $g\prime \in G(Q)$.

Definition 4.3. *Q is a relaxation of P if* $F(P) \subseteq F(Q)$*, and considering minimisation problems P and Q where* f_P *and* f_Q *are respectively their objective functions, if* $\forall x \in F(P)$, $f_Q(x) \leq f_P(x)$.

4.2.2 *The Unit Commitment & Economic Dispatch (UC & ED) Problem*

The Unit Commitment and Economic Dispatch (UC & ED) problem is a short-term optimisation problem in power systems. The Unit Commitment (UC) problem is used to select the *on* and *off* statuses of generators connected to the power system, while the Economic Dispatch (ED) problem is solved in order to determine a production schedule for the chosen generators. Together, all the decisions made to solve this problem strive to meet the electrical demand of the system at lowest production cost. In its simplest form, the problem can be mathematically expressed using the equations presented below. The nomenclature for these equations can be found in Page xvii of this thesis.

$$min \sum_{g \in \Upsilon} \sum_{t \in T} (SU_t^g + SD_t^g + \rho_t^g \cdot P_t^g) \tag{4.1}$$

Subject to:

$$\underline{P^g} \leq P_t^g \leq \overline{P^g} \qquad \forall g, t \tag{4.2}$$

$$\sum_{g \in \Upsilon} P_t^g = \sum_{c \in C} P_t^c \qquad \forall t \tag{4.3}$$

This formulation ensures that: (1) the cheapest generators are selected, (2) all the selected generators produce power within their limits, (3) the generation and load balance is maintained, and (4) this is achieved at the lowest cost of operation. The problem belongs in the Mixed-Integer Linear Programming (MILP) class of optimisation problems. Other constraints, like the inclusion of reserves and generator ramping limits [CW87], [WS93] and the introduction of fuel constraints for generators [RR91], [VL92] can be included to render the problem more realistic.

Of late, most of the research in operational planning has been focused on another type of problem, called the Optimal Power Flow (OPF) problem. This is because the UC & ED problem has certain drawbacks. In practice, all the generators and loads in a power system are not connected to one node. This means that the network of lines and nodes which constitute a power system has to be taken into account in the optimisation for it to be realistic.

Therefore, new constraints related to the network's physical characteristics, like line flows and voltage limits have to be introduced. This is especially important when power systems begin operating near their physical limits, meaning that certain generator schedules provided by the UC & ED problem may cause violations of physical constraints like the power flows in a line. This subsequently implies that the state of the network, characterised by four variables – the voltage magnitude, the voltage angle, and the active and reactive power injections, has to be computed. The UC & ED problem, a linear programming problem that focuses on generation dispatch only, does not provide a means for such a calculation.

4.2.3 *The Optimal Power Flow (OPF) Problem*

Unlike the UC & ED problem, the Optimal Power Flow (OPF) problem can take into account the physical characteristics of the network for which the production schedule is being optimised. In its simplest form, the problem can be mathematically expressed using the equations presented below [SM12]. The nomenclature for these equations can be found in Page xvii of this thesis.

$$min \sum_{g \in \Upsilon} \sum_{t \in T} \rho_t^g \cdot P_t^g \tag{4.4}$$

Subject to:
$\forall t \in T$:

$$\underline{P^g} \leq P_t^g \leq \overline{P^g} \qquad \forall g, t \tag{4.5}$$

$$\underline{S_{ij}} \leq S_{ijt} \leq \overline{S_{ij}} \qquad \forall ij \in \Omega \tag{4.6}$$

$$\underline{V_i} \leq V_{it} \leq \overline{V_i} \qquad \forall i \in \Gamma \tag{4.7}$$

$$P_{jt}^g - P_{jt}^c = \sum_{i \in \Gamma^u(j)} V_{it} \cdot V_{jt} \Big[G_{ij} \cdot cos(\theta_{jt} - \theta_{it}) + B_{ij} \cdot sin(\theta_{jt} - \theta_{it}) \Big] \tag{4.8}$$

$$Q_{jt}^g - Q_{jt}^c = \sum_{i \in \Gamma^u(j)} V_{it} \cdot V_{jt} \Big[G_{ij} \cdot sin(\theta_{jt} - \theta_{it}) - B_{ij} \cdot cos(\theta_{jt} - \theta_{it}) \Big] \tag{4.9}$$

The objective of the problem is to minimise the overall generation cost (4.4), subject to many constraints. Constraint (4.5) is the same as the constraint (4.2) and imposes a maximum production limit for each generator. Constraints (4.6) and (4.7) impose power and voltage limits across lines and nodes respectively. Finally, constraints (4.8) and (4.9) describe the relation between injected active and reactive power at a given node and the voltage magnitude and angle in the node.

This OPF problem, though computationally difficult to solve, is versatile, meaning that even with the advent of DRES and flexibility in power systems, researchers can continue to use it as a base upon which short-term generator and flexibility scheduling problems can be formulated. In its simplest, the left hand side of constraints (4.8)–(4.9) can be used to represent the various power flexibilities that are integrated into the optimisation mix. Of course, additional constraints pertaining to the physical characteristics of these flexibilities have to be added in order for the OPF to be able to handle them.

4.2.4 The Branch Flow OPF Model

The Branch Flow model (BFM) for optimal power flows, also called the DistFlow model, was first developed by Baran and Wu [BW89a], [BW89c], and is an exact reformulation of the OPF problem. The model describes radial distribution networks based on the power flows in lines, as opposed to other methods, like the Bus Injection model (BIM) which relies, as the name suggests, on equations that describe the power flows as a function of the injections at various buses in the network. Fig. 4.1 shows a network with n nodes and m lines. The power flows and loads in this network are also shown.

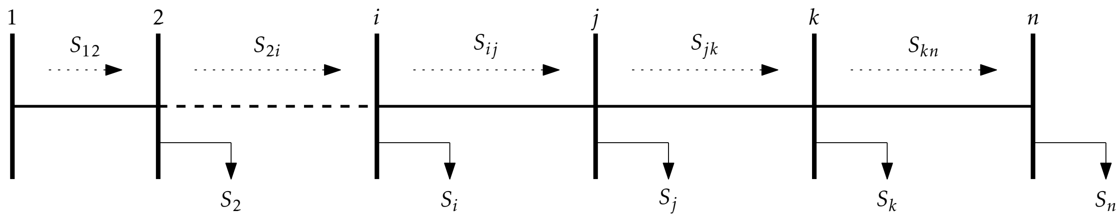


Figure 4.1: Branch Flow Model – A Network with n Nodes

For this network, the BFM model can be described by the following complex equations:

$$S_{ij} = V_i \cdot I^*_{ij} \tag{4.10}$$

$$V_j = V_i - z_{ij} \cdot I_{ij} \tag{4.11}$$

$$S_j = \sum_{i \in \Gamma^u(j)} (S_{ij} - z_{ij} \cdot I^2_{ij}) - \sum_{k \in \Gamma^d(j)} S_{jk} \tag{4.12}$$

Equation (4.10) expresses the apparent power in the line ij as the product of the voltage in the node i and the complex conjugate of the current in the line ij. The apparent power can flow from node i to j, or from node j to i. Equation (4.11) states that the voltage at node j is equal to difference between the voltage of the source node i and the voltage drop in the line ij connecting the two nodes. Equation (4.12) describes Kirchoff's current law (KCL), which states that the net apparent power consumed in the node j is equal to the difference between the sum of apparent powers imported from the upstream nodes and the sum of that exported to the downstream nodes. The line power losses are aggregated to the upstream nodes, as evidenced by the location of the term for losses. In order to obtain equations for active and reactive power flows from equations (4.10)–(4.12), we decompose the following variables:

$$S_i = P_i + jQ_i \tag{4.13}$$

$$S_{ij} = P_{ij} + jQ_{ij} \tag{4.14}$$

$$z_{ij} = r_{ij} + jx_{ij} \tag{4.15}$$

$$z^*_{ij} \cdot S_{ij} + z_{ij} \cdot S^*_{ij} = 2Re(z_{ij} \cdot S^*_{ij}) \tag{4.16}$$

Baran and Wu then derive the final equations which can be applied to optimal power flows. The net consumption in each node is decomposed into the generation and loads.

$$P^c_j - P^g_j = \sum_{i \in \Gamma^u(j)} (P_{ij} - r_{ij} \cdot I^2_{ij}) - \sum_{k \in \Gamma^d(j)} P_{jk} \tag{4.17}$$

$$Q^c_j - Q^g_j = \sum_{i \in \Gamma^u(j)} (Q_{ij} - x_{ij} \cdot I^2_{ij}) - \sum_{k \in \Gamma^d(j)} Q_{jk} \tag{4.18}$$

$$V^2_j = V^2_i - 2(r_{ij} \cdot P_{ij} + x_{ij} \cdot Q_{ij}) + I^2_{ij}(r^2_{ij} + x^2_{ij}) \tag{4.19}$$

$$I^2_{ij} = \frac{P^2_{ij} + Q^2_{ij}}{V^2_i} \tag{4.20}$$

The advantage of the branch flow model is that the power flow equations take a neat recursive structure, simplifying computation. This is especially useful for developing optimisation algorithms based on the optimal power flow (OPF), and the OP formulation developed in Section 4.5 is based on this model.

4.3 A LITERATURE REVIEW

Operational Planning (OP) can be thought of as OPF for multiple time steps, with or without inter-temporal constraints linking them. The OP problem's mathematical characteristics are inherited from the characteristics of the OPF problem. The OPF problem, as detailed in Section 4.2.3, is non-linear, and therefore possesses certain disadvantages:

1. The OPF problem does not scale well with network size and complexity.
2. There is no guarantee for a globally optimal solution. Depending on how the OPF problem is cast – and the problem has been cast in several different ways so far in literature – solution methods generally settle into local optima, if they find these optima at all. Furthermore, some of these solution methods offer no guarantee for global optimality of the physical solution.

In order to try and overcome these difficulties, several researchers have developed, simplified, and reformulated the OPF problem since its introduction. Additionally, they have also employed meta-heuristic solution techniques in order to circumvent these difficulties. In this section, we highlight the past research work done in the OPF problem formulation and solution, and in OP formulations specific to distribution networks. It is to be noted that we concentrate on centralised approaches to solving these problems. Other approaches like decentralised, hierarchical, heterarchical [Van16] among others have been explored by other researchers who have also highlighted the advantages and disadvantages of each of these approaches. Such approaches are not in the scope of this thesis. Also, this literature review does not, by any means, hope to provide a complete picture of the research being carried out in OPF problems. The reader is invited to consult references [PJ08], [FSR12a] and [FSR12b] for extensive surveys of OPF in literature.

When using deterministic solution techniques, the nature of the OPF problem to be solved plays an important role in the efficiency, speed, and precision. Therefore, it may be useful to explore the different classifications of OPF and OP problems in literature. In this classification, we first begin with a review of non-linear programming problems, problems with little or no reformulations to the OPF. We then present a review of second-order cone programming (SOCP) and other relaxations for the OPF, where exact reformulations are performed. Subsequently, we present a review of linear programming problems (LP) for the OPF and OP, where approximations are performed in order to develop the models. This is followed by a review of mixed-integer formulations for the OPF and OP. Finally, we also present a review of literature in the field of meta-heuristic solution techniques for these problems.

4.3.1 Classification of OPF and OP Problems

Advances in OPF formulations over the years have been in linearisation and convexification techniques, while trends in OP formulations include using these advances: the original non-linear OPF, its DC counterpart, a linearised version of the OPF around a particular operating point, or a reformulated quadratic non-linear or quadratic convex OPF. Models that integrate uncertain parameters are also a trend lately, as methods to handle uncertainty and ways to solve these problems continue to improve. Such models are explored further in Chapter 6.

4.3.1.1 Non-Linear Programming (NLP)

To the authors' knowledge, the first known OPF formulation proposed in literature was from Carpentier [Car62]. This formulation is non-linear in nature. The development of NLP formulations, in spite of the disadvantages they had, was due to the fact that NLP formulations captured the characteristics of power systems accurately. Certain approximations were albeit performed, like the continuous approximations for discrete decision variables like the OLTCs and reconfiguration [HW68]. Recent NLP formulations for the OPF almost always integrate discrete decision variables, and therefore are classed in the Mixed Integer Programming (MIP) class of problems.

In [SDC15a] and [SDC15b], the authors propose a dynamic programming based operational planning solution with Non Linear Programming (NLP) OPF problems at each instance of the dynamic programming tree. They also advocate the use of costs for flexibilities as opposed to reduction of losses, therefore obtaining a techno-economic local optimum rather than a purely technical optimum. The non-linear nature of the OPF, and its associated disadvantages, was one of the main reasons for research in reformulations of the OPF. Such formulations are detailed below.

4.3.1.2 The Second-Order Cone & Other Convex Relaxations

Convex relaxations of the optimal power flow have recently generated significant interest in the research community. This is due to the fact that using these relaxations, the OPF problem can potentially be solved feasibly with global optimality. This is due to the fact that using these relaxations, the OPF problem can potentially be solved feasibly, faster, and with global optimality. The increase in speed is due to a reduction of the solution space brought about by the relaxation. There exist other reasons for this interest. The first one is that the solution to such a relaxed OPF provides a bound for the quality of locally optimal solutions provided by its non-linear non-convex counterpart. The second one is that the relaxed OPF can be used to prove definitively that a particular OPF problem is not feasible. The main types of convex relaxations for the OPF that have been explored recently are the Semi-Definite Programming (SDP) relaxation [BWFW08], the Second Order Cone (SOC) relaxation [Jab06], and the Quadratic Convex (QC) relaxation [CVH13]. These relaxations are not equivalent, and have their respective advantages and disadvantages which have been discussed by the respective authors. In this thesis, we focus solely on the SOC relaxation for the following reasons:

1. The SOC relaxation can be solved by industrial-grade robust solvers like CPLEX without any additional modifications. The same cannot be said about the SDP relaxation, for example, solvers for which are still evolving.

2. Solutions to the SOC relaxation have been shown to be the fastest to find [CHVH15]. The relaxation is generally faster than the QC relaxation, and in some cases, much faster than the SDP relaxation.

The relaxation consists essentially in relaxing equation (4.20) to an inequation. It is done as follows:

$$I_{ij}^2 \geq \frac{P_{ijt}^2 + Q_{ijt}^2}{V_{it}^2} \tag{4.21}$$

In order to recover a physically meaningful solution to the OP problem with the relaxation, one has to ensure that the relaxation holds. While Jabr [Jab06] was the first researcher to explore this relaxation for OPF, a study of the exactness of the relaxation was first only performed later, in [LL12]. Farivar and Low [FL12] were the first to extend the formulation to the branch flow model (BFM). They prove that the relaxation is exact for radial networks as long as upper bounds on the loads do not exist. In [GLTL12], the relaxation is proven to be exact under less restrictive conditions, namely no upper bounds on voltages and one of four other sufficient criteria. However, these criteria are unrealistic as they restrict the direction of the power flows, or the reactance to resistance (X/R) ratio. Farivar and Low [FL13a], [FL13b] then derive even lesser restrictive conditions for exactness, which are outlined below:

1 The network graph is connected.

2 The objective function of the optimisation problem is convex.

3 The objective function is strictly increasing in I_{ij}^2, non-increasing in load, and independent of the apparent power S.

4 The OPF problem solved using the relaxation is feasible.

Condition 1 is trivial as it refers to the state of the network (no islanding). Condition 4 is also trivial as it imposes feasibility of the OPF. If the OPF problem were infeasible, one would obtain no results, even in a model with no relaxation. Conditions 2 and 3 depend on the objective function, and therefore on the developed formulation. Low has summarised quite well the current state of understanding with respect to the SOC relaxation for radial and meshed distribution networks in a two-part tutorial [Low14a],[Low14b].

4.3.1.3 Linear Programming (LP)

Linear Programming (LP) formulations of the OPF gained traction because of the advantages that it offered: simplicity, computational tractability, and excellent convergence speed. Any LP formulation of the OPF involves some form of approximation, given the non-linear nature of the power flow equations.

The simplest of all the LP OPF formulations is called the DC Optimal Power Flow (DC-OPF) [Nar03]. In this linearised, simplified OPF formulation, the constraint (4.9) from the original OPF presented is neglected. In constraint (4.8), the resistance of the branches are neglected, all the voltages are assumed to take their nominal values (1.0 $p.u.$), and the difference between the angles is assumed to be small, eliminating the need to apply the $sin()$ function. The new constraint is therefore:

$$P_{jt}^g - P_{jt}^c = \sum_{i \in \Gamma^u(j)} B_{ij}(\theta_{jt} - \theta_{it}) \tag{4.22}$$

The objective function (4.4) and the constraints (4.2)–(4.7) and (4.22) thus make up the DC-OPF problem. The DC-OPF is non-iterative, meaning that computational optimisation programs employing it can solve the problem in one go. This improves the tractability of the OPF problem leaps and bounds. This is also the reason why the DC-OPF is widely used in the industry today.

In other LP techniques such as Sequential Linear Programming (SLP), the original NLP problems are approximated through a series of linear approximations [SJA09]. An iterative process is therefore needed, where successive linearisations are performed around the solutions at every iteration. Das [Das02] argues that SLP methods for OPF with only a few binding constraints are generally rapid with respect to detecting infeasibility of the problem. However, if the linearisation of the NLP OPF gives an unconstrained search direction, SLP approximations do not generally find an optimum [FSR12a]. We can cite attempts at using SLP for OPF like the research done by Zhang et al. [ZRP06] where the linearisation around solution points is done via the generation of a 1st order Taylor series, or [ZS08] for a multi-objective OPF using the SLP technique.

Other recent formulations that employ multiple linearisations include Christakou [Chr16] who has developed a unified centralised approach to real-time active distribution network management using a sensitivity coefficient-based linearised OPF. The flexibility employed to achieve voltage and power control in this work includes distributed storage systems and responsive loads. Bolognani et al. [BZ16] derive an explicit linear approximation of the AC-OPF, and also show that the errors in their formulation can be bounded as a function of the network parameters.

4.3.1.4 Mixed Integer Programming (MIP)

In the context of distribution networks, continuous NLP, convex, and LP formulations do not accurately model certain network flexibilities like reconfiguration and OLTCs. To achieve this, mixed-integer programming (MIP) formulations are necessary. While these formulations can accurately capture the behaviour of discrete flexibilities and control elements in networks, they have a downside. This is one of the reasons why most of these formulations are solved using meta-heuristic methods and not using deterministic methods [FSR12a]. This is discussed later on, in Section 4.3.2.

Interest in solving MIP formulations using deterministic solution techniques increased with the advent of convex relaxations of the OPF. One such relaxation, the second-order cone relaxation, creates convex a solution space restricted by a second-order cone (see Fig. 4.2) allowing researchers to find globally optimal solutions to the OPF. allowed researchers to use LP solvers without worrying about the optimality of the successive restrictions they apply (for e.g. the Branch-and-Cut method used by CPLEX) [Tou14]. The authors of [JSP12] derive a minimum loss reconfiguration problem based on the SOC relaxation, but there is no proof provided for optimality of their method. The authors of [HJL+15] derive a formulation for the reconfiguration problem that is shown to be more computationally efficient. Peng et al. [PTL15] then develop a reconfiguration problem with the SOC relaxation that is similar to Merlin and Back's sequential branch opening method [MB75]. Their method is generally very fast, and provides solutions that are near-optimal. Tian et al. [TWZB16] have developed a MISOCP problem with reconfiguration and VAR compensation. However, the OLTC model employed by them approximates the OLTC impedance to the primary of the transformer and may not provide correct results in large systems.

Second-Order Cone ($z^2 \geq x^2 + y^2$)

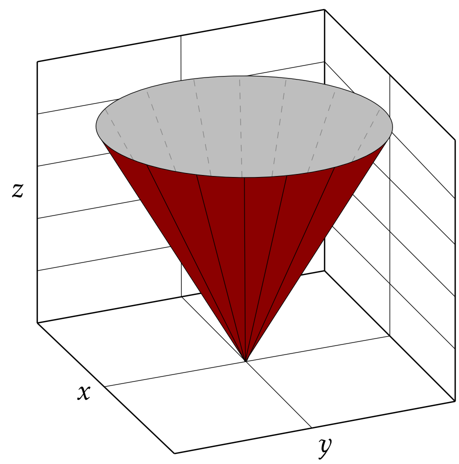


Figure 4.2: The Second Order Cone Relaxation

In [Tou14], the author casts the OPF problem for distribution networks with reconfiguration and VAR compensation, as a Mixed-Integer Second Order Cone program (MISOCP) using the reformulation techniques presented in [LCT09]. The author is able to cast an OLTC model in this work without any simplifications. And based on the work in [Sar09], the author also proves that this formulation can be solved with global optimality by commercial solvers such as CPLEX using the Branch-and-Cut (B&C) algorithm. Vanet [Van16] extends this formulation to include discrete active power flexibilities for a single time-step and develops a simple solution recovery algorithm capable of recovering a globally optimal solution when the relaxation fails.

As for the OP problem, Borghetti et al. [BBG+10] have developed a two-stage linear scheduling algorithm for distribution networks. The day-ahead stage of their algorithm is formulated as a DC-OPF problem. They argue that this is sufficient owing to the fact that the uncertainties in the parameters during the day-ahead stage already contribute to inexactness in the solution, and that an exact model is therefore unnecessary. While taken separately, this argument seems justified, the fact that they formulate the second, real-time stage, of their model using an iterative linearised algorithm that uses sensitivity coefficients to linearise the non-linear OPF around an operating point lends more weight to the theory that simplified modelling was their original intention. The objective of their optimisation is to minimise dispatch costs in the day-ahead stage, and the minimisation of dispatch costs, losses, and penalties for voltage changes in the real-time stage. The flexibility employed by them in order to achieve optimal operation of the network includes scheduling of generators, reactive power compensators, and On-Load Tap Changers (OLTC).

Other researchers like Gemine et al. [GEC16] cast the OP problem as a convex relaxed program using the SOC relaxation. The discrete nature of their problem arises from the discrete activation signals for load modulation. They also argue that curtailing DRES for operational planning purposes could be detrimental and should be used as a last resort.

4.3.2 Meta-Heuristic OPF Solution Techniques

Meta-heuristic methods to solve optimisation problems are a set of methods that either evolve naturally or imitate natural phenomena to find an optimal solution to a problem. They primarily interest researchers for the following reasons [FSR12a]:

1 They are very flexible and can often model practical constraints with ease.

2 For feasible problems, they generally provide near-optimal solutions[1].

3 They circumvent the mathematical difficulties faced by deterministic solvers with complicated formulations, like the ones involving discrete decision variables. They are therefore robust, and solution times often are independent of problem size and complicating variables.

4 In cases like those with MINLP problems, these methods may be the only practical alternative with respect to the time available for optimisation.

Recently, there has been a proliferation of research into the different types of meta-heuristic optimisation techniques. A non-exhaustive list of such methods includes

[1] They do not provide any proof of optimality, nor a measure of how far they are from the optimum.

Ant Colony Optimisation (ACO) [AMV91], Artificial Neural Networks (ANN) [Ger05], Genetic Algorithm (GA) [MTK99], Particle Swarm Optimisation (PSO) [KE95], Simulated Annealing (SA) [KGJV83], and Artificial Immune Systems (AIS) [Jef94] among others. Such methods have been quite successfully applied to OPF problems in literature. Reviews of such OPF problems can be found in references [FSR12b], [NWX14].

Some of these methods have been applied to the OP problem as well. We can cite the following references among others for such applications. The authors of [GAA14] solve a day-ahead scheduling problem using GA. The flexibilities they employ include reconfiguration, dispatchable distributed generation, and responsive loads. Through tests on a 33-bus IEEE network, they show that considering reconfiguration in daily dispatching can have a considerable effect on the optimal scheduling of these networks. A number of other methods use the GA technique to solve the OP problem, with different considerations [QL09], [SMV11], [MB11].

Zaidi et al. [ZTOF14] test a formulation based on the PSO method while considering controllable loads and a high penetration of PV generation. They also formulate a battery sizing problem, and show that the use of controllable loads has advantages for the network, like the reduction of battery sizes. This implies that intermittent flows are reduced by using controllable loads. Tan et al. [TXP13] formulate the OP problem for distribution networks using four different meta-heuristic algorithms: GA, PSO, AIS, and vaccine-AIS. The results from this research show that the final solutions provided by the different algorithms differ from one another.

Given the variety of mathematical models and solution techniques for OPF and OP problems, choosing a particular model and solution technique is necessary in the development of any such problem. In the next section, a discussion and analysis on the ideal OPF formulation for OP problem in distribution networks is presented.

4.4 THE IDEAL OPF FORMULATION FOR OP?

A good deal of research has been conducted into the different modelling and solution techniques for OPF problems. Reformulation techniques like approximation, exact reformulations, and relaxations have been applied to the OPF equations in an attempt to simplify the problem resolution. Discrete decision variables in these formulations have also been subject to these reformulations, and researchers have circumvented the difficulty of these problems by successfully employing nature-inspired solution techniques. Finally, many of these techniques have also been applied to the OP problem.

In this section, we attempt to choose an ideal formulation technique for the OPF problem in the particular case of its application to the OP problem in distribution networks. To achieve this, we analyse the characteristics of different OP modelling and solution techniques. To this end, we use three characteristics. They are: (1) the computational tractability, (2) the mathematical solution optimality, and (3) the real-world solution accuracy.

4.4.1 *Computational Tractability*

Computational tractability is a measure of how easily a computer can solve an optimisation problem. For deterministic solution techniques, this depends on the nature of the underlying model. The OP problem is a short-term optimisation problem. It is designed for a time-frame of several days to one day before real-time operations. Potential OP formulations can therefore be allowed take a few hours to find solutions without there being a need for imposing restrictions.

The tractability notably increases with an increase in the number of discrete decision variables in the formulation. This means that mixed-integer formulations are less tractable than their continuous counterparts. The combinatorial nature of these problems means that their solution space of can be intractable in certain cases. Care should therefore be taken when modelling MIP, MINLP, and MISOCP problems when deterministic solution techniques are employed. Meta-heuristic solution methods can be used as an alternative to overcome the issue of computational tractability. This is because the solution times for such methods do not directly depend on the problem size. In cases where severe restrictions on tractability exist, they may be better suited to solving such problems than deterministic solution techniques.

4.4.2 Mathematical Solution Optimality

The optimality of solutions to various OPF formulations is an internal characteristic of the type of formulation. When solutions to these formulations found deterministically, they can be guaranteed to be optimal in certain cases. Solutions to LP formulations of the OPF can always be guaranteed to be optimal. Solutions to SOCP formulations can be guaranteed to be optimal under the condition that the relaxation holds. Solutions to mixed-integer versions of these formulations can also be guaranteed to attain at least one global optimum. Solutions to NP and MINLP formulations can however not be guaranteed to provide globally optimal solutions.

Nature-inspired solution methods not only provide no guarantee for optimality of their solutions, they do not provide a measure of how far away their solutions are from the global optimum either. Furthermore, different nature-inspired methods have been shown to produce different results for the same problem [TXP13]. Research has shown that a 0.5% difference in objective function values for power system studies, especially when the objective is to minimise costs, can lead to very high expenditures in large-scale networks [Sal07]. Therefore, while nature-inspired approaches are easy to adopt, they can be detrimental in the long run.

4.4.3 Real-World Solution Accuracy

Real-world solution accuracy is a measure of the accuracy of a mathematical solution when applied to a real-world optimisation problem. It differs from mathematical optimality in the sense that it integrates the errors in the solution caused by simplifications to the optimisation model. Mathematical reformulations therefore affect this characteristic. The DC-OPF and other LP formulations of the OPF are approximations. They rely on neglecting resistances among other parameters in the network to be optimised. This may work for transmission networks, where line resistances are low and the reactance-to-resistance ratio (X/R) is high [PMVDB05]. However, the power lines used in distribution networks have a higher resistance. Therefore, the resistance cannot be neglected for distribution networks. As a result, these formulations may provide erroneous results.

Other authors have also worked on the errors in linearised OPF problems for distribution networks [BZ16]. While they show that approximation approaches do exist where these errors are low, the fact that errors still exist eclipses the qualities of these linearised methods, notably their execution speed. Das [Das02] argues that LP approaches work quite well for networks in general where the objective function is separable and convex, such as the minimisation of the total generation costs. However, in the case of non-separable objective functions like the minimisation of losses, these formulations are not as effective, producing significant inaccuracy. From our side, we also verify the unsuitability of the DC-OPF for distribution networks in Appendix A.

NLP and SOCP formulations presented in the literature review can accurately capture the physical characteristics of distribution networks. This means that they are better from the point of view of real-world solution accuracy.

4.4.4 *Summary of the Analysis*

Table 4.1 summarises the different approaches in techniques for modelling and solving OP problems that work best for each of the analysed characteristics. This information can serve as a reference to choose a suitable OP formulation if the developer is aware of the desired characteristics of the OP problem to be developed.

Table 4.1: Performance of OP Formulations based on Desired Characteristics

Analysed	**Deterministic Solutions**						**Meta-**
Characteristics	LP	NLP	SOCP	MILP	MINLP	MISOCP	**Heuristics**
Discrete Variables	No	No	No	Yes	Yes	Yes	Yes
Tractability	+++	+	+*	−	−−	−−*	?
Optimality	+++#	+	+++*	+++#	+	+++*	++
Accuracy	−−	−	−*	−	+++	+++*	+

Legend:
*−− to +++ : Degrees of Conformity; * : Subject to Relaxation Exactness;*
 # : For the Approximated Problem; ? : Relationship Unknown

Meta-heuristic solution techniques generally perform decently well across all the analysed characteristics. Their tractability with respect to the underlying problem model cannot be ascertained as there is no direct relationship between them. Continuous LP formulations provide low real-world accuracy, but are mathematically optimal for the approximated problem and highly tractable. Continuous NLP formulations may provide feasible accurate solutions, but they are less tractable. The continuous SOCP relaxed formulation provides the same levels of accuracy and tractability as the continuous NLP counterpart, but can provide a guaranteed optimal solution for the reformulated problem. The MIP counterparts of each of these problem types all perform better in terms of accuracy, are as optimal for the respective formulations, but are less tractable.

It is difficult to choose one particular formulation and solution technique to implement in an OP for distribution networks. This is because each of these formulations and solution techniques has its advantages and disadvantages, and depend on the decision variables and other practical constraints like the time available for optimisation. The diversity of formulations of the OPF that exist in literature means that choice of a technique can only be done if the exact modelling criteria are known. This means that OPF formulations are generally tailor-made for specific applications.

In the context of this thesis, the criteria or the desired characteristics of the OP formulation for distribution networks are known. The two desired characteristics of the formulation are the ability to provide globally optimal solutions, and the ability to handle discrete decision variables. The first desired characteristic arises out of the necessity to decrease DSO expenditures in operational planning. This characteristic imposes mathematical solution optimality and real-world solution accuracy. The second characteristic is desired due to the fact that distribution networks contain discrete flexibility like OLTCs and reconfiguration switches, and employing these flexibilities is necessary in OP formulations. Given these desired characteristics, modelling the OP formulation as an MISOCP problem is the best choice.

Apart from this choice of mathematical model and solution technique, the development of any OP formulation has to satisfy certain general requirements. These requirements are explained below.

4.4.5 *General Requirements for an Ideal OP Formulation*

Any OP formulation developed with the applicability in DSO environment in mind has to take into account the current context under which these DSOs operate. In Chapter 2, the current context in power systems was introduced. This context imposes practical constraints on the approaches to OP formulation. For these problems to be practically applicable, they will have to take into account the capabilities and limits of DSOs.

All the optimisation actions in OP formulations must come at a cost. These costs may be internally incurred by the DSO, as is the case with the use of DSO-owned flexibility, or paid to third-parties like aggregators against their offer of specific flexibility. At the very least, a preliminary evaluation of these costs is necessary for operational planning. More importantly, whatever the costs are in actual numbers, they have to be integrated into the optimisation process in operational planning. Searching for technical optima in networks is interesting from a research point-of-view, as it results in better models and methods. But for this research to be practically applicable, techno-economic optima have to be obtained. In situations where DSOs cannot own or dispatch generation, new objectives like loss reduction or minimisation of the cost of flexibilities used could also take their place. The novel OP formulation developed in the next section takes into account these general requirements.

4.5 A NOVEL MIXED-INTEGER CONVEX OP FORMULATION

In the previous sections, a review of the state-of-the-art various approaches to OPFs was presented. This was followed by a discussion on the best OPF approach for OPs in distribution networks. A mixed-integer SOCP model was chosen to be the best for the formulation of an OP problem. In this section, we develop a novel deterministic OP formulation for MV distribution networks using the SOCP relaxation of the OPF. The main features of this formulation are as follows:

1 This SOCP OP formulation includes a wide variety of flexibilities, discrete and continuous, and for the first time integrates the economics of these flexibilities.

2 The problems caused by the non-linear non-convex nature of some of these flexibilities are overcome through exact reformulations. The models of these flexibilities are thus preserved, ensuring solution accuracy.

3 A solution recovery algorithm to recover physically meaningful and globally optimal solutions in case the relaxation fails.

In order to formulate the OP problem, we make the following assumptions:

1 The MV distribution network is considered to be balanced across its phases, allowing for a single-phase representation. For unbalanced networks, three-phase modelling can be eventually be adopted through the use of sequence components. Also, the transverse components of the network are ignored since they have very little effect on the voltages when the networks are normally loaded.

2 The loads and generation in the LV network are considered to be aggregated at each node of the MV network (secondary substation).

3 The loads are considered to be of the type *PQ-constant*. Subsequently, two types of nodes are considered for the OPF: (1) slack nodes, representing the interface between the transmission network and the distribution network, and (2) PQ nodes, representing all the other nodes in the network[2]. Other types of loads, such as *Z-constant*, *I-constant* and *ZIP* can eventually be tested as well, as is the case in reference [Tou14]. This will however necessitate changes in active power flexibility models.

NB The nomenclature for the equations developed below can be found in Page xvii.

Before we begin, we express the following new variables for the square of current and voltage:

$$l_{ij} = I_{ij}^2 \tag{4.23}$$

$$v_i = V_i^2 \tag{4.24}$$

4.5.1 *Objective Function*

The objective of the problem is to minimise the overall expenditures of the DSO. Since the utilisation of all flexibilities entails a cost, they are included in the objective function: OLTC, load modulation, reconfiguration, and DRES curtailment. The functional and economic aspects of these flexibilities are developed in Chapter 3 and are integrated into the formulation below.

$$\begin{aligned} \min \sum_{(ij)\in\Omega} \sum_{t=1}^{24} & \left(\rho^{l} \cdot r_{ij} \cdot l_{ijt}\right) + \left(\rho_1^{oltc} + \rho_2^{oltc} \cdot \Delta w\right) + \left(\rho_1^{rec} + \rho_2^{rec} \cdot \Delta e\right) \\ + \sum_{i} \sum_{t=1}^{24} & \Bigg[\left(\rho_t^{cur} \cdot P_{it}^{fg}\right) + \left(\rho_t^{ch} \cdot P_{it}^{bat,in}\right) + \left(\rho_t^{dc} \cdot P_{it}^{bat,out}\right) \\ & + \left(\rho^{lcup} \cdot P_{it}^{fcup}\right) + \left(\rho^{lcdn} \cdot P_{it}^{fcdn}\right) + \left(\rho^{act} \cdot a_{it}^{act} \cdot \overline{P_{it}^{fcact}}\right)\Bigg] \end{aligned} \tag{4.25}$$

[2] A special case for PQ nodes exists at the secondary of OLTCs, see Section 4.5.6.

In this function, the cost of losses and all the flexibilities that the DSO can use in OP are minimised. Note that we abuse notation in this thesis with respect to losses. Where it is used, and unless otherwise specified, the term losses referes to the active power (ohmic) losses in the network. The cost components of flexibility use are represented by the parameter ρ. The superscripts l, $oltc$, rec, cur, ch & dc, $lcup$ & $lcdn$, and act represent each of the flexibilities. They are the losses, the OLTC, reconfiguration, DRES curtailment, batteries, types 1 & 2 load modulation, and type-3 load modulation respectively.

The associated variables indicate the use of these components. For the losses, this is the active power losses $r_{ij} \cdot l_{ijt}$. For OLTC and reconfiguration, the use pertains to the number of operations, described by variable Δ. For all others, this is the active power P. We abuse notation in the summation for i. The node i belongs in different sets for different flexibilities, as defined in Page xvii of this thesis.

4.5.2 Power Flow Equations

For the slack node(s), at each time step, the power imported from the transmission network must be equal to the power flowing to the downstream nodes. There is no component for losses in these equations owing to the fact the branch flow model aggregates the losses in the upstream power flows. The constraints on the slack bus are presented in equations (4.26) and (4.27).

$$P_{it}^{G} = \sum_{i\in\Omega} P_{ijt} \qquad \forall j \in \Gamma^{d}(i) \tag{4.26}$$

$$Q_{it}^{G} = \sum_{i\in\Omega} Q_{ijt} \qquad \forall j \in \Gamma^{d}(i) \tag{4.27}$$

For PQ nodes, at each time step, the net power consumption at the node must be equal to the difference between the sum of powers imported from the upstream nodes and the sum of powers exported to the downstream nodes. Keeping with style of aggregating losses to the upstream power flows, the losses appear in the first summation.

$$P_{jt} = \sum_{i\in\Gamma^{u}(j)} (P_{ijt} - r_{ij} l_{ijt}) - \sum_{k\in\Gamma^{d}(j)} P_{jkt} \tag{4.28}$$

$$Q_{jt} = \sum_{i\in\Gamma^{u}(j)} (Q_{ijt} - x_{ij} l_{ijt}) - \sum_{k\in\Gamma^{d}(j)} Q_{jkt} \tag{4.29}$$

The secondary nodes of transformers with OLTC are a special case of the PQ node, where the power flow is modelled through linearised variable δ_{qijt} for the current flow through the transformer based on the chosen tap. The linearisation is presented in Section 4.5.6.

$$P_{jt} = \sum_{i\in\Gamma^{u}(j)} \left(P_{ijt} - r_{ij} \sum_{q\in\Psi_{ij}} d_{qij}\delta_{qijt}\right) - \sum_{k\in\Gamma^{d}(j)} P_{jkt} \tag{4.30}$$

$$Q_{jt} = \sum_{i\in\Gamma^{u}(j)} \left(Q_{ijt} - r_{ij} \sum_{q\in\Psi_{ij}} d_{qij}\delta_{qijt}\right) - \sum_{k\in\Gamma^{d}(j)} Q_{jkt} \tag{4.31}$$

At all the nodes except for the slack node(s), the net power consumption is calculated as follows. This is subject to the availability of different flexibilities in the particular node.

$$P_{jt} = P^{c}_{it} - P^{g}_{it} - P^{fcup}_{it} + P^{fcdn}_{it} + P^{fg}_{it} \tag{4.32}$$

$$Q_{jt} = Q^{c}_{it} - Q^{g}_{it} - Q^{fcup}_{it} + Q^{fcdn}_{it} + Q^{fg}_{it} \tag{4.33}$$

4.5.3 *Reconfiguration Constraints*

We use the radiality constraints developed in Chapter 3 in order to constrain the binary reconfiguration variable e_{jt}. These constraints are expressed below once again, for ease of reading.

$$\sum_{ij\in\Omega} e_{ijt} = n_N - 1 \qquad \forall t \in T \tag{4.34}$$

$$\sum_{ij\in C} e_{ijt} \leq n_C - 1 \qquad \forall C, \forall t \in T \tag{4.35}$$

For reconfiguration to take effect on power lines, e_{ijt} has to be introduced to the power flow equations in Section 4.5.2. However, the product of a binary variable and a continuous variable introduces non-convexities. In order to avoid this, a polyhedral system of equations (4.36) - (4.37) is used. Finally, equation (4.38) forces the non-manoeuvrable components of the network to be connected at all times. The notation ij refers to a line from node i to j.

$\forall ij \in \Omega$ and $\notin \xi$, and $\forall t \in T$:

$$-e_{ijt}\underline{P_{ij}} \leq P_{ijt} \leq e_{ijt}\overline{P_{ij}} \tag{4.36}$$

$$-e_{ijt}\underline{Q_{ij}} \leq Q_{ijt} \leq e_{ijt}\overline{Q_{ij}} \tag{4.37}$$

$\forall ij \in \xi$ and $\forall t \in T$:

$$e_{ijt} = 1 \tag{4.38}$$

In the polyhedral system presented above, e_{ijt} is multiplied with the upper and lower limits of power flows in lines. Since these limits are parameters, there is no loss of convexity. It is to be noted that these limits can be arbitrarily chosen, as the limits imposed on line flows are usually expressed in terms of apparent power, or current. If we want to express the reconfiguration variable as a variable independent of time period (i. e. we allow each power line only one state during the entire time period of the optimisation), we will have to modify equations (4.34)-(4.38). The new equations are presented below.

$$\sum_{ij\in\Omega} e_{ij} = n_N - 1 \tag{4.39}$$

$$\sum_{ij\in C} e_{ij} \leq n_C - 1 \qquad \forall C \tag{4.40}$$

$$-e_{ij}\underline{P_{ij}} \le P_{ijt} \le e_{ij}\overline{P_{ij}} \tag{4.41}$$

$$-e_{ij}\underline{Q_{ij}} \le Q_{ijt} \le e_{ij}\overline{Q_{ij}} \tag{4.42}$$

$\forall ij \in \xi$:

$$e_{ij} = 1 \tag{4.43}$$

4.5.4 *Voltage and Current Constraints*

The squared voltage terms in the constraint (4.19) are replaced by v as per equation (4.24), and equation (4.44) is obtained as a result. However, a potential problem arises with reconfiguration. In the case where a particular component ij is open (i. e. $e_{ijt} = 0$ or $e_{ij} = 0$), equation resolves to $v_{jt} = v_{it}$. In order to avoid this, it is transformed as disjoint constraints [LCT09]. We obtain constraints (4.45) - (4.48) as a result.

$\forall i, j \in \Gamma$ and $\forall t \in T$:

$$v_{jt} = v_{it} - 2(r_{ij}P_{ijt} + x_{ij}Q_{ijt}) + l_{ijt}(r_{ij}^2 + x_{ij}^2) \tag{4.44}$$

$$v_{jt} \le v_{it} - 2(r_{ij}P_{ijt} + x_{ij}Q_{ijt}) + l_{ijt}(r_{ij}^2 + x_{ij}^2) + M(1 - e_{ijt}) \tag{4.45}$$

$$v_{jt} \ge v_{it} - 2(r_{ij}P_{ijt} + x_{ij}Q_{ijt}) + l_{ijt}(r_{ij}^2 + x_{ij}^2) - M(1 - e_{ijt}) \tag{4.46}$$

$$v_{jt} \le v_{it} - 2(r_{ij}P_{ijt} + x_{ij}Q_{ijt}) + l_{ijt}(r_{ij}^2 + x_{ij}^2) + M(1 - e_{ij}) \tag{4.47}$$

$$v_{jt} \ge v_{it} - 2(r_{ij}P_{ijt} + x_{ij}Q_{ijt}) + l_{ijt}(r_{ij}^2 + x_{ij}^2) - M(1 - e_{ij}) \tag{4.48}$$

Here, M is a large value introduced to make sure that there is no overlap between constraints (4.45) & (4.46), and between constraints (4.47) & (4.48). The safe range of values that M can take in this case should be greater than the difference between the square of the voltage limits $\overline{v_i} - \underline{v_i}$. The voltage and current limits in the network are expressed below. Constraint (4.51) is a special case for the slack node where the node voltage is imposed.

$\forall i \in \Gamma$ and $\forall t \in T$:

$$v_{it} \le \overline{v_i} \tag{4.49}$$

$$v_{it} \ge \underline{v_i} \tag{4.50}$$

$$v_{it} = (V_t^G)^2 \tag{4.51}$$

$\forall ij \in \Omega$ and $\forall t \in T$:

$$l_{ijt} \le \overline{I_{ij}^2} \tag{4.52}$$

4.5.5 *Load Modulation Constraints*

We recall that in Chapter 3, three different types of load modulation are modelled. Here, we describe these flexibilities mathematically. In the first type, the flexible load is purchased in a fixed gate auction market with a 100 % minimum acceptance ratio (all-or-nothing order). We model such an upward flexible load through the constraint below.

$$P_{it}^{fcup} = a_{it}^{aon} \cdot P_{it}^{faon} \tag{4.53}$$

In the second type, for each time step, the upward or downward load flexibility is modelled as a continuous variable with power limits. Such a flexibility is modelled through the constraints below.

$$P_{it}^{fcup} \leq \overline{P_{it}^{fcup}} \qquad \forall i \in \Gamma_{mod}, \forall t \in T \tag{4.54}$$

$$P_{it}^{fcdn} \leq \overline{P_{it}^{fcdn}} \qquad \forall i \in \Gamma_{mod}, \forall t \in T \tag{4.55}$$

In the third type, the DSO reserves a particular upward capacity for a fee. This capacity can come with a constraint for the maximum number of activations. The DSO may or may not be required to equalise the activated power (energy) inside the time horizon of the optimisation, according to different rules (rebound). A linearised model for this flexibility is developed via the constraints (4.56) and (4.57). Here, ϵ represents an infinitesimal value. Equation (4.58) imposes a maximum number activations of modulation within the reserved capacity in the given time period. Two different types of rebounds are modelled. In the first type (4.59), the DSO has the entire time horizon of the optimisation (before or after the activation) to perform the rebound. In the second type, two thirds of the activated flexibility has to be restored in the time period immediately succeeding the activation, and the remaining one-third in the next time period. This is modelled through constraints (4.60) and (4.61).

$\forall i \in \Gamma_{act}$ and $\forall t \in T$:

$$P_{it}^{fcup} \geq a_{it}^{act} \cdot \epsilon \tag{4.56}$$

$$P_{it}^{fcup} \leq a_{it}^{act} \cdot \overline{P_{i}^{fcact}} \tag{4.57}$$

$$\sum_{t} a_{it}^{act} \leq \overline{a_{it}^{act}} \tag{4.58}$$

$$\sum_{t} P_{it}^{fcup} - \sum_{t} P_{it}^{fcdn} = 0 \tag{4.59}$$

$$\sum_{t}^{t+2} a_{it}^{act} \leq 1 \tag{4.60}$$

$$P_{it}^{fcdn} = (1/3) \cdot P_{it-1}^{fcup} \tag{4.61}$$

4.5.6 OLTC Constraints

We recall that in Chapter 3, the OLTC was modelled as a line with a transformation ratio (k_{ijt}). In order integrate the OLTC into the OP problem, we rely on the convexification adopted by [Tou14]. For the bi-valued variable k_{qijt}, the following is expressed:

$\forall ij \in \kappa$, $\forall q \in \Psi_{ij}$, and $\forall t \in T$:

$$k_{qijt} = d_{qij} \cdot w_{qijt} \tag{4.62}$$

$$k^2_{qijt} = d^2_{qij} \cdot w_{qijt} \tag{4.63}$$

$$\frac{1}{k_{qijt}} = \frac{1}{d_{qij}} \cdot w_{qijt} \tag{4.64}$$

$$\frac{1}{k^2_{qijt}} = \frac{1}{d^2_{qij}} \cdot w_{qijt} \tag{4.65}$$

$\forall ij \in \kappa$ and $\forall t \in T$:

$$\sum_{q \in \Psi_{ij}} w_{qijt} = 1 \tag{4.66}$$

$$k_{ijt} = \sum_{q \in \Psi_{ij}} d_{qij} \cdot w_{qijt} \tag{4.67}$$

$$k^2_{ijt} = \sum_{q \in \Psi_{ij}} d^2_{qij} \cdot w_{qijt} \tag{4.68}$$

$$\frac{1}{k^2_{ijt}} = \sum_{q \in \Psi_{ij}} \frac{1}{d^2_{qij}} \cdot w_{qijt} \tag{4.69}$$

This means that the variable k_{qijt} will hold the transformation ratio d_{qij} if the tap q is chosen at time t. Otherwise, its value will be 0. The binary variable w_{qijt} indicates whether or not the tap q is chosen. Of course, only one tap can be chosen for each time period as indicated by constraint (4.66). The final transformation ratio is the sum of the individual "transformation ratios."

The OLTC has to be integrated into the voltage and current equations in the OPF. However, the product between the binary variable w_{qijt} and the continuous variables l_{ijt} and v_{it} can still lead to non-convexities. This is the reason we adopt another reformulation. For each tap, we introduce continuous variables δ_{qijt} and γ_{qijt} such that:

$$0 \leq \delta_{qijt} \leq \overline{I^2_{ij}} \cdot w_{qijt} \tag{4.70}$$

$$l_{ijt} - \overline{(I_{ij})^2}(1 - w_{qijt}) \leq \delta_{qijt} \leq l_{ijt} \tag{4.71}$$

$$\underline{V^2_i} \cdot w_{qijt} \leq \gamma_{qijt} \leq \overline{V^2_i} \cdot w_{qijt} \tag{4.72}$$

$$v_{it} - \overline{V^2_i}(1 - w_{qijt}) \leq \gamma_{qijt} \leq v_{it} - \underline{V^2_i}(1 - w_{qijt}) \tag{4.73}$$

Constraints (4.74) and (4.75) are then introduced are special cases of (4.45) and (4.46) respectively. Constraints (4.76) and (4.77) are also introduced are special cases of (4.47) and (4.48) respectively.

$\forall ij \in \kappa$, $\forall q \in \Psi_{ij}$ and $\forall t \in T$:

$$v_{jt} \leq \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P_{ijt} + x_{ij} \cdot Q_{ijt}) + M(1 - e_{ijt}) \tag{4.74}$$

$$v_{jt} \geq \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P_{ijt} + x_{ij} \cdot Q_{ijt}) - M(1 - e_{ijt}) \tag{4.75}$$

$$v_{jt} \leq \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P_{ijt} + x_{ij} \cdot Q_{ijt}) + M(1 - e_{ij}) \tag{4.76}$$

$$v_{jt} \geq \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P_{ijt} + x_{ij} \cdot Q_{ijt}) - M(1 - e_{ij}) \tag{4.77}$$

$$\Delta w_{ij} \leq \overline{\Delta w} \tag{4.78}$$

4.5.7 *Linearisation of Register Variables*

In order to count number of reconfigurations and tap changes, two register variables Δe_{ij} and Δw_{ij} exist. Here, we present a linearised method to evaluate them. We introduce temporary variables e^x and e^c. Then, we express the following:

$\forall ij \in \Omega$ and $\notin \xi$, and $\forall t \in T$:

$$e^x_{ijt} \leq \begin{cases} e^0_{ij}, & t = 1 \\ e_{ijt-1}, & t > 1 \end{cases} \tag{4.79}$$

$$e^x_{ijt} \geq \begin{cases} e^0_{ij} + e_{ijt} - 1, & t = 1 \\ e_{ijt-1} + e_{ijt} - 1, & t > 1 \end{cases} \tag{4.80}$$

$$e^c_{ijt} = \begin{cases} e^0_{ij} + e_{ijt} - 2 \cdot e^x_{ijt}, & t = 1 \\ e_{ijt-1} + e_{ijt} - 2 \cdot e^x_{ijt}, & t > 1 \end{cases} \tag{4.81}$$

$$\Delta e_{ij} = \sum_t e^c_{ijt} \tag{4.82}$$

$$\Delta e_{ij} \leq \overline{\Delta e_{ij}} \tag{4.83}$$

$$\Delta e = \sum_{ij} \Delta e_{ij} \tag{4.84}$$

Once again, in case the reconfiguration variable can take only one value for the entire time period of the optimisation, we will proceed to calculate the number of reconfigurations as follows:

$\forall ij \in \Omega$ and $\notin \xi$:

$$e^x_{ij} \leq e^0_{ij} \tag{4.85}$$

$$e^x_{ij} \leq e_{ij} \tag{4.86}$$

$$e^x_{ij} \geq e^0_{ij} + e_{ij} - 1 \tag{4.87}$$

$$\Delta e_{ij} = e_{ij} + e^0_{ij} - 2e^x_{ij} \tag{4.88}$$

$$\Delta e = \sum_{ij} \Delta e_{ij} \tag{4.89}$$

In both cases, the number of reconfigurations performed is calculated with respect to an original configuration e^0. In order to count the number of tap changes of the OLTC in a linearised manner, we express the following:

$\forall ij \in \kappa$, $\forall q \in \Psi_{ij}$ and $\forall t \in T$:

$$w^x_{qijt} \leq w_{qijt} \tag{4.90}$$

$$w^x_{qijt} \leq w_{qijt-1} \tag{4.91}$$

$$w^x_{qijt} \geq w_{qijt} + w_{qijt-1} - 1 \tag{4.92}$$

$$\Delta w_{ij} = 0.5\left(\sum_q \sum_t (w_{qijt} + w_{qijt-1} - 2w^x_{qijt}) \right) \tag{4.93}$$

$$\Delta w = \sum_{ij} \Delta w_{ij} \tag{4.94}$$

4.5.8 Battery System Constraints

To control the charging and discharging power of battery systems present in the network, we impose the following constraints. These constraints have already been developed in Chapter 3. Equation (4.95) describes the state of charge of the battery, while equations (4.96)–(4.98) provide the limits for the state of charge and the charging and discharging powers for the battery.

$\forall i \in \Gamma_{bat}$ & $\forall t \in T$:

$$E_{it}^{soc} = E_{i,t-1}^{soc} + \eta_i^{in} \cdot P_{it}^{bat,in} - \eta^{out} \cdot P_{it}^{bat,out} \tag{4.95}$$

$$\underline{E_i^{soc}} \leq E_{it}^{soc} \leq \overline{E_i^{soc}} \tag{4.96}$$

$$P_{it}^{bat,in} \leq \overline{P_i^{bat}} \tag{4.97}$$

$$P_{it}^{bat,out} \leq \overline{P_i^{bat}} \tag{4.98}$$

4.5.9 DRES Flexibility Constraints

The models for flexibility from DRES connected to the network were elaborated in Chapter 3 of this thesis. Here, we mathematically describe these limits as constraints. The constraint (4.99) expresses the limits for for DRES curtailment, while constraint (4.100) does the same for reactive power control of DRES.

$\forall i \in \Gamma_g$:

$$P_{it}^{fg} \leq \overline{P_{it}^{fg}} \tag{4.99}$$

$$\underline{Q_{it}^{fg}} \leq Q_{it}^{fg} \leq \overline{Q_{it}^{fg}} \tag{4.100}$$

4.5.10 Other Constraints

Since we consider only PQ loads for the scope of this thesis, we need to constrain the reactive power of the activated load flexibility as a function of the load's power factor. This is done through constraints (4.101)-(4.102) expressed below.

$$Q_{it}^{fcup} = P_{it}^{fcup} \cdot tan(\phi)_i \tag{4.101}$$

$$Q_{it}^{fcdn} = P_{it}^{fcdn} \cdot tan(\phi)_i \tag{4.102}$$

4.5.11 Second-Order Cone Relaxation

The second-order cone relaxation described in equation (4.21) becomes equation (4.103) when the variable changes are performed. A computationally tractable version of the relaxation (without the division) is shown in equation (4.104). The feasibility of this relaxation can be measured by evaluating the left hand side of the same equation.

$$l_{ijt} \geq \frac{P_{ijt}^2 + Q_{ijt}^2}{v_{it}} \qquad \forall i \in \Gamma, \forall ij \in \Omega, \forall t \in T \tag{4.103}$$

$$4P_{ijt}^2 + 4Q_{ijt}^2 + (l_{ijt} - v_{it})^2 - (l_{ijt} + v_{it})^2 \leq 0 \tag{4.104}$$

4.5.12 Baseline Expenditures

In order to measure the major aspect of the performance of the novel OP formulation, the expenditures "incurred" by the DSO without the optimisation have to be computed. This can subsequently be compared to the expenditures incurred by the DSO with the optimisation, as computed by the objective function (4.25). These baseline expenditures can be established by computing the expenditures of losses and the expenditures due to the energy not distributed, as shown below:

$$\rho^{org} = \left(\rho^{l} \cdot r_{ij} \cdot l_{ijt}\right) + \sum_{i \in \Gamma!} \sum_{t \in T} \left(\rho^{end} \cdot P^{c}_{it}\right) + \sum_{ij \in \Omega!} \sum_{t \in T} \left(\rho^{end} \cdot P_{ijt}\right) \tag{4.105}$$

It is to be noted that this formula considers that during a particular time period, any voltage violation in a node (represented by the set $\Gamma!$) or current violation in a line (represented by the set $\Omega!$) renders the injected / transported energy as *energy not distributed*. The DSO is penalised accordingly. However, this penalty is only imposed in order to compute a cost for benchmarking purposes. These costs for violations are not really incurred by the DSO.

4.5.13 Final Model Equations

All the flexibilities described in Chapter 3 have thus been integrated into the novel mixed-integer convex OP formulation. Now, to test this formulation, we develop test cases. Based on the type of flexibility available for optimisation, 7 test cases are thus developed. Table 4.2 in page 87 presents the equations and constraints that constitute each of these cases.

4.6 SOLUTION RECOVERY – THE DICHOTOMIC SEARCH HEURISTIC

In section 4.3.1.2, the conditions necessary for the exactness of the second-order cone relaxation were discussed. For the operational planning problem described in this chapter, the objective function satisfies condition 2 (convexity). However, it may not always respect condition 3. This means that under certain cases, this relaxation can fail. While it is to be noted that we obtain a lower bound for the overall expenditures even if the relaxation fails, what we are really interested in is obtaining a usable optimal solution.

The easiest way to achieve this is to change the objective function, and the simplest objective function that satisfies condition 3 is shown in equation (4.106). However, since the purpose of the optimisation is to minimise overall expenditures of the DSO, and not just the cost of losses, the remainder of the original objective function has to be taken into consideration as well. This is achieved by transforming the remainder into a new constraint (4.107).

$$\min \sum_{ij \in \Omega} \sum_{t \in T} (\rho^{da}_{t} r_{ij} l_{ijt}) \tag{4.106}$$

Table 4.2: Novel OP Formulation – Equations Constituting the Different Test Cases

Equations common to all test cases: (4.25) – (4.33), (4.49) – (4.52), (4.62) – (4.73), (4.78), (4.90) – (4.102), (4.104)

Test Case	**Description**		**Equations Specific to the Test Case**
	Reconfiguration	Load Modulation	
$OP-eol2$	1 for the optimisation horizon	Type-2	(4.39) – (4.43), (4.47) – (4.48), (4.54) – (4.55), (4.74) – (4.75), (4.85) – (4.89)
$OP-eol3a$	1 for the optimisation horizon	Types 1 to 3 – No Rebound	(4.39) – (4.43), (4.47) – (4.48), (4.53) – (4.58), (4.74) – (4.75), (4.85) – (4.89)
$OP-eol3b$	1 for the optimisation horizon	Types 1 to 3 – Rebound Type-1	(4.39) – (4.43), (4.47) – (4.48), (4.53) – (4.59), (4.74) – (4.75), (4.74) – (4.75), (4.85) – (4.89)
$OP-eol3c$	1 for the optimisation horizon	Types 1 to 3 – Rebound Type-2	(4.39) – (4.43), (4.47) – (4.48), (4.53) – (4.58), (4.60) – (4.61), (4.76) – (4.77), (4.85) – (4.89)
$OP-etol3a$	1-T for the optimisation horizon	Types 1 to 3 – No Rebound	(4.34) – (4.38), (4.45) – (4.46), (4.54) – (4.58), (4.76) – (4.77), (4.79) – (4.84)
$OP-etol3b$	1-T for the optimisation horizon	Types 1 to 3 – Rebound Type-1	(4.34) – (4.38), (4.45) – (4.46), (4.54) – (4.59), (4.76) – (4.77), (4.79) – (4.84)
$OP-etol3c$	1-T for the optimisation horizon	Types 1 to 3 – Rebound Type-2	(4.34) – (4.38), (4.45) – (4.46), (4.54) – (4.58), (4.60) – (4.61), (4.76) – (4.77), (4.79) – (4.84)

NB The other modelled flexibilities are available for optimisation in all the problems.

$$\sum_i \sum_{t=1}^{24} \Bigg[\Big(\rho^{act} \cdot a_{it}^{act} \cdot \overline{P_{it}^{fcact}} \Big) + \Big(\rho^{lcup} \cdot P_{it}^{fcup} \Big) + \Big(\rho^{lcdn} \cdot P_{it}^{fcdn} \Big) + \Big(\rho_t^{ch} \cdot P_{it}^{bat,in} \Big) + \Big(\rho_t^{dc} \cdot P_{it}^{bat,out} \Big) + \Big(\rho_t^{cur} \cdot P_{it}^{fg} \Big) \Bigg] + \Big(\rho_1^{oltc} + \rho_2^{oltc} \cdot \Delta w \Big) + \Big(\rho_1^{rec} + \rho_2^{rec} \cdot \Delta e \Big) \leq \rho^{lim} \tag{4.107}$$

In this new formulation, all the equations for the different test cases presented in Table 4.2 remain the same, except for the objective function (4.25). This function is replaced by (4.106) and the constraint (4.107) is added to all the test cases. In order to obtain a globally optimal solution in case the relaxation fails, we present a simple heuristic procedure to be followed. A similar approach to obtaining globally optimal solutions with only discrete load modulation flexibilities is presented in [Van16]. In our case, the heuristic procedure works with all types of load modulation.

$\forall t \in T$: Let f^* be the solution to the original problem. In order to recover a physically meaningful solution f^{**} for the problem, we run our new problem using the following heuristic procedure.

1: **procedure** GlobOpt(f^*)
2: $\quad low \leftarrow f^*$
3: $\quad high \leftarrow \rho^{lim}$
4: $\quad err \leftarrow high - low$
5: $\quad$ **while** $err > 0.01$ **do**
6: $\quad\quad f^{**} = \min$ MISOCP-Π_{DA_b}
7: $\quad\quad$ **if** relaxation holds and $(f^{**} + \rho^{lim})$ decreases **then**
8: $\quad\quad\quad$ store f^{**}, ρ^{lim}
9: $\quad\quad\quad high \leftarrow \rho^{lim}$
10: $\quad\quad\quad \rho^{lim} \leftarrow \rho^{lim} - (\rho^{lim} - low)/2$
11: $\quad\quad$ **else**
12: $\quad\quad\quad low \leftarrow \rho^{lim}$
13: $\quad\quad\quad \rho^{lim} \leftarrow \rho^{lim} + (high - \rho^{lim})/2$
14: $\quad\quad$ **end if**
15: $\quad\quad err \leftarrow high - \rho^{lim}$
16: $\quad$ **end while**
17: $\quad$ **if** $high - low > 0.01$ **then**
18: $\quad\quad \rho^{lim} \leftarrow high - 0.01$
19: $\quad\quad$ Repeat steps 6 to 14
20: $\quad$ **end if**
21: $\quad$ **return results**
22: **end procedure**

The procedure works on a dichotomic search heuristic, decreasing the gap between the current feasible optimum and the global feasible optimum with each iteration. The limiting cost ρ^{lim} decreases with every iteration where the relaxation holds and the final objective (DSO expenditures) decreases. In each of the assignment statements, the cost is rounded-up to the nearest cent (0.01 €). The choice of ρ^{lim} affects the execution time of the algorithm. In the worst case scenario, for a given value of ρ^{lim}, the algorithm executes in logarithmic time. Experimental proof that this procedure produces an optimal result for the novel OP formulation is presented in Section 5.3.4 in Chapter 5.

4.7 CONCLUSIONS

In this chapter, the concepts underlying the operational planning of power systems were first introduced. This included the concept of mathematical reformulations, the unit commitment and economic dispatch (UC & ED) problem, and the optimal power flow (OPF) problem. This was followed by a review of the relevant literature in the field of OPF formulation in general and OP formulations and for distribution networks. This review highlighted the advantages and shortcomings of the methods currently employed in research. A summary of the different approaches helped us select a modelling technique for the novel OP formulation for distribution networks.

The novel OP formulation is a mixed-integer distribution network operational planning method based on a convex relaxation of the optimal power flow (OPF). This formulation was subsequently developed and presented. This method, whose objective is to decrease overall DSO expenditures on flexibilities, integrated both continuous and discrete flexibilities in distribution networks. Discrete flexibilities like on-load tap changers and reconfiguration were integrated without simplification with the aid of reformulation techniques. The conditions under which the convex relaxation used in this method holds, meaning the method can find a global optimum, were also discussed. Different test cases were created based on the types of flexibilities used.

Since the objective function of the developed method does not always satisfy the conditions, meaning that the obtained solution may not be feasible for the original OPF problem, a new problem with a new objective function and an additional constraint was cast. It was further argued that this new problem could be solved with global optimality using a dichotomic search algorithm that is developed and presented.

In the next chapter, we test the novel OP formulation for distribution networks with the test cases developed in Table 4.2. The solution recovery algorithm is also tested in the chapter. The main results from these tests are presented and discussed, and are used to validate the models developed in this chapter.

Novel OP Formulation – Results

5

« One plus one equals three, for very large values of one. »
- Anonymous

5.1 INTRODUCTION

5.1.1 Context

The novel mixed-integer convex operational planning (OP) formulation developed in this thesis was presented in Chapter 4. This formulation integrates discrete flexibilities such as reconfiguration and OLTC, and convexifies the power flow equations, all through reformulations. These reformulations, including the second-order cone programming (SOCP) relaxation enables us to derive a mixed-integer SOCP (MISOCP) model for the OP problem in distribution networks. This formulation represents the distribution network and the flexibilities without loss of exactness. Therefore, its solutions, if feasible for the underlying optimal power flow (OPF) problem, are globally optimal and physically meaningful.

However, the SOCP relaxation may possibly fail under certain conditions. This will render the solution physically useless. To recover a globally-optimal and physically meaningful solution under such circumstances, a solution-recovery procedure based on a dichotomic search heuristic was also presented in Chapter 4. Finally, a set of test cases with different combinations of flexibilities was outlined (see Table 4.2).

In this chapter, the results for tests of the novel OP formulation are presented. These tests are performed for the day-ahead optimisation stage, and are conducted based on the test cases outlined in Table 4.2. The contributions of this chapter to the thesis are as follows (numbering consistent with the contributions listed in Chapter 1):

- C5 Tests of the novel OP formulation with networks, for varying levels of DRES integration, and for different levels of flexibility utilisation.
- C7 A discussion of the use of flexibility in operational planning, and the effects on the solution characteristics of the problem.

The inputs required for the novel OP formulation are outlined below:

1. *Flexibilities & Costs*: The economic information pertaining to the flexibilities that are considered in these tests is presented in Chapter 3. The linearised models for these flexibilities have already been integrated into the novel OP formulation.
2. *Test Networks*: Two test networks are used to test the novel OP formulation. One of them is an IEEE test network, and the other is a real-world test network present in PREDIS platform of Grenoble INP-Ense3, in the University of Grenoble-Alps. The test networks are briefly presented in Section 5.1.2. Additional information for these networks can be found in Appendix B.

3 *Test Parameters*: Parameters like the load and DRES forecasts are based on load / production curves available or used in literature. Other parameters like the limits on flexibilities are based on intuitive decisions. In all cases, the choice of parameters is explained. The test parameters are presented in Section 5.1.3.

5.1.2 Test Networks

As mentioned earlier, two test distribution networks are used to evaluate the performance of the developed novel OP formulation. Both the networks are briefly described below. Further information on them can be found in Appendix B. This information includes the resistances and reactances of the lines, information related to type, size and location of DRES, and the calculations for load and DRES forecasts.

5.1.2.1 The Baran Network

The Baran test network [BW89b] is a 12.66 kV test network with 33 nodes and 37 lines. Out of the 37 lines, 32 are normally closed, and 5 are normally open. The network has one OLTC installed between nodes 1 and 2. This OLTC has 5 taps. An illustration of the network is shown in Fig. 5.1.

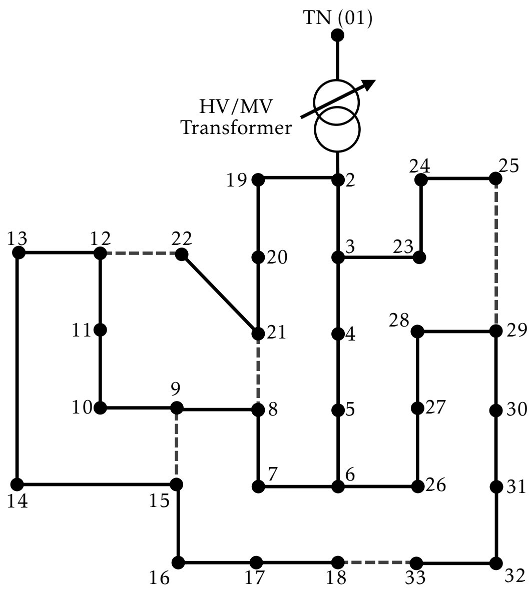


Figure 5.1: The Baran Test Network

This network does not have any DRES installed originally. To insert DRES into the network, we first refer to the details related to the DRES installed capacity in the distribution networks of Enedis, the largest DSO in France [ENE16]. The type, location, and rating of the DRES to be inserted into the network is then chosen based on the available data. For our tests, we choose a 20 % insertion rate. Further information on this calculation is presented in Appendix B. The main characteristics of the network are summarised in Table 5.1.

Table 5.1: Baran Test Network – Main Characteristics

<table>
<tr><th>Characteristics</th><th colspan="4">Value</th></tr>
<tr><td>Nodes</td><td colspan="4">33 (1 Slack, 32 PQ)</td></tr>
<tr><td>Lines</td><td colspan="4">37 (32 NC, 5 NO, All Manoeuvrable)</td></tr>
<tr><td>Connected Load</td><td colspan="4">3.71 MW (4.37 MVA)</td></tr>
<tr><td>OLTC</td><td colspan="4">5 Taps, 0.025 pu per tap</td></tr>
<tr><td rowspan="4">DRES (20 %)</td><td colspan="2">Wind</td><td colspan="2">PV</td></tr>
<tr><td>Node</td><td>W_p</td><td>Node</td><td>W_p</td></tr>
<tr><td>4</td><td>0.423 MW</td><td>26</td><td>0.417 MW</td></tr>
<tr><td></td><td></td><td>27</td><td>0.273 MW</td></tr>
</table>

5.1.2.2 The PREDIS Network

The PREDIS test network [LTCR+09] is an 11 kV mixed urban-rural network is reduced scale test distribution network in G2ELab/Grenoble INP-Ense3, at the University of Grenoble Alps. This network has 13 nodes and 17 lines. Out of the 17 lines, 5 lines are normally open and 12 are normally closed. The network has 3 OLTCs installed between the nodes {1-2, 1-3, 1-10}. The network has been extracted from a 20kV real distribution network in South of France respecting both sizing and voltage drop characteristics, and is shown Fig. 5.2.

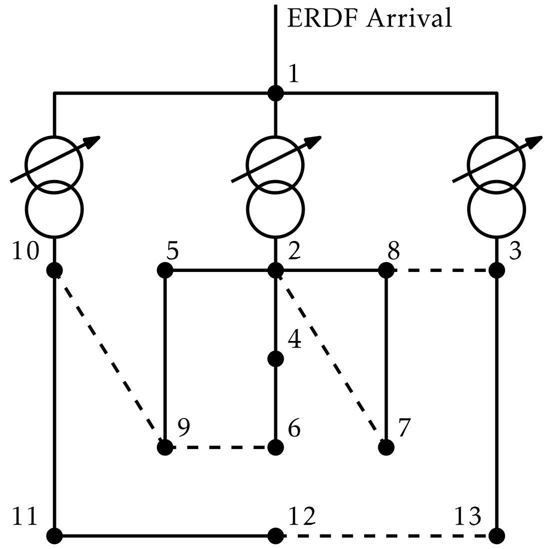


Figure 5.2: The Baran Test Network

The PREDIS network (with urban and sub-urban characteristics) is strong enough to withstand a large integration of DRES. To this end, for tests with the PREDIS network, we use a DRES insertion rate of 50 % instead of 20 %. This network has wind DRES installed in nodes 4, 6, 8/12, & 9/11. Given these locations of the DRES in the network, we choose to apply only forecast weights to the DRES to obtain the final forecasts. The values for these final forecasts are illustrated in Section 5.1.3.

The connection points of the DRES connected to nodes 8/12 and 9/11 can be modified nased on the need. Nodes 11-13 are rural nodes, and tests with DRES connected to these nodes can therefore be made if necessary. In our test case, we consider the following. The DRES connected to node 12 moves to node 8 during the 9th hour, while the DRES connected to node 9 moves to node 11 during the 12th hour of the day. Further, all the loads connected to this network can be controlled in a continuous manner. This means that they can be modelled using type-2 load modulation. The main characteristics are presented in Table 5.2.

Table 5.2: PREDIS Test Network – Main Characteristics

Characteristics	**Value**			
Nodes	13 (1 Slack, 12 PQ)			
Lines	17 (12 NC, 5 NO, All Manoeuvrable)			
Connected Load	18.75 MW (19 MVA)			
OLTC	5 Taps, 0.025 pu per tap			
DRES (50 %)	Wind			
	Node	W_p	Node	W_p
	4	1.5 MW	8/12	5.5 MW
	6	1.5 MW	9/11	5.5 MW

The reasoning behind the choice of networks is as follows. Firstly, the Baran network has an OLTC, can be reconfigured, and has all types of flexibilities available. This allows us to test all the flexibilities and the performance of the OP formulation on difficult test cases. Secondly, in our tests, the SOCP relaxation fails for the PREDIS test network. This will allow us to test the solution recovery search heuristic on the network.

5.1.3 *Test Parameters*

To test the novel OP formulation with the test networks presented in the next section, values have to be chosen for various input parameters. These parameters include the load and DRES forecasts, the DRES insertion rate, the voltage limits, the choice of load modulation and the respective limits, the DRES curtailment and reactive power compensation limits, battery characteristics, and the costs for flexibility among others. The choice of these values is explained in this section.

5.1.3.1 Forecasts

The novel OP formulation requires input forecasts for all the loads and DRES present in the network to be optimised. Three different types of loads are considered in the tests: residential, industrial, and commercial. Each of these types of loads shows different consumption patterns during the day. We create weights to model this behaviour. These weights are based on a modified, normalised version of the weights presented by Shih-An and Chan-Nan [SC09].

A typical PV forecast is constructed from the output measurements made between 2007 and 2014 on the PV systems at G2ELab. Wind forecasts are considered to be random. These forecasts are then converted to weights. The load forecast weights are illustrated in Fig. 5.3.

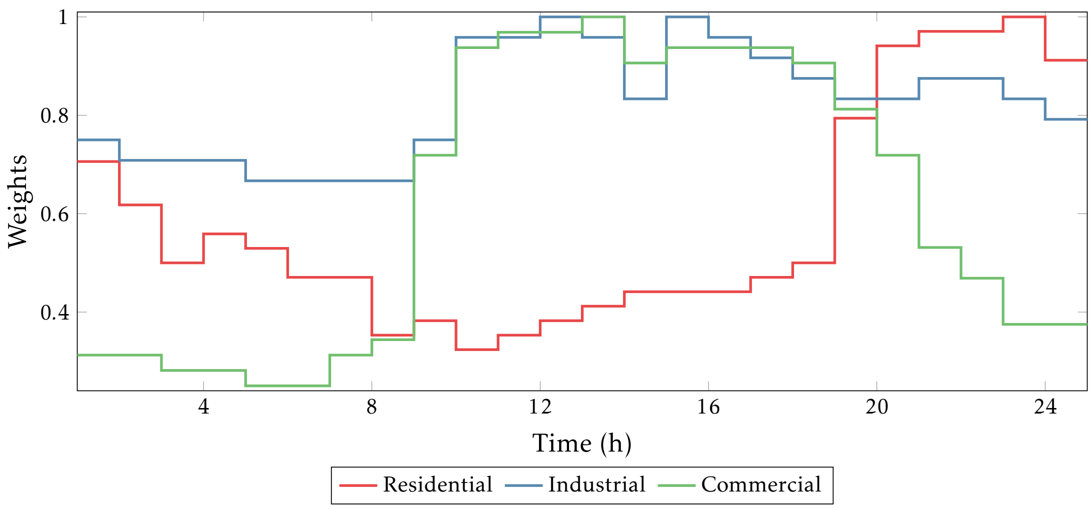


Figure 5.3: Load Forecasts – Weights by Type

DRES forecast weights for the Baran network are illustrated in Fig. 5.4. For the PREDIS network, they are illustrated in Fig. 5.5.

5.1.3.2 The Use of Reconfiguration and OLTC

We model two types of problems for network reconfiguration in Chapter 4. In the first problem, the statuses of reconfiguration switches are time dependent. This means that reconfiguration actions can be performed at any hour inside the optimisation

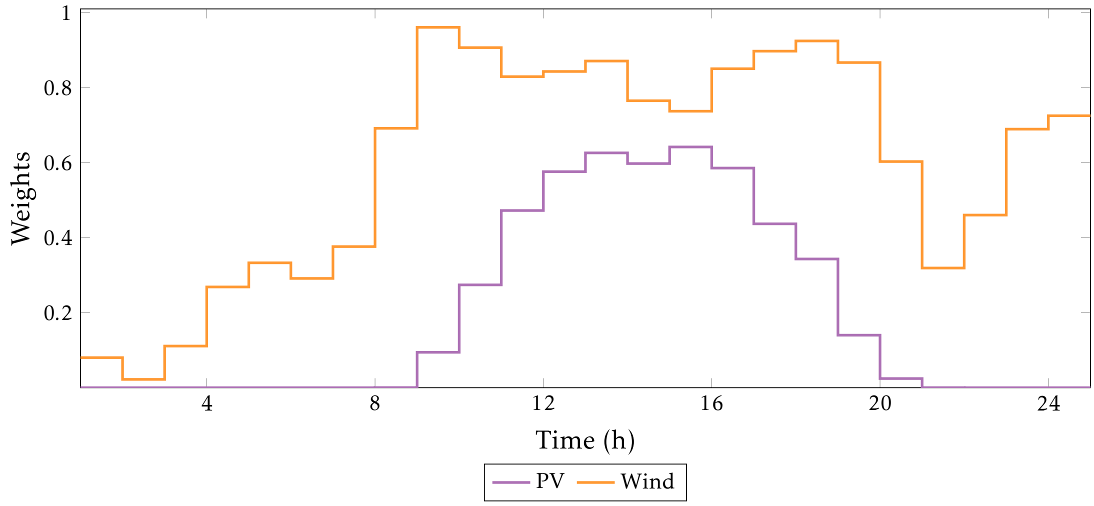


Figure 5.4: DRES Forecasts for the Baran Network – Weights by Type

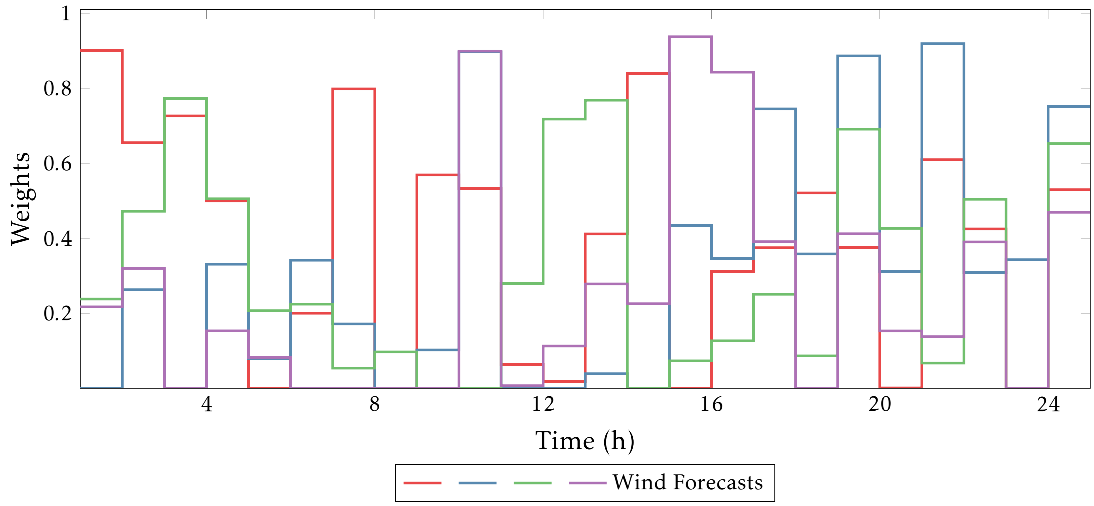


Figure 5.5: DRES Forecasts for the PREDIS Network – Weights by Type

horizon. This is subject to a limit on the total number of reconfiguration actions allowed for each switch during the entire optimisation time horizon. It is imposed by a constraint on the variable Δe_{ij}. In the second problem, the configuration of the network is time independent. The reconfiguration actions are therefore imposed on the entire time period. The second model is more tractable, but comes with the disadvantage of not being able to change the configuration when needed, and also forcing changes in the configuration of the network at the beginning of the optimisation period in a systematic manner. In the first model, the tractability of the novel OP formulation is influenced by the limits on Δe_{ij}.

When weighing the effectiveness of the problems, the tractability of the problem should however not be the only criterion. In practice, DSOs use reconfiguration for seasonal / yearly reconfiguration of their networks. They do not use it on a daily basis. This stems from the consideration that network reconfiguration switches are expensive and unreliable, and that frequent reconfigurations create transients. Reconfiguration can nevertheless be a highly valuable flexibility, and research has shown the added value of network reconfiguration time and again.

We therefore test reconfiguration in three different ways. In the first, we allow the OP formulation to choose one configuration for every time-step of the optimisation. This means that Δe_{ij} is limited to 24 changes a day. In the second, we allow the OP formulation to change the status of a line ij once, at any time-step of the optimisation. This means that Δe_{ij} is limited to 1. In the third, we impose the the time independent reconfiguration model.

As for OLTCs, the number of tap changes permitted for each OLTC in the optimisation time horizon can be controlled by imposing a constraint on the register variable Δw_{ij}. In practice, OLTCs automatically change taps based on the measurement of downstream voltages. The advantage of this method is that it allows for as many tap changes as required, without any need for exhaustive computation. However, we have already shown in this thesis why such an automatic system would not be suitable with a high integration of DRES (see Chapter 2, Section 2.4.2). Allowing the OLTC to be controlled by the novel OP formulation can overcome this issue.

For operational planning done over 24 one-hour periods like the novel OP formulation, a maximum of 24 tap changes can be allowed. As is the case with reconfiguration, this influences the tractability. However, there is more clarity with the practical use of OLTCs than that of reconfiguration. In keeping with the current DSO practices, we therefore decide to allow for as many tap changes as possible. In order to see whether these considerations on the use of endogenous flexibilities have any impact on the results, we perform an analysis of the results with respect to their use. This is presented after the results, in Section 5.4.

5.1.3.3 Load Modulation

We recall that three types of load modulation were modelled in Chapter 4. The parameters for these load modulation types are outlined in Table 5.3. These parameters outline the limits for each type, along with the time-frame for these limits.

Table 5.3: Load Modulation – Characteristics & Parameters

Type	Limits
Type-1	1 %, 2 %, 4 % and 8 % of load for each t
Type-2	Minimum load in T
Type-3	[-20 %, +10 %] for each t

For test cases with type-1 load modulation, a total of 6 nodes are chosen, resulting in 576 type-1 flexibility offers (4 x 6 x 24). For the Baran network, the nodes chosen for type-1 load modulation are nodes {3, 11, 17, 23, 27, 32}. This choice is made as these nodes have industrial loads connected to them, with potential processes allowing for load modulation based on capacity reservation.

We also arbitrarily decide to choose all odd-numbered nodes in the network other than any nodes with type-1 modulation for type-2 modulation. Similarly, all even-numbered nodes other than any nodes with type-1 modulation are chosen for type-3 modulation.

5.1.3.4 DRES, Battery & Voltage Limits

For DRES curtailment we choose a limit of 100 % of the produced power. For DRES reactive power compensation, this limit is [-35 %, +40 %]. This means that each DRES can inject upto 40 %, and consume 35 % of its actual active power production in terms of reactive power. This is in line with the model developed in Chapter 3, based on the guidelines used by DSOs like Enedis [ENE17]. As far as the batteries are concerned, all the networks are considered to have a certain number of 250kWh batteries. These batteries are installed in even-numbered nodes of the networks, and can ramp to 100 % in one hour. The voltage limits imposed on the network throughout the optimisation period are ±5 %, in accordance with the widely accepted limits imposed by DSOs on their MV distribution networks. These limits are imposed based on contractual rules and allow for better voltage control on their LV networks. The voltage of the slack node is set at 1.02 pu for all the optimisation tests.

5.1.3.5 Cost Parameters

The novel OP formulation is a technico-economic optimisation formulation. It requires the costs of the flexibilities it uses, in order to calculate the final expenditures to the DSO. The calculation of costs for the flexibilities used in the formulation has already been done as a part of the economic analysis of flexibilities in Chapter 3. For convenience, we outline the costs of the flexibilities again in Table 5.4.

Table 5.4: Test Parameters – Flexibility Costs

Flexibility		**Cost**
	OLTC	14.21 € per day + 11.875 € per tap change
	Reconfiguration	0.898 € per day + 4.5 € per switching action
	Active Power Losses	50 € per MWh
Load Modulation	Types 1 & 2	Day-Ahead Market Price
	Type-3	18 € per MWh for every activation
Battery	Charge	-522.81 to -507.22 € per MWh
	Discharge	563.19 to 578.78 € per MWh

5.1.4 *Test Environment*

The General Algebraic Modeling System (GAMS) [GAM13] with a Matlab® interface is used to model the novel OP formulation. The Branch-and-Cut method in the IBM CPLEX® solver is used to solve the MISOCP problems with global optimality. The proof of optimality of the solution with this method is presented Appendix A. All the tests for which the results are presented in this chapter and in Appendix B have been carried out on a computer with a 32-core Intel® Xeon® E5-2690 processor and 96 GB of RAM, running Windows Server 2008.

5.1.5 *Organisation of Results*

The rest of this chapter is organised as follows. The main test results for the Baran test network are presented in Section 5.2. This is followed by the results for the PREDIS network, presented in Section 5.3. A discussion of the performance of the novel OP formulation and the flexibilities is then presented in Section 5.4. Finally, the conclusions on the test cases and the results are presented in Section 5.5. Test results for some combinations of the test cases / networks that have not been included in this chapter can be found in Appendix B. An overview of the test cases and the location of the corresponding results are presented is shown in Table 5.5.

Table 5.5: Organisation of Results for Test Cases

Test Networks	**Test Cases**	**Main Results**	**Additional Results**
Baran	$OP-eol3a$ – $OP-eol3c$	Section 5.2	Appendix B
	$OP-etol3a$ – $OP-etol3c$	Section 5.2	Section 5.2
	$OP-eol3a$[1]	Section 5.3	—
PREDIS	$OP-eol2$ (Solution Recovery)	Section 5.3	—

In order to illustrate the working of the solution recovery search heuristic, a simple test case $OP-eol2$is presented. The algorithm is also applied to a test case for the Baran network, for which the relaxation holds. This is done to prove that both the original optimisation and the solution recovery algorithm converge to the same objective.

5.2 RESULTS – THE BARAN NETWORK

In this section, the results obtained when the novel OP formulation is tested using the Baran network are presented. Due to the paucity of space, the results of three test cases are elaborated and discussed, while the results of the other test cases are simply outlined. A comparison of the performance of the algorithm across the test cases is also presented. First, the original conditions in the network are outlined.

5.2.1 Original Conditions

We run simulations for the Baran network with the load and DRES forecasts, without the use of flexibility. This provides an idea of the refereccnce / original conditions, including the violated constraints. The original network voltages across the 24-hour test period are shown in Fig. 5.6. This illustration is a heat-map of the different voltages in the nodes, with colours ranging from dark blue (1.05 pu) to yellow (0.87 pu).

The lowest voltage observed, 0.875 pu, occurs at hour 20 in node 18. Among the 792 voltages calculated for the network, there are 326 violations of the lower voltage limit of 0.95 pu, but no violations of the upper limit of 1.05 pu. There are no current violations in the network. It can be concluded that this network therefore suffers only from under voltage problems in this case. The nodes with major voltage issues are the end nodes of the two longest feeders, nodes 18 and 33, with 21 hours of under voltages. Upstream, there is a progressive decrease in the number of hours when under voltages occur, with node 6 exhibiting 4 violations. The other feeders do not have any voltage violations. The active power losses in the network over the 24-hour period are 6.86 MWh. Finally, the expenditures “incurred” by the DSO, over the 24-hour period and on the entire network, without the optimisation amount to 428 990.9 €, as computed using the formula (4.105). Note that these costs are not actually incurred, but serve as a reference to benchmark the improvement attained with the novel OP formulation.

[1] For verification of optimality of the solution recovery heuristic.

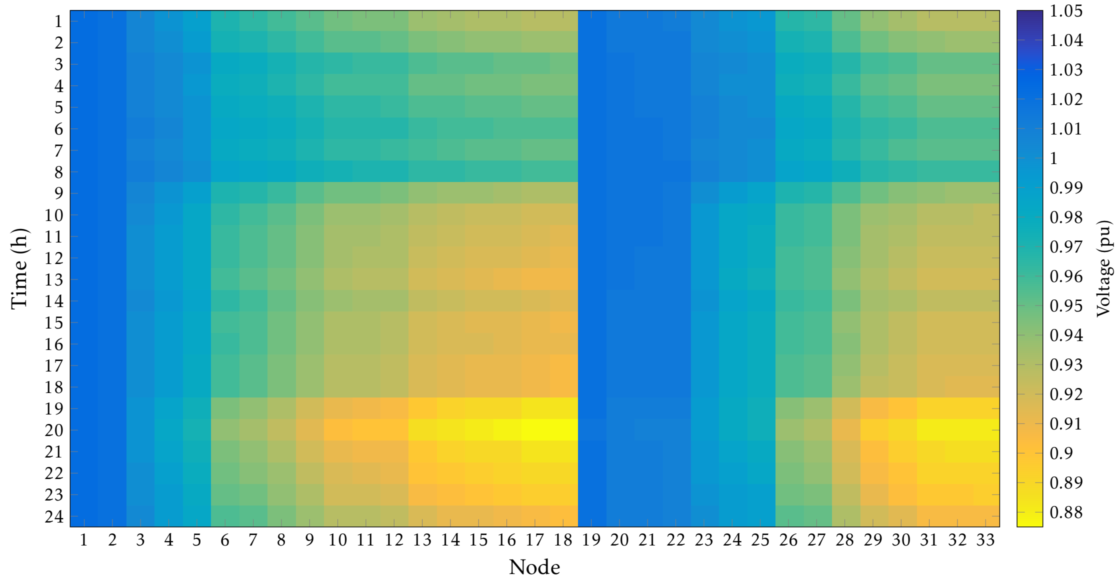


Figure 5.6: Baran Network – Original Voltages for 20 % DRES Insertion Rate

5.2.2 *Results – All Flexibilities without Rebound*

We now test the Baran network using all available flexibilities, without imposing any rebound on type-3 load modulation. The test case in question is $OP-etol3a$. The number of switching actions for every reconfiguration switch and the tap changes for all OLTCs is set at one per time period. This translates to a total of 24 actions for each of these flexibilities.

Because of the high number of discrete variables, this case is hard to solve. However, by allowing the highest possible number of changes for every reconfiguration switch and OLTC, this test case will, in the best scenario, provide the lowest objective function value among all the cases. In the worst scenario, its objective function should be the lowest as well. But depending on the results, other, more tractable cases may produce similar results. More information on this is presented in Section 5.4. A summary of the results obtained for this test case is outlined in Table 5.6.

Table 5.6: Baran Network – Results for Test Case $OP-etol3a$

<table>
<tr><th>Description</th><th>Value</th></tr>
<tr><td>DSO Expenditures (Objective)</td><td>310.66 €</td></tr>
<tr><td>Execution Time</td><td>15978.3 seconds</td></tr>
<tr><td>Active Losses</td><td>4.52 MWh</td></tr>
<tr><td>Tap Setting</td><td>4 (Hours 1–24)</td></tr>
<tr><td>Open Switches</td><td>C1 (Hours 1–24)</td></tr>
<tr><td>Load Modulation (kWh)</td><td><table><tr><td>Type-1</td><td>Type-2</td><td>Type-3</td></tr><tr><td>2.75</td><td>44.11</td><td>375.28</td></tr></table></td></tr>
<tr><td>DRES Curtailment</td><td>—</td></tr>
<tr><td>DRES Reactive Compensation</td><td>3.775 MVArh (Injection)</td></tr>
<tr><td>Average Relaxation Error</td><td>0.13 VA²</td></tr>
</table>

The final objective function value (DSO expenditures) for this test case amounts to

310.66 €. This is very little compared to the original expenditures, and this is mainly owing to the fact that there are no violations of the operating limits, and hence no *energy not distributed*. The execution time for the optimisation is around 4½ hours. There is a 34.01 % reduction in active losses over the optimisation period. The OLTC in the network is set to tap 4 for all the hours. Configuration C1 corresponds to the set of open switches {6–26, 8–21, 9–15, 11–12, 18–33} in the network.

All three load modulation types are used. The total load modulation achieved is around 0.42 MWh. None of the DRES is curtailed, while 3.775 MVArh of reactive power compensation is used from the three DRES present in the network. Finally, the average relaxation error is around 0.13 VA^2, meaning that the relaxation holds well for this test case. Note that this error is calculated by evaluating the equation (4.104) with the values of the decision variables obtained from the OP formulation. It is the difference between the left and right hand sides of the equation.

The optimised network voltages for this test case are presented in Fig. 5.7. For uniformity, the colour-space from Fig. 5.6 is preserved. The lowest optimised voltage in the network is 0.95 pu, observed at node 33 during hour 19. The highest optimised voltage is 1.0454 pu, observed at node 2 during hours 6 and 8.

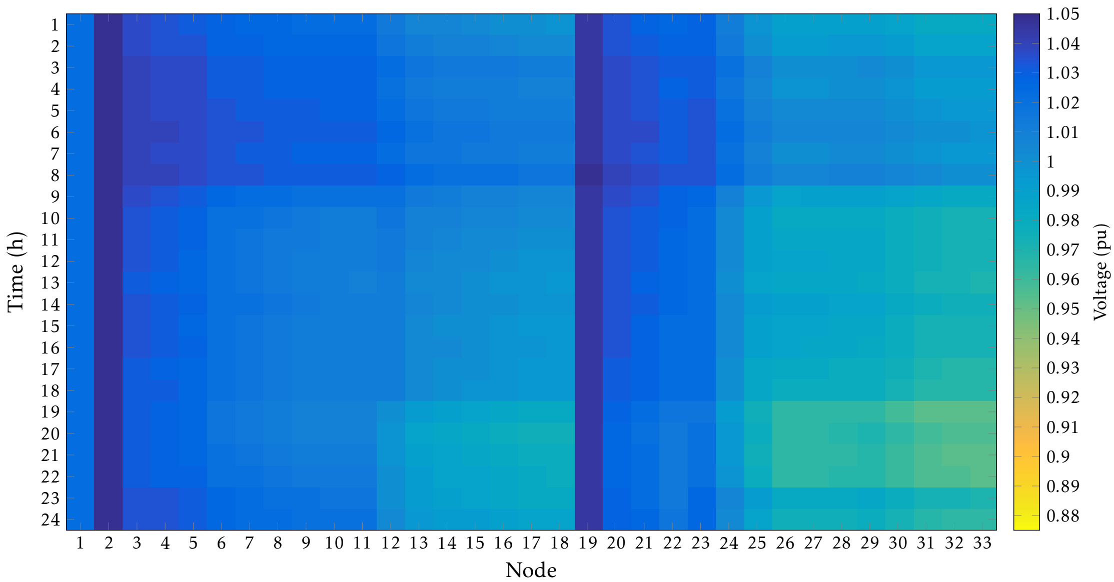


Figure 5.7: Baran Network – Optimised Voltages for Test Case *OP – etol3a*

The aggregated load curves for the network before and after load modulation are shown in Fig. 5.8. Since there is no rebound, there is no load shifting observed in this test case. Instead, it is only peak load shaving that occurs, during hours 19, 20, 21, & 23, in nodes 26, 28, & 30-33. The total load modulation used by the novel OP formulation corresponds to only 0.38 % of the total load in the network.

Node 32 is the only one chosen for Type-1 load modulation. A total of 2.75 kWh is shaved off in this node during hour 21. This is illustrated in Fig. 5.9. Type-2 load modulation is employed in node 33. A total of 44.1 kWh is reduced from the peak load during hours 19 and 21. This is illustrated in Fig. 5.10a.

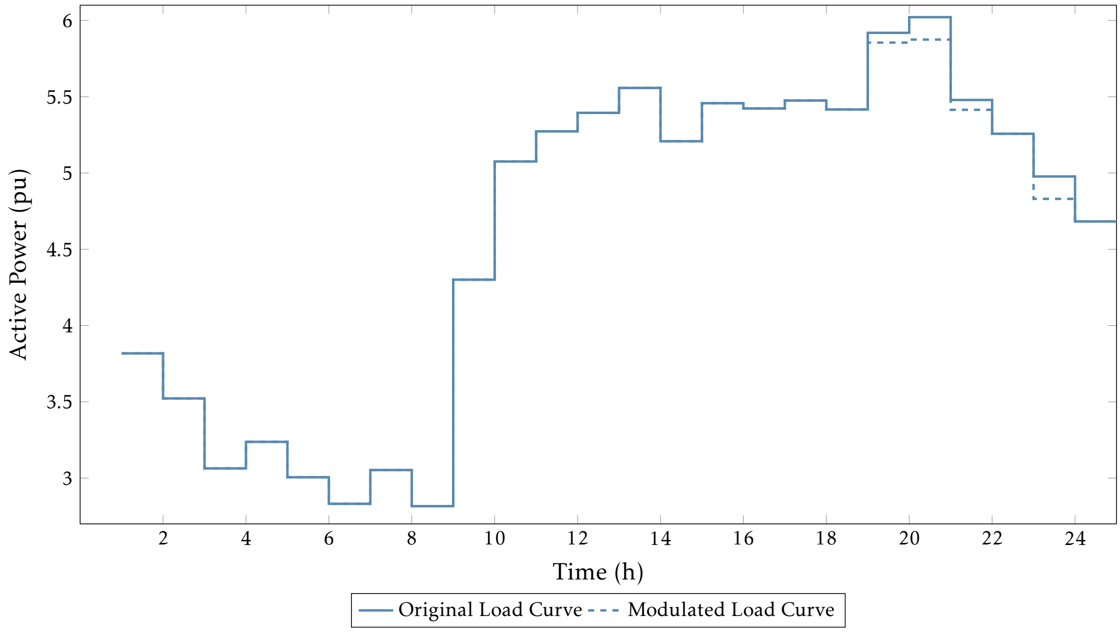


Figure 5.8: Baran Network – Aggregated Load Modulation Curves for Test Case $OP-etol3a$

As for type-3 load modulation, three nodes – 26, 28, and 30 – are chosen. Without any need to reinject the modulated energy, a total of 375.28 kWh of energy is shaved off in these three nodes. Node 26 contributes to a reduction of 38.7 kWh of energy during hour 21. This is illustrated in Fig. 5.10b. Node 28 contributes to a reduction of 42.9 kWh during hour 19, as illustrated in Fig. 5.11a. Finally, node 30 contributes to a reduction of 293.7 kWh during hours 20 and 23 and this is illustrated in Fig. 5.11b.

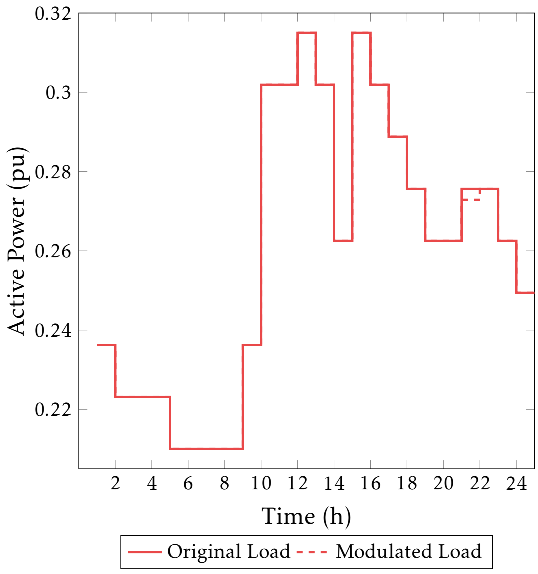
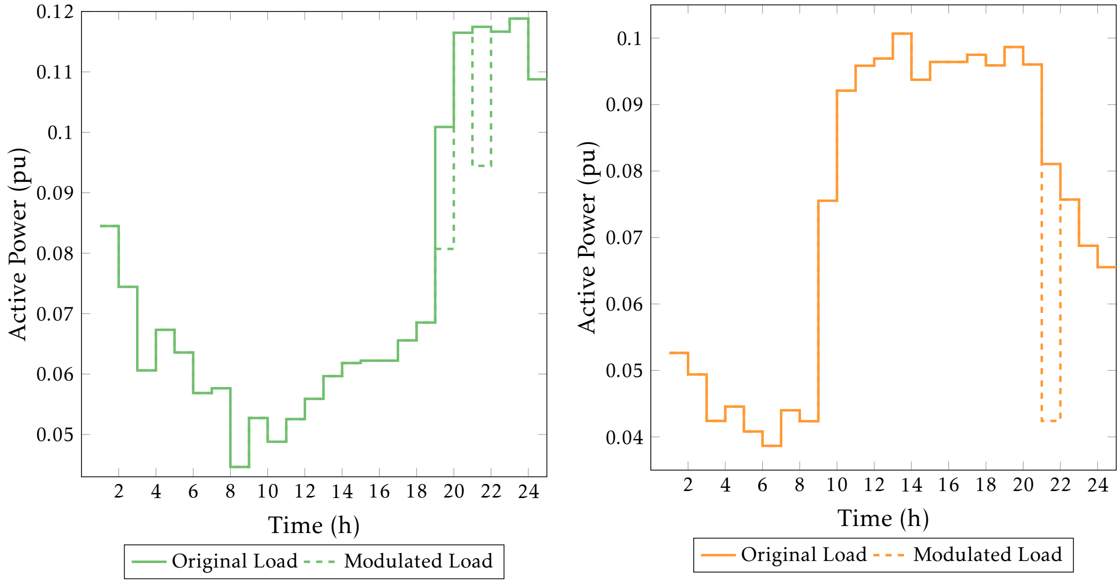


Figure 5.9: Baran Network – Type-1 Modulation (Node 32) for Test Case $OP-etol3a$

The 3 DRES generators present in the network contribute to the mitigation of the voltage deviations in the network via reactive power compensation. This contribution is illustrated in Fig. 5.12. In fact, all the generators are all maxed-out in terms of their reactive power injection limit ($tan\,\phi = 0.4$) throughout the optimisation period. In the next section, the results for the Baran test network with all flexibilities and type-1 rebound are presented.

5.2.3 *Results – All Flexibilities with Type-1 Rebound*

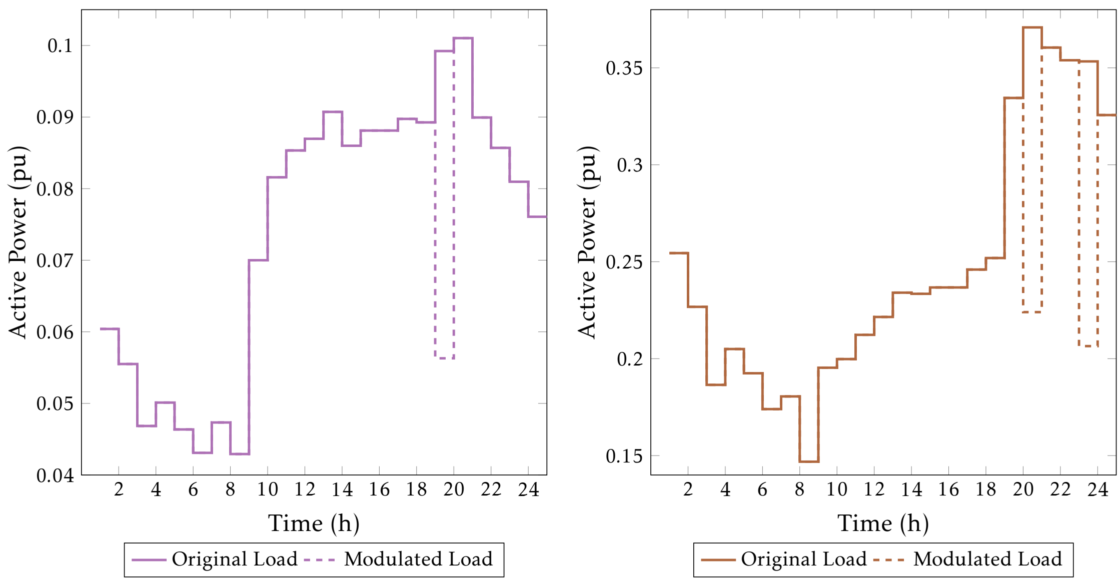
We now impose type-1 rebound on all the type-3 load modulation available in the network. This corresponds to the test case $OP-etol3b$. We recall that in type-1 rebound, the novel OP formulation is able to equalise the decrease in consumption over the entire time horizon of the optimisation. A summary of the results obtained for this test case is outlined in Table 5.7.



(a) Type-2 Load Modulation (Node 33)

(b) Type-3 Load Modulation (Node 26)

Figure 5.10: Baran Network – Load Modulation Types 2 & 3 for Test Case $OP - etol3a$



(a) Type-3 Load Modulation (Node 28)

(b) Type-3 Load Modulation (Node 30)

Figure 5.11: Baran Network – Type-3 Load Modulation for Test Case $OP - etol3a$

Because of the high number of discrete variables, this case is once again hard to solve. The final objective function value (DSO expenditures) for this test case amounts to 312.61 €. The execution time for the optimisation is around 4½ hours as well. There is a 32.7 % reduction in active losses over the optimisation period. The OLTC in the network is set to tap 4 for all the hours. Configuration C1, which is the same as the configuration chosen for the test case $OP - etol3a$, corresponds to the set of open switches {6–26, 8–21, 9–15, 11–12, 18–33} in the network.

Once again, all three load modulation types are used. The total load modulation achieved is around 0.257 MWh. None of the DRES is curtailed, while 3.775 MVArh

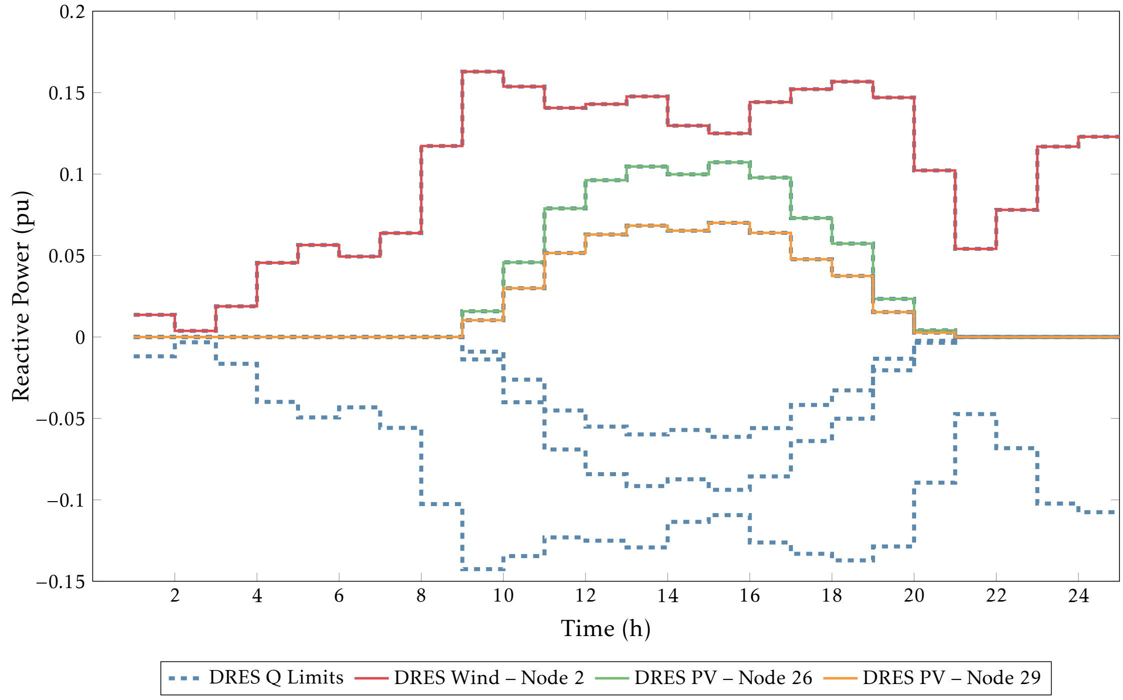


Figure 5.12: Baran Network – DRES Reactive Power Compensation for Test Case *OP – etol3a*

Table 5.7: Baran Network – Results for Test Case *OP – etol3b*

<table>
<tr><th>Description</th><th colspan="3">Value</th></tr>
<tr><td>DSO Expenditures (Objective)</td><td colspan="3">312.61 €</td></tr>
<tr><td>Execution Time</td><td colspan="3">16247.3 seconds</td></tr>
<tr><td>Active Losses</td><td colspan="3">4.61 MWh</td></tr>
<tr><td>Tap Setting</td><td colspan="3">4 (Hours 1–24)</td></tr>
<tr><td>Open Switches</td><td colspan="3">C1 (Hours 1–24)</td></tr>
<tr><td rowspan="2">Load Modulation (kWh)</td><td>Type-1</td><td>Type-2</td><td>Type-3</td></tr>
<tr><td>29.0</td><td>43.12</td><td>185.5</td></tr>
<tr><td>DRES Curtailment</td><td colspan="3">—</td></tr>
<tr><td>DRES Reactive Compensation</td><td colspan="3">3.775 MVArh (Injection)</td></tr>
<tr><td>Average Relaxation Error</td><td colspan="3">2.45 VA²</td></tr>
</table>

of reactive power compensation is used from the three DRES present in the network. This is means that the reactive power injection from the DRES is maxed-out for this test case as well. Finally, the average relaxation error is around 2.45 VA^2, meaning that the relaxation holds well for this test case.

The optimised network voltages for this test case are presented in Fig. 5.13. Once again, the colour-space from Fig. 5.6 is preserved for uniformity. The lowest optimised voltage in the network is 0.95 pu, observed at node 33 during hour 21. The highest observed voltage in the optimised network is 1.0454 pu, at node 2 during hour 8.

The aggregated load curves for the network before and after load modulation are shown in Fig. 5.14. This is a classic example of peak load shaving and shifting. During peak loading hours 19 – 21, there is a reduction in the load. Part of this reduced load

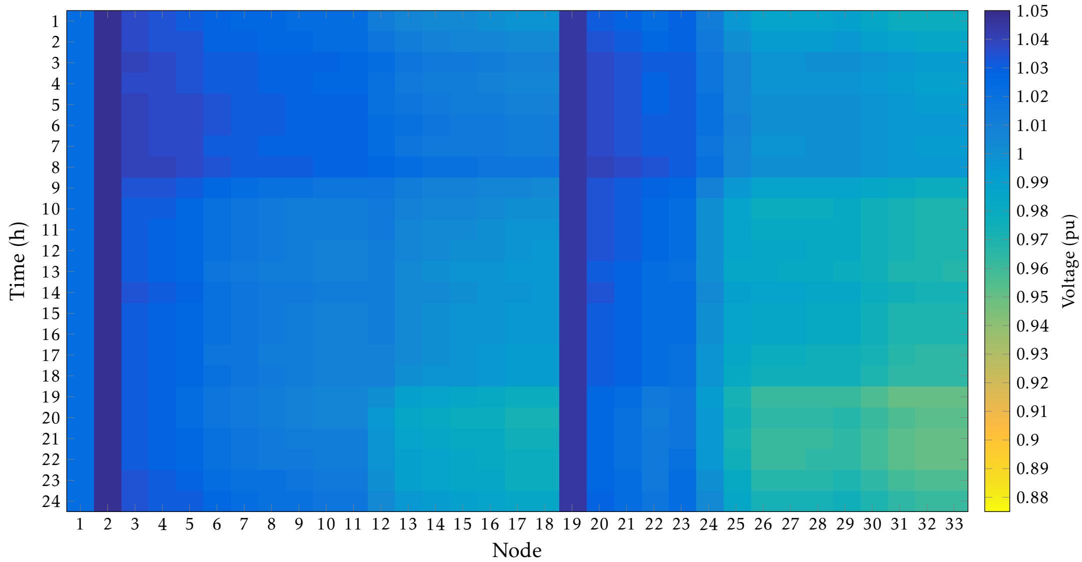


Figure 5.13: Baran Network – Optimised Voltages for Test Case *OP – etol – 3b*

(type-3 load modulation) is moved to off-peak hours 3, 5, 6, 7, and 8, in an anticipation of the reduction that occurs later in the day. The total load modulation in this test case corresponds to 0.22 % of the total load in the network.

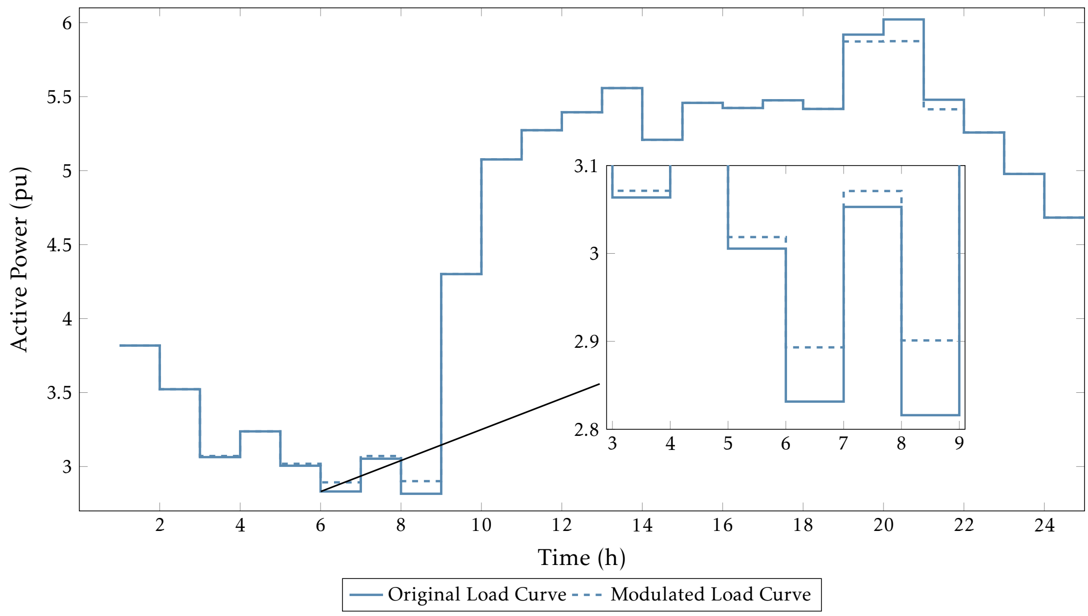
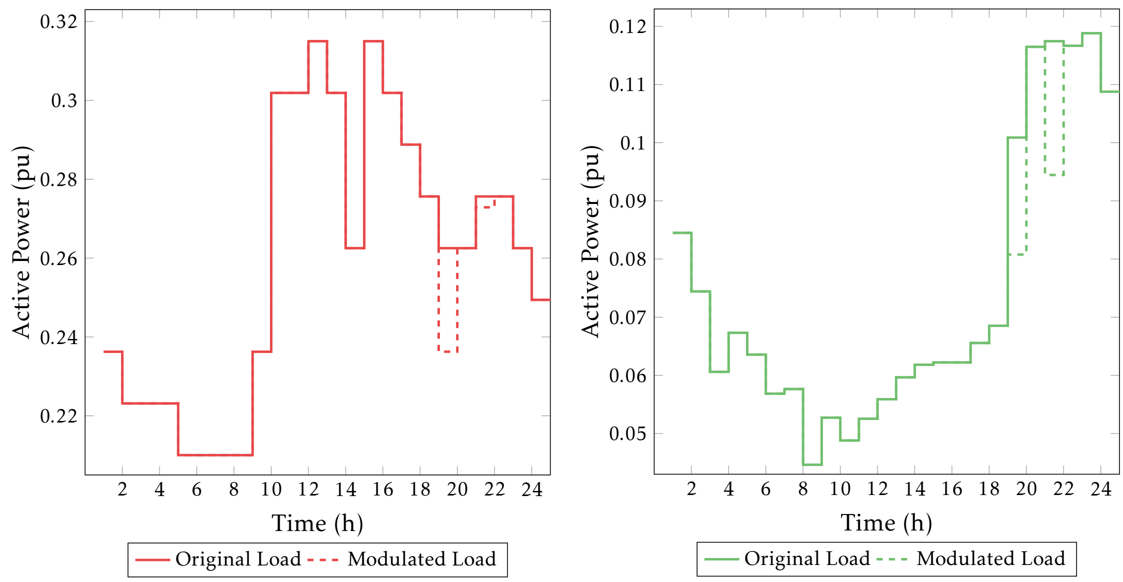


Figure 5.14: Baran Network – Aggregated Load Modulation Curves for Test Case *OP – etol – 3b*

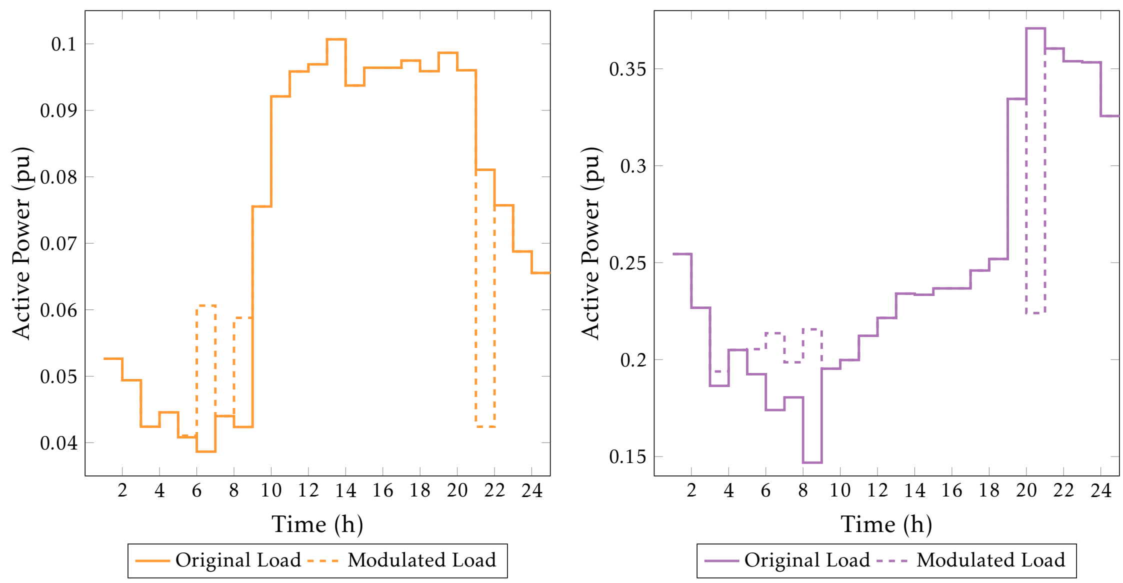
Four Type-1 modulation offers are chosen in node 32. Among these, 3 are in hour 19 and 1 is in hour 21. A total of 29 kWh is decreased using this flexibility. This is illustrated in Fig. 5.15a. Type-2 modulation occurs during hours 20 and 22, in node 33, and corresponds to a reduction of 43.12 kWh. This is illustrated in Fig. 5.15b. Two nodes are chosen by the novel OP formulation for type-3 load modulation for this test case – nodes 26 and 30. The modulation performed on the loads in these nodes is illustrated in Fig. 5.16. In node 26, a load reduction of 38.7 kWh occurs at hour 21, and this load is shifted to hours 6 and 8. In node 30, a reduction of 146.8 kWh occurs during hour 20, and the reduced load is shifted to hours 3, 5, 6, 7 & 8.



(a) Type 1 Load Modulation (Node 32)

(b) Type 2 Load Modulation (Node 33)

Figure 5.15: Baran Network – Type 1 and Type 2 Load Modulation for Test Case $OP - etol - 3b$



(a) Node 26

(b) Node 30

Figure 5.16: Baran Network – Type 3 Load Modulation for Test Case $OP - etol - 3b$

As mentioned earlier in the section, the reactive power compensation for this test case from the 3 DRES present in the network is the same as that for test case $OP - etol3a$. This has already been illustrated in Fig. 5.12. In the next section, the results obtained for the Baran network when the type-3 load modulation is used with type-2 rebound are presented.

5.2.4 *Results – All Flexibilities with Type 2 Rebound*

The test case $OP - etol3c$ corresponds to the use of all flexibility, and all type-3 load modulation is used with type-2 rebound. We recall that type-2 rebound corresponds to a rebound of one-third of the decreased load in the hour immediately after the decrease, with a possibility to equalise the remaining two-thirds of the decreased energy during the entire time horizon of the optimisation. Given of the high number of discrete variables and also the additional constraints imposed by the rebound, this case is probably the hardest to solve. A summary of the results obtained for this test case is presented in Table 5.8. The optimised network voltages are illustrated in Fig. 5.17. The colour-space from Fig. 5.6 is preserved once again for uniformity.

Table 5.8: Baran Network – Results for Test Case *OP – etol3c*

Description	Value
DSO Expenditures (Objective)	315.95 €
Execution Time	18644.2 seconds
Active Losses	4.62 MWh
Tap Setting	4 (Hours 1–24)
Open Switches	C1 (Hours 1–24)
Load Modulation (kWh)	Type-1: 67.6 Type-2: 94.3 Type-3: 185.5
DRES Curtailment	—
DRES Reactive Compensation	3.775 MVArh (Injection)
Average Relaxation Error	5.06 VA^2

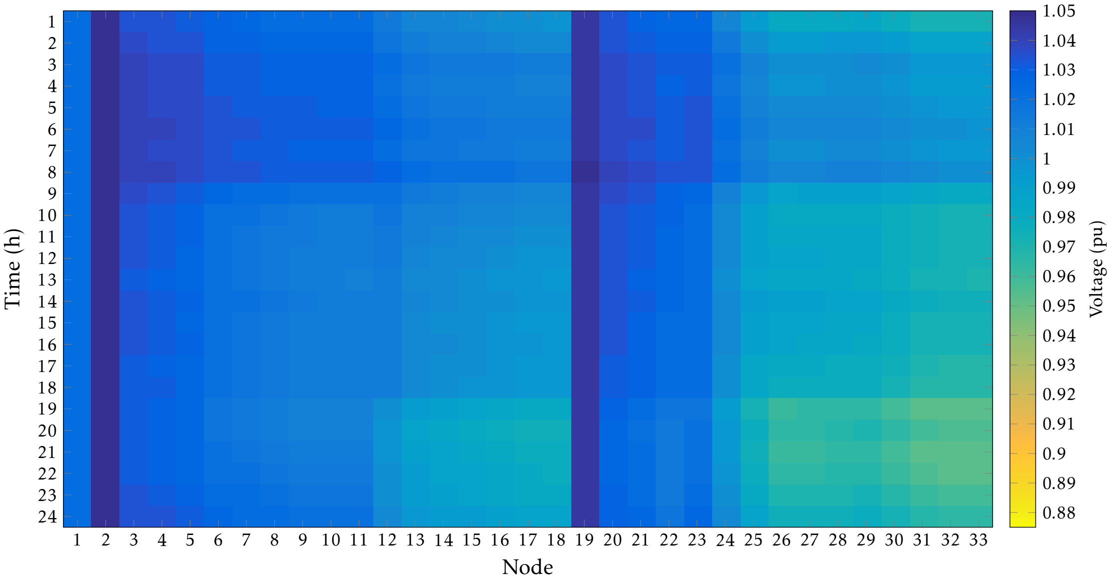


Figure 5.17: Baran Network – Optimised Voltages for Test Case *OP – etol3c*

The final objective function value (DSO expenditures) for this test case amounts to 315.95 €. The execution time for the optimisation is around 5 hours and 10 minutes. There is a 32.7 % reduction in active losses over the optimisation period. The OLTC in the network is set to tap 4 for all the hours. Configuration C1, which is the same as the configuration chosen for the test case *OP – etol3a*, corresponds to the set of open switches {6–26, 8–21, 9–15, 11–12, 18–33} in the network. Once again, all three load modulation types are used. The total load modulation achieved is around 0.347 MWh.

None of the DRES is curtailed, while 3.775 MVArh of reactive power compensation is used from the three DRES present in the network. This is means that the reactive power injection from the DRES is maxed-out for this test case as well. Finally, the average relaxation error is around 5.06 VA^2, meaning that the relaxation holds well for this test case. The lowest optimised voltage is 0.95 pu, observed at node 33 during hour 21. The highest optimised voltage observed is 1.0454 pu, at node 2 during hours 6 and 8.

The aggregated load curves for the network before and after load modulation are shown in Fig. 5.18. This is another example of peak load shaving and shifting. During peak loading hours 19 – 21, there is a reduction in the load. Part of this reduced load is moved to off-peak hour 1. Another part is equalised during hours 21 and 22, due to the type-2 rebound constraint. The rebound during hour 21 is not reflected on the aggregated curve because of a larger load reduction at another node. The total load modulation in this test case corresponds to 0.302 % of the total load in the network.

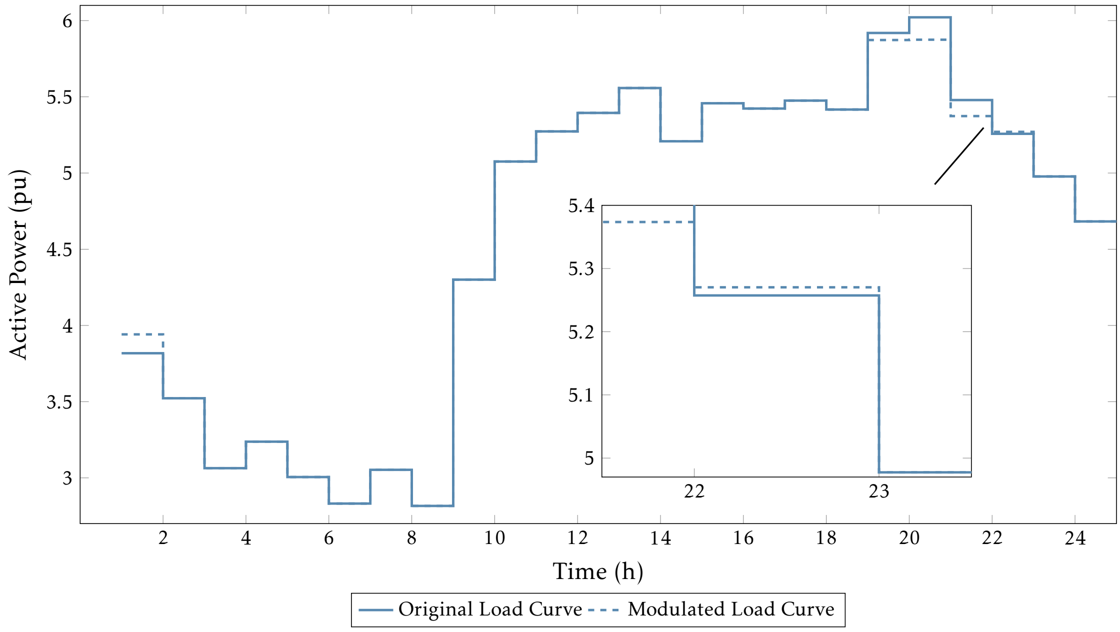


Figure 5.18: Baran Network – Aggregated Load Modulation Curves for Test Case $OP - etol - 3c$

Six type-1 load modulation offers from node 32 are selected. Two of these offers are during hour 19, and contribute to a reduction of 26.3 kWh. The four remaining offers are selected during hour 21 and contribute to a reduction of 41.3 kWh. This is illustrated in Fig. 5.19.

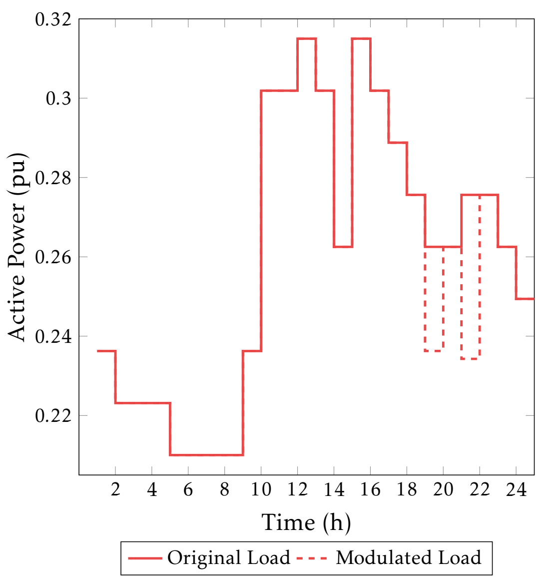
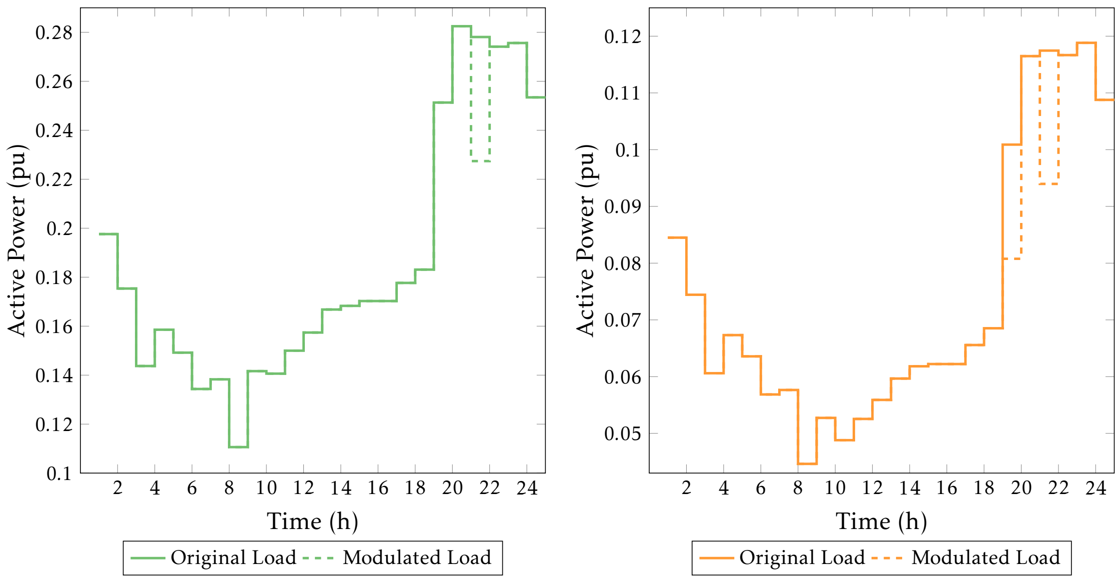


Figure 5.19: Baran Network – Type-1 Modulation (Node 32) for Test Case $OP - etol3c$

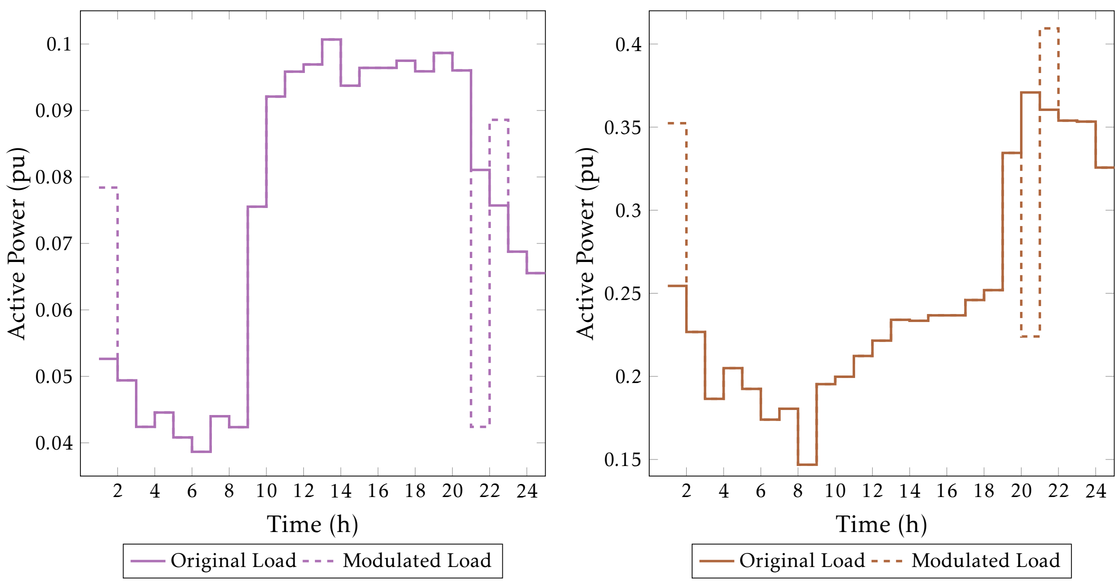
Nodes 31 and 33 are chosen for type-2 load modulation. In node 31, there is a reduction of 50.7 kWh during hour 21. This is illustrated in Fig. 5.20a. In node 33, a load reduction of 43.6 kWh occurs during hours 19 and 21. This is illustrated in Fig. 5.20b.

Nodes 26 and 30 are chosen for type-3 load modulation. In node 26, there is a reduction of 38.7 kWh during hour 21. One-third of this energy, 12.9 kWh is equalised during hour 22. The remaining energy is equalised during hour 1. This is illustrated in Fig. 5.21a. In node 30, there is a reduction of 146.9 kWh during hour 20, with the equalisation happening on hour 21 (48.95 kWh) and hour 1 (97.9 kWh). This is illustrated in Fig. 5.21b.



(a) Node 31 (b) Node 33

Figure 5.20: Baran Network – Type-2 Load Modulation for Test Case $OP - etol3c$



(a) Node 26 (b) Node 30

Figure 5.21: Baran Network – Type 3 Load Modulation for Test Case $OP - etol - 3c$

The DRES reactive power compensation from the 3 DRES in the network amounts to 3.775 MVArh (injection). This is the same compensation as in the test cases $OP - etol3a$ and $OP - etol3b$. This compensation was illustrated in Fig. 5.12.

5.2.5 *Results for Other Test Cases & Analysis*

In the previous sections, the results obtained with the Baran network for the test cases $OP - etol3a$, $OP - etol3b$ & $OP - etol3c$ were elaborated. In this section, a brief presentation of the results for other test cases is done. This brief presentation includes an outline of the results of the additional tests and a comparative presentation of the different main results obtained. These results are further presented in Appendix B. The 6 test cases explored are $OP - etol3a^*$, $OP - etol3b^*$, $OP - etol3c^*$, $OP - eol3a$, $OP - eol3b$ and $OP - eol3c$. The equations that make up these test cases can be found in Table 4.2 in Chapter 4. A summary of the main results for these test cases is presented in Table 5.9 in page 110.

We recall that between the different test cases, only the nature of reconfiguration changes. For the test cases $OP - etol3a$ to $OP - etol3c$, 24 reconfigurations (1 per time period) are permitted for each switch. For test cases $OP - etol3a^*$ to $OP - etol3c^*$, a maximum of one reconfiguration is permitted per switch, at any point during the time horizon. And for the test cases $OP-eol3a$ to $OP-eol3c$, the statuses of the reconfiguration switches are independent of time (one configuration for the whole time horizon). For the given DRES and load forecasts, the Baran network exhibits a peculiar phenomenon. The reconfiguration results returned for the most difficult test cases ($OP - etol3a$ to $OP - etol3c$) correspond to those of the most tractable cases ($OP - eol3a$ to $OP - eol3c$). This means that the latter cases not only solve the OP problem faster, they are also as optimal as the former cases. More information on this can be found in Section 5.4.

We now test the novel OP formulation using different DRES insertion rates, ranging from 10 % to 100 %, for the test case $OP - eol3b$. For all these insertion rates, the choice of type, size, and location of the DRES in the network is made using the procedure presented in Appendix B. The distributions of the original and optimised voltages in the network when the novel OP formulation is tested are shown in Fig. 5.22. The distributions presented are for 10 different DRES insertion rates ranging from 10 % to 100 %. The main results for these tests are outlined in Table 5.10. The problems in the un-optimised network are mostly under-voltages in the peripheral nodes. The case with 90 % DRES insertion is an exception, showing over-voltage issues as well. The novel OP formulation is able to solve all these issues optimally, with reasonable solution times.

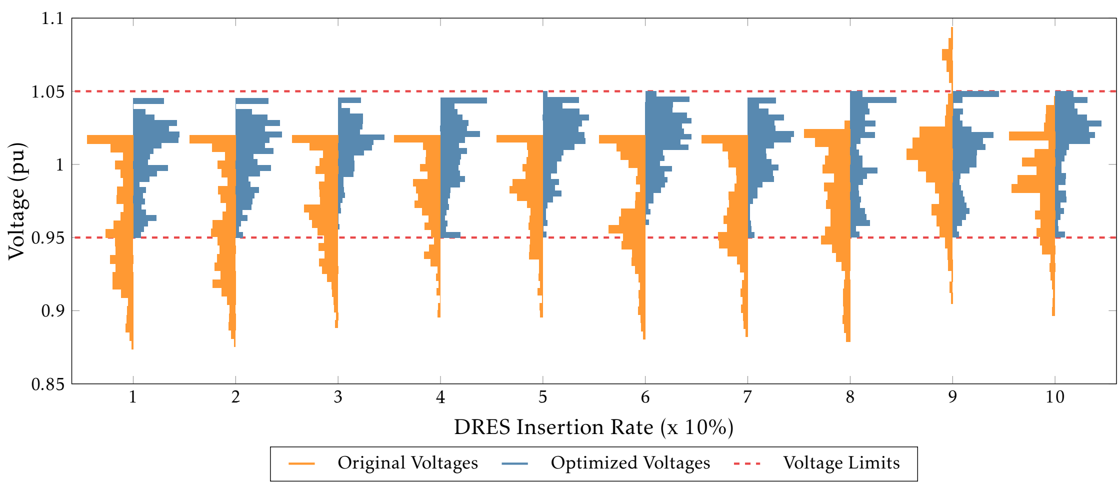


Figure 5.22: Baran Network – Network Voltage Distributions – DRES Insertion Rates from 10 % to 100 %

Table 5.9: Baran Network – Results for Test Cases

Test Case	Objective Value (€)	Execution Time (sec)	Active Power Losses (MWh)	Tap Setting	Open Switches	Load Modulation (kWh)	DRES Curtailment (MWh)	DRES Q Compensation (MVArh)	Avg. Error (Relaxation) (VA^2)
*OP – etol3a**	310.66	279.3	4.52	4 (h1-24)	C1 (h1-24)	422.1	—	3.775	0.16
*OP – etol3b**	312.61	286.1	4.61	4 (h1-24)	C1 (h1-24)	257.6	—	3.775	2.92
*OP – etol3c**	315.95	251.8	4.62	4 (h1-24)	C1 (h1-24)	347.4	—	3.775	4.38
OP – eol3a	310.66	84.28	4.52	4 (h1-24)	C1 (h1-24)	422.1	—	3.775	2.32
OP – eol3b	312.61	149.9	4.61	4 (h1-24)	C1 (h1-24)	257.6	—	3.775	2.78
OP – eol3c	315.95	52.5	4.62	4 (h1-24)	C1 (h1-24)	347.4	—	3.775	4.74

Table 5.10: Baran Network – Results for Test Case *OP – eol3b* for DRES Insertion Rates from 10 % to 100 %

Result	**DRES Insertion Rate (%)**									
	10 %	20 %	30 %	40 %	50 %	60 %	70 %	80 %	90 %	100 %
Objective (€)	338.99	312.61	218.38	284.09	256.92	224.23	259.32	370.79	339.06	245.13
Execution Time (sec)	141.5	149.9	59.4	175.6	158.3	91.5	51.2	112.3	230.5	216.45
Active Power Losses (MWh) – Original	7.06	6.86	5.19	5.19	4.96	5.63	5.49	6.22	6.77	5.50
Active Power Losses (MWh) – Optimised	5.08	4.61	3.02	3.81	3.70	2.96	3.59	5.61	4.94	2.52
Tap Setting	4 (h1–24)	4 (h1–24)	4 (h1–24)	4 (h1–24)	4 (h1–24)	4 (h1–24)	4 (h1–24)	4 (h1–24)	3 (h1–18), 4 (h19–24)	4 (h1–24)
Open Switches	C1	C1	C2	C3	C2	C1	C2	C4	C5	C6
DRES Q Compensation (MVArh)	1.13	3.775	9.06	10.67	11.28	15.42	15.33	0.105	7.75	23.95
Load Modulation (kWh)	372.7	257.6	—	803.5	200.7	—	481.1	992.6	675.5	1318.8
Average Relaxation Error (VA^2)	0.51	2.78	0.27	0.44	0.78	0.15	2.8	1.91	0.11	4.8

Legend: Open Lines – C1: {6-26, 8-21, 9-15, 11-12, 18-33}, C2: {8-21, 9-15, 11-12, 18-33, 25-29}, C3: {6-26, 8-21, 9-15, 11-12, 12-22}, C4: {6-26, 8-21, 9-15, 12-22, 18-33}, C5: {8-21, 11-12, 12-22, 18-33, 25-29}, C6: {4-5, 6-26, 9-15, 11-12, 12-22}

Overall, the utilisation of the flexibility to solve the constraint violations in this network has been minimal. We analyse the results obtained for different DRES insertion rates with the test case $OP - eol3b$ to identify the flexibility procurement costs for different flexibilities.

On an average, the following expenditures were made for the various flexibilities. There was no DRES curtailment in any of the test cases. Type-1 load modulation was procured for an average cost of 1.8 € per test case. Type-2 load modulation was procured for about 4.12 €, while type-3 load modulation was procured for about 5.81 €. A single tap change was registered for the OLTC for 9 out of the 10 test cases, with a cost of 26.09 €. The only exception was the test case with 90 % DRES insertion, where two tap changes, with a total cost of 37.97 €, were made. Around 46.73 € was spent on reconfiguring the network in each test case. Finally, there was an imperceptible use of the battery systems in 3 test cases, to the order of 0.02 c€.

A discussion of the overall flexibility usage and the results for the test cases can be found later in this chapter, in Section 5.4. More illustrations for the tests with the different DRES insertion rates, for test case $OP - eol3b$, can be found in Appendix B.

5.3 SOLUTION RECOVERY WITH THE PREDIS NETWORK

In this section, the results obtained when the novel OP formulation is tested using the PREDIS network are presented. The SOCP relaxation fails for this network. Therefore, we employ the solution recovery algorithm developed in Chapter 4 to obtain a globally optimal solution. First, the original conditions in the network are outlined.

5.3.1 *Original Conditions*

We test the PREDIS test network with the original load and DRES forecasts, without the use of flexibility.The voltages in the network for the given time period are illustrated via a heat-map in Fig. 5.23.

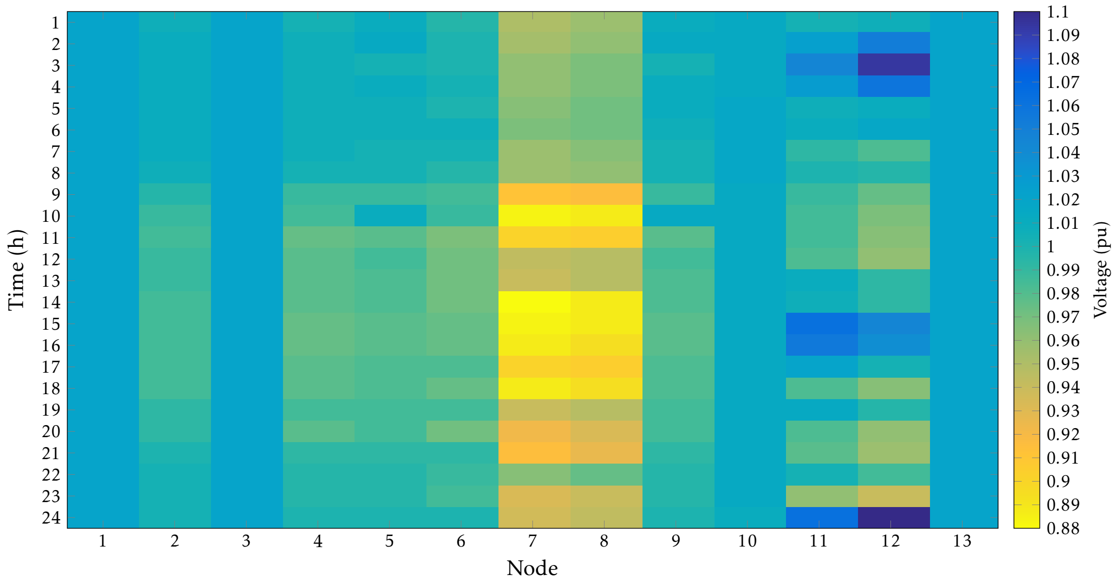


Figure 5.23: PREDIS Network – Original Voltages for 50 % DRES Insertion Rate

With a 50 % DRES insertion rate, this network exhibits both under-voltage and over-voltage problems. It is to be noted that this network has higher than normal loading (generally not found in France), and this is the reason for the under-voltage issues. The lowest observed voltage is 0.882 pu, at node 7 during hour 14. The highest observed voltage is 1.097 pu, at node 12 during hour 24. There are a total of 31 under-voltages and 6 over-voltages in a total of 312 voltage calculations. There is one current violation, at hour 10 in the line connecting nodes 5 and 9, of 0.011 pu. The active power lost in the network during the given time periods amounts to 8.825 MWh. The total DSO expenditures for the original case, using the formula (4.105), are 503 374.91 €.

5.3.2 *Relaxation Failure - Example with Test Case $OP-eol2$*

In our tests with this network, the second-order cone programming (SOCP) relaxation has been shown to fail consistently. We present the results of the test case $OP-eol2$ to illustrate this failure. We recall that all the loads in this network can be controlled in a continuous manner and are therefore modelled using type-2 load modulation. The results provided by the novel OP formulation are outlined in Table 5.11.

Table 5.11: PREDIS Network – Results for Test Case $OP-eol2$

Description	**Value**
DSO Expenditures (Objective)	233.74 €
Execution Time	60.9 seconds
Active Losses	3.598 MWh
Tap Setting	T1 (Hours 1–24)
Open Switches	C1 (Hours 1–24)
Load Modulation	—
DRES Curtailment	—
DRES Reactive Compensation	17.8 MVArh (Injection)
Average Relaxation Error	555.9 VA^2

Tap setting T1 corresponds to the taps {4, 4, 4} for the OLTCs 1-2, 1-3, and 1-10 respectively. The configuration C1 corresponds to open switches {2-7, 2-8, 6-9, 12-13} in the network. However, the high value of the relaxation error indicates that the SOCP relaxation fails. This can be further confirmed, if necessary, by running load flow calculations based on the flexibility set-points.

5.3.3 *The Solution Recovery Algorithm*

Given that the relaxation fails for the test case $OP-eol2$, we apply the solution recovery algorithm presented in Chapter 4, Section 4.6 to the problem, in an attempt to recover a globally optimal solution. The objective function value of the original problem, 233.74 €, gives us a lower bound for the final DSO expenditures. It is impossible for a practically feasible solution to the novel OP formulation to yield an objective value that is below 233.74 €.

To run the solution recovery algorithm, its input parameters *high* and *low* have to be chosen. We know that the original objective value of 233.74 € is the lower bound for a feasible OPF solution to the novel OP formulation in this case. The choice of *low* is therefore simple. The choice for *high* is more complicated. The advantage of choosing a large value is that in case the objective value of the actual optimum is very high, compared to the lower bound, we make sure that the search heuristic can always converge. The disadvantage is that the exponential time nature of the problem increases the solution time with a large value of $high$. In our case, we choose to use a value 20 times that of low. Therefore, we choose $high = 4674.8$. We then run the search heuristic. The results obtained are presented below.

The number of iterations to find the optimal solution using the search heuristic was 19. The path taken by the dichotomic search is illustrated in Fig. 5.24. It shows the progressive decrease in the gap to the optimal solution. The optimal solution, as indicated by the algorithm is 2327.08 €. This corresponds to the cost constraint ρ^{lim} of 2291.17 €, yielding a cost of 35.91 € for active power losses.

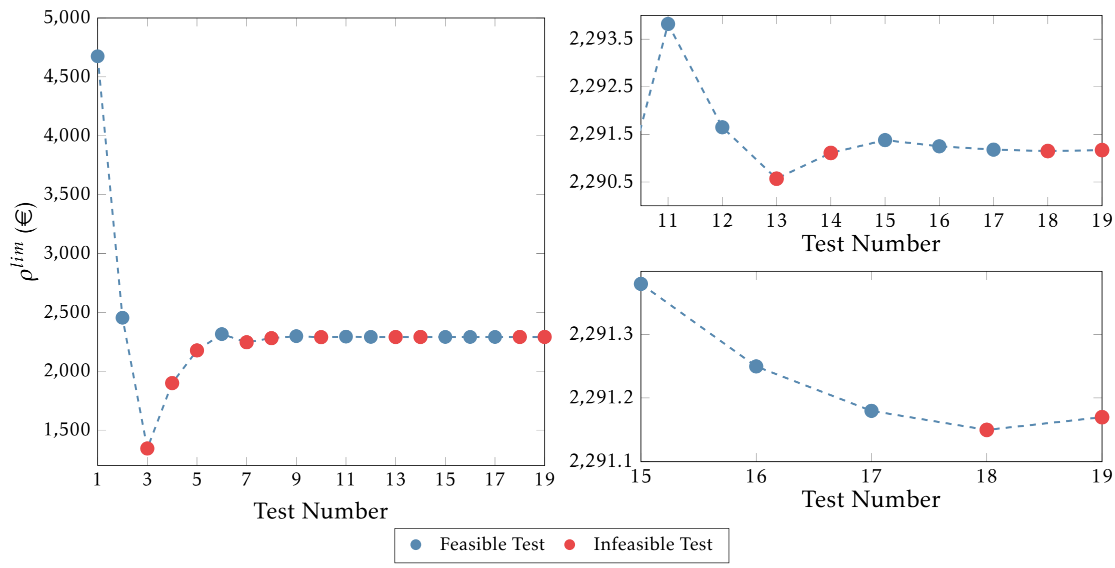


Figure 5.24: PREDIS Network – The Dichotomic Solution Recovery Algorithm

The optimised voltages for the network are presented in Fig. 5.25 as a heat-map. We conserve the colours from Fig. 5.23 for uniformity. The lowest observed voltage is 1.018 pu, at node 11 during hour 23. The maximum observed voltage is 1.049 pu, at node 11 during hours 13, 15, 16, 17, 19 & 24, and at node 12 during hours 2, 3, 4 & 24. The set-points for flexibilities and the main results obtained using the solution recovery algorithm are presented in Table 5.12.

The optimised network shows a 91.8 % reduction in losses, mainly owing to the high use of load reduction and DRES curtailment. The optimised voltages also contribute to this reduction in losses. The tap setting T1 corresponds to tap positions {4, 4, 4} for the three OLTCs. The configuration C1 corresponds to open switches {2-5, 2-8, 4-6, 4-7, 11-12} in the network. In the next section, experimental proof of the optimality of the dichotomic search heuristic is presented.

5.3.4 *Verification of Optimality*

In order to experimentally verify the optimality of the solution recovery algorithm, we test the Baran network, a network for which the relaxation has held in all our tests, with the test case $OP - eol3a$. The results of this verification are presented here. We use the parameters $high = 1000$ and $low = 0$ for the solution recovery algorithm. A

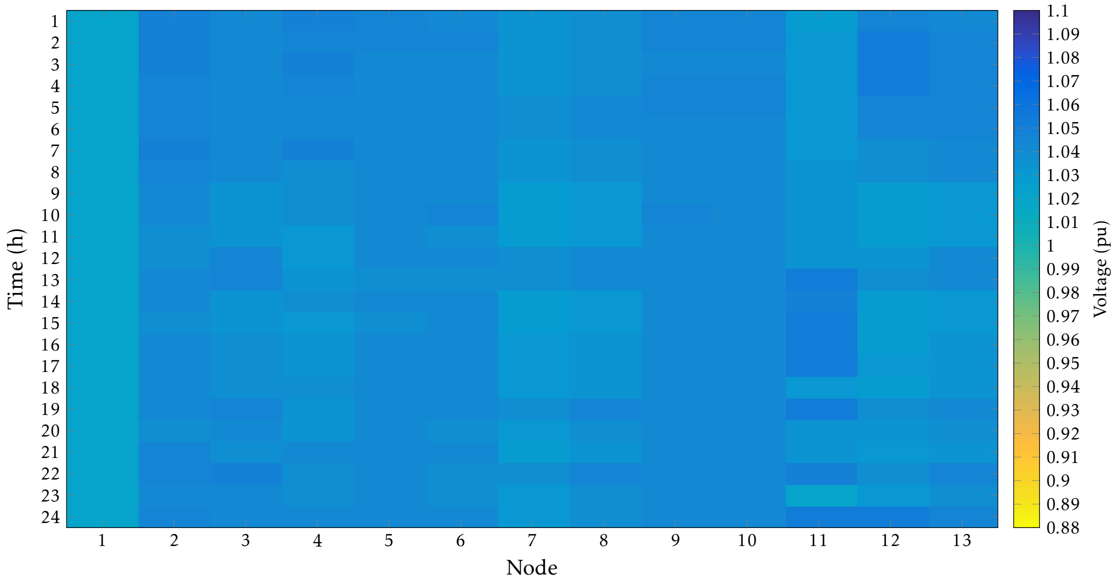


Figure 5.25: PREDIS Network – Optimised Voltages for 50 % DRES Insertion Rate

Table 5.12: PREDIS Network – Results with Solution Recovery Algorithm for Test Case *OP – eol2*

Description	**Value**	
DSO Expenditures (Objective)	2327.08 €	
Execution Time	1436.5 seconds	
Active Losses	0.718 MWh	
Tap Setting	T1 (Hours 1–24)	
Open Switches	C1 (Hours 1–24)	
Load Modulation (MWh)	Type-2	
	21.466 (Decrease)	1.775 (Increase)
DRES Curtailment	13.414 MWh	
DRES Reactive Compensation	15.59 MVArh (Injection)	
Average Relaxation Error	3.43 VA^2	

comparison of the results obtained with and without the solution recovery algorithm is presented in Table 5.13.

The minor differences in the solutions are due to the following reasons: (1) the rounding-up of the cost constraints to the nearest cent €, and (2) the existence of multiple global optima for mixed-integer programming problems. The path taken by the search heuristic is illustrated in Fig. 5.26.

The results prove that the solution recovery algorithm works, although it takes a much higher execution time. For this test case, a total of 17 iterations were required to find the optimal solution. One of the ways to improve the solution time of the search heuristic could be to use a parallel asynchronous search algorithm. This could be considered as a future improvement. In the next section, a discussion of the results obtained for the test networks is presented.

Table 5.13: Baran Network – Comparison with Solution Recovery Algorithm for Test Case *OP – eol3a*

Description	Results	
	Original	**Solution Recovery**
DSO Expenditures (€)	310.66	310.66
Execution Time (sec)	84.28	1573.6
Active Losses (MWh)	4.51	4.51
Tap Setting	4 (Hours 1–24)	4 (Hours 1–24)
Open Switches	C1 (Hours 1–24)	C1 (Hours 1–24)
Load Modulation (kWh)	422.1	422.3
DRES Curtailment	–	–
DRES Reactive Compensation (MVArh)	3.775 (Injection)	3.775 (Injection)
Average Relaxation Error (VA²)	2.32	0.05

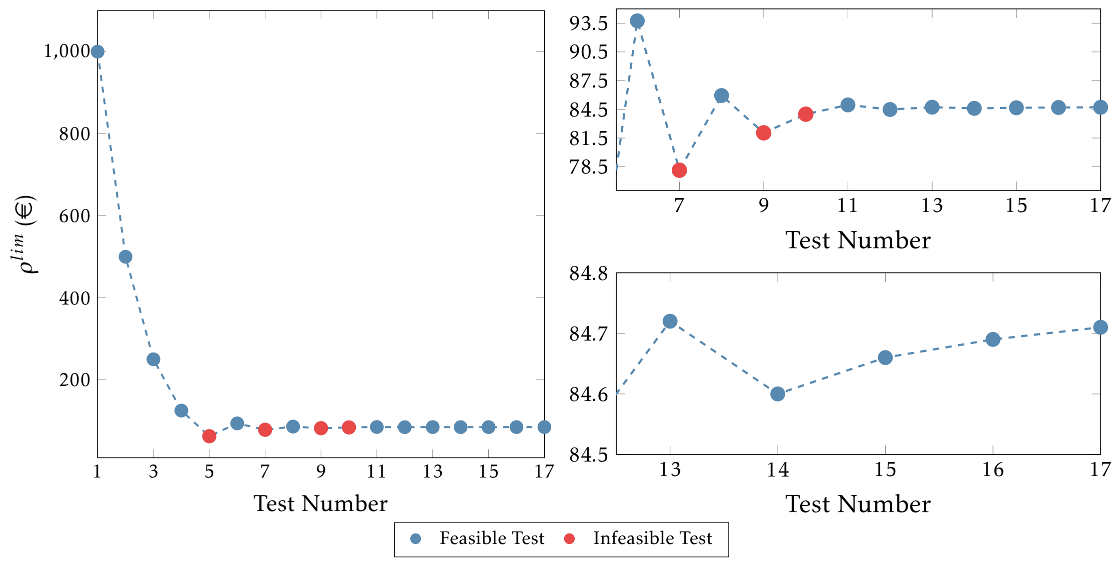


Figure 5.26: PREDIS Network – The Dichotomic Solution Recovery Algorithm

5.4 A DISCUSSION ON RESULTS

The results obtained for the novel OP formulation were presented in Sections 5.2 – 5.3. The show that:

1 The novel OP formulation solves all the test cases for the Baran network with global optimality. The SOCP relaxation holds, with a very low error.

2 For the PREDIS network, the SOCP relaxation fails. The solution recovery algorithm, based on a dichotomic search heuristic, converges to the globally optimal solution. This is experimentally proven through a test of the algorithm on a test case for the Baran network.

A discussion on the role of flexibilities in the test cases is presented here. This discussion mainly concentrates on the use of exogenous flexibilities, and the practicality of imposing certain constraints on endogenous flexibilities in the novel OP formulation.

5.4.1 *The Use of Exogenous Flexibilities*

In all the tests, the exogenous flexibilities available for optimising the networks were DRES curtailment, DRES reactive power compensation, load modulation, and batteries. DRES reactive power compensation was by far the most used flexibility. The reason for this is simple. The flexibility came at no cost, and therefore did not affect the objective function of the optimisation. In most of the test cases, the DRES reactive power compensation was used to 100 %.

The second most used flexibility was load modulation. All the three types of load modulation were used to varying degrees in the test cases. Type-3 load modulation, being cheaper than the other two, was generally preferred more. This preference however varied slightly, depending on the type of rebound.

DRES curtailment was used relatively less. The only test case where it was used was in the PREDIS test network. This is because of the high cost of DRES curtailment. A cheaper combination of other flexibilities always proved to be sufficient to solve the constraint violations in the Baran network. Finally, battery systems were imperceptibly used in 3 test cases. Once again, this is because of the exceedingly high cost to store and receive energy to / from these batteries.

The relationship between flexibility use and its price is clear. However, other conclusions may also be deduced from the results in terms of flexibility use. In the tested networks, the main issues related to the under-voltages. This was the case even with a large DRES integration, primarily owing to their location in nodes with severe under-voltages. The only exception was the case with 90 % DRES, where the DRES was placed on nodes with good voltage profiles, causing over-voltages. This meant in general that DRES curtailment, which would have resulted in further decreases in voltages, was used very rarely.

In type-3 load modulation, the presence of a rebound decreased the final use of the flexibility. This is understandable, given that load increases provoke voltage reductions. The other aspect of the rebounds in the overall load modulation was related to peak shifting. In the event where load modulation with rebound was the only choice of flexibility, the rebound invariably occurred during hours with low loads. In the case with type-2 rebound, the mandatory power rebound occurred in the hour succeeding the reduction, but the energy rebound invariably occurred during hours with low loads.

5.4.2 *Internal Flexibilities – Practical Reconfiguration Actions and Tap Changes*

Two of the major network flexibilities, reconfiguration and OLTC, are modelled as discrete variables in the novel OP formulation. For practicality, certain considerations have to be made when using these flexibilities. These considerations are discussed below.

5.4.2.1 Network Reconfiguration

The test cases in the chapter allowed us to test three different ways to reconfigure the Baran network. Two of these ways consisted of allowing time-dependent configuration changes, with limits of 24 and 1 imposed on the number of status changes of lines (Δe_{ij}). The third consisted of imposing time independent reconfiguration on the network. The results obtained lead us to believe that limiting the number of reconfiguration actions per switch to 1 is the best solution. This is due to the following reasons.

Firstly, there is no change in the objective value (DSO expenditures) among the tests. This is due to the technico-economic nature of the optimisation, where the improvement in the objective brought about by additional reconfiguration actions is lower than the cost of these actions. This could however change with other test networks / conditions, notably with a low reconfiguration cost.

Secondly, the tractability of the solutions varies greatly depending on the type of reconfiguration allowed. The cases with time independent reconfiguration are the most tractable. Time dependent reconfiguration with $\Delta e_{ij} = 1$ have comparable tractability. However, time dependent reconfiguration with $\Delta e_{ij} \leq 24$ takes several hours to find the same optimal solution as the other cases.

Thirdly, DSOs are not disposed to performing reconfiguration actions frequently, meaning that they may find it difficult to adopt hourly reconfiguration. Eventually, the choice between time dependent ($\Delta e_{ij} = 1$) and time independent reconfiguration should be up to the DSOs, or any other end-user of the novel OP formulation.

5.4.2.2 On-Load Tap Changers

In the OP formulation, we allowed a maximum of 24 tap changes per day ($\Delta w_{ij} \leq 24$) for the OLTC. However, we see that a large majority of the test cases, the OP formulation chooses only one tap change over the optimisation period. The only exception is the test case $OP\check{}eol3a$ in the Baran network, for a 90 % DRES insertion rate, where there are two tap changes occurring.

This reduced number of tap changing actions decided by the OP formulation is, as with reconfiguration, due to the fact that the formulation is a technico-economic optimisation. The improvement in the objective function (as a result of an improvement in network conditions) brought about through additional tap changes is lower than the cost to perform a tap change. The exception, the test case $OP\check{}eol3a$ in the Baran network, for a 90 % DRES insertion rate, arises out of the peculiar voltage conditions in the network. Over-voltages provoked by the presence of DRES in nodes where reference voltages without the DRES were already high necessitates the use of an additional tap change to bring them inside the allowed limits.

5.5 CONCLUSIONS

In this chapter, the novel OP formulation was validated using two test networks. The first, the Baran network is a medium-sized IEEE test network, while the second, the PREDIS network, is a reduced scale test distribution network in G2ELab/Grenoble INP-Ense3, at the University of Grenoble Alps. These networks were first presented.

The test parameters used in the novel OP formulation were then outlined, and parameter values were associated to each of them. These parameters included the DRES and load forecasts, limits for the load modulation, the DRES curtailment and reactive compensation, the batteries, & the voltages, and the costs flexibilities.

Nine different test cases were solved by the novel OP formulation for the Baran network with global optimality. The results of three of these test cases $OP-etol3a$, $OP-etol3b$, and $OP-etol3c$ were presented, illustrated, and discussed. The results for the six remaining test cases were outlined. Further, a range of DRES insertion rates were tested for the test case $OP-eol3b$, and the results obtained were outlined as well.

For the PREDIS network, tests showed that the SOCP relaxation did not hold. Therefore, the solution recovery algorithm based on a dichotomic search heuristic was employed. A globally optimal solution was recovered for the test case $OP-eol2$ for the network. In order to prove that the dichotomic search heuristic converges to a global optimum, it was employed on the test case $OP-eol3a$ for the Baran network. The results showed that a convergence to the original solution occurred when the search heuristic was employed. This experimentally proved that the algorithm worked. These tests comprised contribution C5 of this thesis.

Finally, a discussion on the use of exogenous flexibilities and the practicalities of using discrete endogenous flexibilities like reconfiguration and OLTCs was presented. This discussion provided context for the optimisation from the perspective of the power system. The choice to limit the number of operations for reconfiguration and OLTC was justified in this discussion. This discussion comprised contribution C7 of this thesis.

In the next part of this thesis, we explore approaches to operational planning of active distribution networks under uncertainty. We develop three different approaches to OP, and solve them on the Baran test network. We also analyse the best approaches to OP uncertainty.

PART III

ACTIVE DISTRIBUTION NETWORK OPERATIONAL PLANNING UNDER UNCERTAINTY

6 Operational Planning under Uncertainty – Formulations

« As far as the laws of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality. »
- Albert Einstein

6.1 Introduction

6.1.1 Context

Deterministic OPF formulations assume that the input parameters to these studies, DRES generation forecasts for example, are accurate, and not susceptible to variations. This is the case for the novel operational planning formulation presented in Chapter 4 as well. In the real world, this is seldom the case. Generation forecast techniques for DRES have greatly evolved in the past few years. However, even the most recent techniques cannot guarantee a 100 % accurate day-ahead forecast. This means that there is always a chance for these forecasts to be inaccurate.

In optimisation, an uncertainty can be broadly defined as a factor that is unknown but which may be modelled and taken into account. The inaccuracies in DRES forecasts can therefore be considered as an uncertainty if this variation can be quantified, modelled, and integrated into optimisation formulations. There is a need to integrate this uncertainty in optimisation, failing which these problems can be rendered useless. This is illustrated by the following example.

Consider the following maximisation problem:

$$max\ x + y \tag{6.1}$$

$$3x + 4y \leq 12 \tag{6.2}$$

$$x \geq 0\ ,\ y \geq 0 \tag{6.3}$$

Fig. 6.1(a) shows the feasible region (shaded in blue) of the maximisation problem in equation (6.1), subject to constraints (6.2) and (6.3). The red marker indicates the optimal value of the objective, and it is attained when $x = 4$ and $y = 0$ ($\{4, 0\}$). Now, assuming that there is a slight variation in the coefficients of x and y, equation (6.2) is replaced by constraints (6.4)–(6.6).

$$Ax + By \leq 12 \tag{6.4}$$

$$A \geq 2\ ,\ B \geq 2 \tag{6.5}$$

$$6 \leq A + B \leq 8 \tag{6.6}$$

Suppose A and B are integers, the 11 extra constraints added to the problem (dashed blue lines), the new feasible region (shaded green), and the new optimum at $x = 1.5$ and $y = 1.5$ (red circle) are shown in Fig. 6.1(b). It can be seen that the original solution at $\{4, 0\}$ is no longer feasible with the new constraints, as it is outside the solution space.

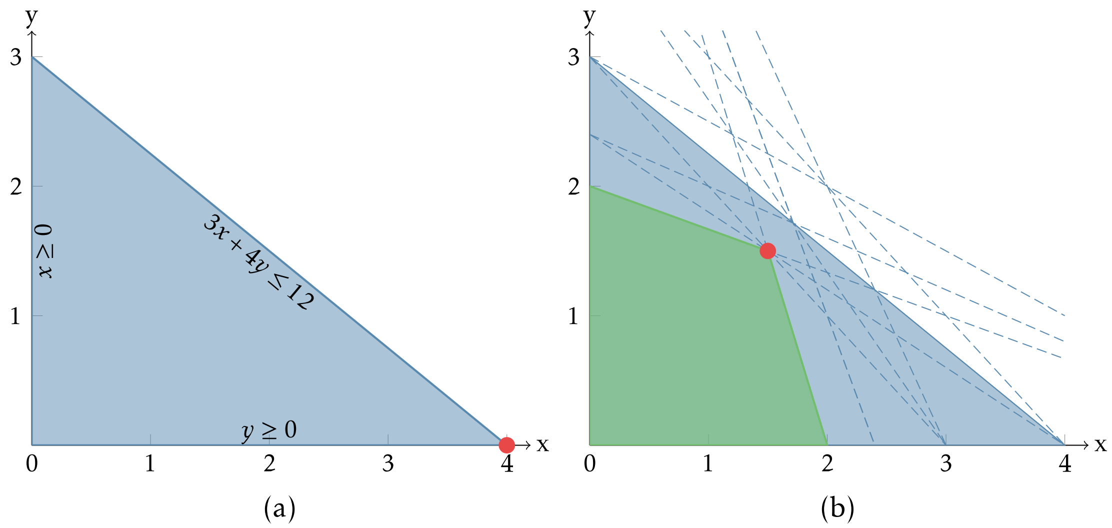


Figure 6.1: Feasible Regions and Optimum for Certain and Uncertain Case

This example clearly illustrates the need for considering uncertainty, and is main theme of this chapter. In this chapter, we deal with the characterisation, modelling, and integration of uncertainty in DRES generation forecasts into the novel operational planning formulation presented in Chapter 4. The contributions of this chapter to this thesis are as follows (the numbering is consistent with the summary in Chapter 1):

- C8 An analysis of different approaches to operational planning under uncertainty for distribution networks to identify the approaches that offer the best compromise between five different factors.

- C9 The development of an exact two-stage optimal deterministic operational planning formulation to counter uncertainties. This formulation optimises the distribution network in the day-ahead, and hour-ahead stages, treating the additional information on uncertainty in the second stage.

- C10 The development of an exact two-stage optimal stochastic operational planning formulation to counter uncertainties. This formulation optimises the distribution network under uncertainty based on the scenario characterisation of uncertainty.

- C11 The development of an exact optimal interval operational planning formulation to counter uncertainty. This formulation treats uncertainty in the form of bounds and optimises a deterministic forecast, while ensuring feasibility across the bounds.

In all the developed formulations, the exact nature of the physical network and its flexibilities is retained. This is done to guard mathematical optimality for the given choice of uncertainty characterisation, in spite of the fact that this uncertainty provokes loss of physically global optimality.

6.1.2 Organisation of this Chapter

This chapter is organised as follows. A discussion and literature review of the various approaches to handling uncertainty in short-term power system studies is first presented in Section 6.2. Four different approaches in power system studies are highlighted, based on the characterisation of the uncertainty. A summary at the end of the section analyses their suitability, advantages, and disadvantages for the specific case of an OP formulation under uncertainty for distribution networks.

Based on this analysis, the novel OP formulation developed in Chapter 4 is then extended and cast in three different formulations in Section 6.3 – a deterministic formulation in Section 6.3.1, a discrete stochastic formulation in Section 6.3.2, and an interval formulation in Section 6.3.3 (contributions C9 to C11). A method to compare the performances of the three formulations is also presented, in Section 6.3.4. This is finally followed by a conclusion in Section 6.4

6.2 A DISCUSSION ON OPF AND OP UNDER UNCERTAINTY

Two major types of uncertainty exist in short-term power system studies: uncertainty in the network element state and uncertainty in the network injections. The former arises out of lack of knowledge on whether or not elements in the network function properly or on their parametric values like resistance and reactance among others. The latter arises out of doubt over the accuracy of measurements / forecasts of the input parameters to these studies. Uncertainty in network element state can be easily overcome through close monitoring and supervisory actions in the network. In the short-term, it is easier to predict whether or not a particular element will fail, and with preventive maintenance schemes, unwanted network component failures can be prevented.

In this thesis, we deal with the second type of uncertainty, the uncertainty in network injections. We concentrate specifically the case of DRES forecasts. The novel operational planning formulation presented in Chapter 4 considers two main types of DRES, namely PV farms and wind turbines. Forecast techniques for these two different sources of energy have vastly improved in the last few years. Such forecast techniques have increased in accuracy over time. However, controlling networks based on results from deterministic optimisation formulations can still provoke network constraint violations, as the variation in production may take network conditions beyond the imposed limits.

The OPF and subsequently the OP formulations must therefore consider these variations. A review of various approaches to OPF and OP formulations without the consideration of uncertainty was presented in Chapter 4. In this section, we extend this review to formulations under uncertainty, focusing on the different methods in which the uncertainty is handled.

This review is organised as follows. Probabilistic formulations and approaches to the OPF are first reviewed in Section 6.2.1. This is followed by the review of formulations which use bounds or ranges for uncertainties in Section 6.2.2. All the reviewed approaches have their advantages and disadvantages. We do not cite them along with the approaches themselves. Instead, we do so at the end of the review in Section 6.2.3, where we discuss the challenges in formulating OP problems in one of the discussed approaches. Finally, in a similar vein to Chapter 4, a comparison of the different approaches is done in Section 6.2.4. This summary lays a specific emphasis on the applicability of these approaches to operational planning formulations for MV distribution networks.

6.2.1 Probabilistic Formulations

Probabilistic formulations and models incorporate uncertain (or random) variables[1] through the definition of a probability distribution for these variables. The uncertain variables therefore represent an outcome of an event, and the probability distribution assigns probabilities to the outcomes of these variables. By incorporating uncertainty directly into the model, probabilistic formulations provide a way to directly measure the uncertainty that the outputs to the model have, as a function of the uncertain inputs. The accuracy of the model therefore depends on the underlying representation of the probability distribution. In this section, probability distributions for DRES generation are first introduced. This is followed by a review of probabilistic OPFs. Then, the concept of scenarios as a means to represent uncertainty in DRES is presented, followed by a review of discrete stochastic approaches to formulating OPF problems.

6.2.1.1 Probability Distributions and the Probabilistic OPF

When enough information is available on the behaviour of uncertain variables, probability distributions or scenarios can be constructed to illustrate them. These distributions associate a particular value of the random variable to its probability of occurrence. They are therefore a list of all possible values that the variable can take with their associated probabilities.

Probability distributions are often represented as distribution functions. In order to construct these functions, actual measurements of the uncertain variables are first made. When a sufficient number of measurements have been gathered, they are fit onto a well-known mathematical distribution function. This approximation is done with different levels of accuracy, depending on the exactness of the fit. If, for example, an uncertain variable shows a behaviour similar to a normal distribution, it can be fit to a normal distribution. The probability distribution of the variables can then be represented, depending on the type of the variable and on the application, in three different ways:

1 *Probability Density Function (PDF)* is a function of a continuous random variable whose integral across an interval gives the probability that the value of the variable lies within the same interval. If the interval is a single point, the output of the function gives the probability that the value of the variable lies at that particular point.

2 *Cumulative Distribution Function (CDF)* is a function of a random variable which, for a single point interval X, provides the probability that the random variable it describes takes a value less than or equal to X. For continuous variables, the function provides area under the PDF for all values less than or equal to X.

3 *Probability Mass Function (PMF)* is a function that assigns probabilities similar to PDFs, but to the values of discrete random variables, as opposed to continuous variables.

[1] From the point of view of optimisation, uncertain parameters like DRES generation are also considered as variables because their values are not fixed.

Fig. 6.2 provides an example illustration of the PDF, CDF, and PMF (25 samples) for a normal distribution with a mean (μ) of 0 and a variance (σ^2) of 1.

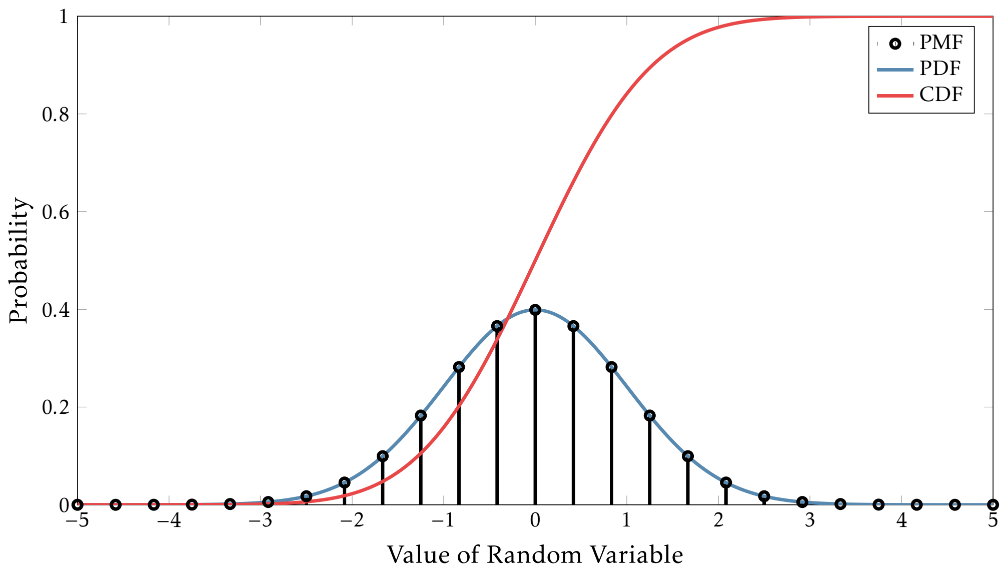


Figure 6.2: PDF, CDF, and PMF of a Normal Distribution with $\mu = 0$ and $\sigma^2 = 1$

To ascertain the probabilistic output powers of the two types of DRES considered in this thesis, PV and Wind power, several probability density functions have been used in the literature. Beta distributions are often used to model PV power generation, while the Weibull distribution has been largely preferred over other distributions to model Wind power generation [AAJM15]. Several authors have however analysed and compared other distributions for these two types of DRES that perform better in specific cases. A discussion on the utility of probability distributions can be found later in this chapter, in Section 6.2.3.2.

The Probabilistic OPF (P-OPF), is an extension of the deterministic OPF (see Section 4.2.3) incorporating uncertainty directly in its formulation. A P-OPF formulation considering uncertainty in DRES generation for example uses the probability distributions for the uncertain forecasts. Its output variables – the voltage magnitudes, the phase angles, and the active & reactive powers – are uncertain. The P-OPF was first proposed in [Bar74], and has subsequently been developed by several researchers. The computational tractability of P-OPF formulations is very low. This is because the formulation necessitates, in principle, the evaluation of a large number of OPFs for every probable combination of uncertain variable inputs. Such combinations can tend to infinity when these inputs are continuous in nature. This is the reason why the resolution of P-OPF problems has been the major subject of research in recent years. Approaches and methods to solving the P-OPF can be largely classified into four different categories: numerical and sampling methods, analytical methods, and approximation methods.

Numerical and sampling methods, such as the Monte-Carlo Simulation (MCS) method rely on repetitive pseudo-random sampling of the uncertain variables according to their PDFs. The advantage of such methods is their accuracy, and the fact that the underlying deterministic OPF formulation can be an exact representation of the power system. In principle, such methods substitute the P-OPF with a large number of deterministic OPFs, one for each sample, and can therefore take a lot of time. This means that they are impractical. Other sampling methods have also been employed by researchers to decrease this impracticality. Techniques like Latin hypercube sampling [YCW+09], and Quasi-MCS [CF13] have been shown to improve tractability.

Analytical methods rely on mathematical formulations in order to find solutions to the P-OPF. Traditionally, they have relied on simplifying the OPFs in order to manage the size of the models. Such simplifications have included the linearisation of the OPF, assumptions of independence among uncertain variables, and simplified PDFs [PJ17]. Convolution techniques like Fourier and Laplace transforms have also been proposed to counter the difficulty in solving these problems mathematically. Other methods like the Cumulant method have been successfully applied to P-OPFs, under assumptions that the uncertain variables are independent. First proposed in [SD86], this method permits the calculation of distributions of linear combinations of the uncertain variables in a single step, thereby increasing computational speed.

Approximate methods rely, as the name indicates, on explicit approximations of the PDFs of the uncertain variables to simplify the solution of P-OPFs. Examples of such methods include the following. Point Estimation methods [MBCM10] guess the best value for an unknown variable based on PDFs. Transformations like the Unscented Transformation method [AFFA12] approximate PDFs to PMFs, allowing for fewer deterministic OPF calculations. These methods allow for correlations between uncertain variables, which is of practical interest. Hybrid methods, combining one or more of the methods above have also been developed by researchers. These methods focus on providing a good trade-off between tractability and accuracy. For further information of approaches to solving the P-OPF problem, the reader may consult the detailed surveys in references [CCBJ08], [Cap16] and [PJ17].

Possibilistic approaches to modelling the OPF problem under uncertainty rely on possibility theory. Fuzzy logic, emerging from fuzzy set theory is one such approach [Zad78]. Fuzzy OPFs use this theory to model uncertainties. As opposed to probability theory, uncertainty is modelled through how much a particular realisation of uncertainty belongs to an uncertainty set, also called a fuzzy set. This degree of belonging is called a degree of membership. Membership functions are functions that express this degree of membership for an uncertain parameter. Membership functions associated to uncertain input parameters are then used to calculate those of output parameters through methods like α-cuts. The advantage of using Fuzzy logic lies in the fact that the bounds of the output parameters can be computed with relative ease, as compared to methods that employ probability theory.

Miranda and Saraiva [VJ92], [JV94] were among the first to model uncertainties in load and generation as fuzzy numbers to be applied in linear DC OPFs. Gladkikh et al. [THJ+15] have recently cast a fuzzy logic based OPF with uncertain load and generation in a planning problem. Fuzzy logic has also been used to model the uncertainty in crisp network constraints, like the ampacity limits by researchers like Guan et al. [GLP95]. Other authors like Vanet [Van16] have modelled uncertainty in flexibility procurement in the OPF using fuzzy logic. Approaches using fuzzy logic have not been explored in this thesis as the modelling of uncertain parameters through possibility distributions causes a loss of information about the uncertainty, when such information is available. When there is already a lack of information, probability and possibility distributions constructed from such information will inevitably be inaccurate. Therefore, these approaches are not explored further.

6.2.1.2 Scenarios and the Discrete Stochastic OPF

Scenarios are a discretised way to represent the behaviour of uncertain variables, as opposed to PDFs and CDFs, which represent them in a continuous way. They are a set of values that a particular uncertainty can take. They are especially useful in describing the temporal evolution of uncertain variables, something that probability distributions are generally incapable of (see Section 6.2.3.2). The representation of scenarios is shown in Fig. 6.3, where an illustration of 10 different scenarios for PV power production for a day is made.

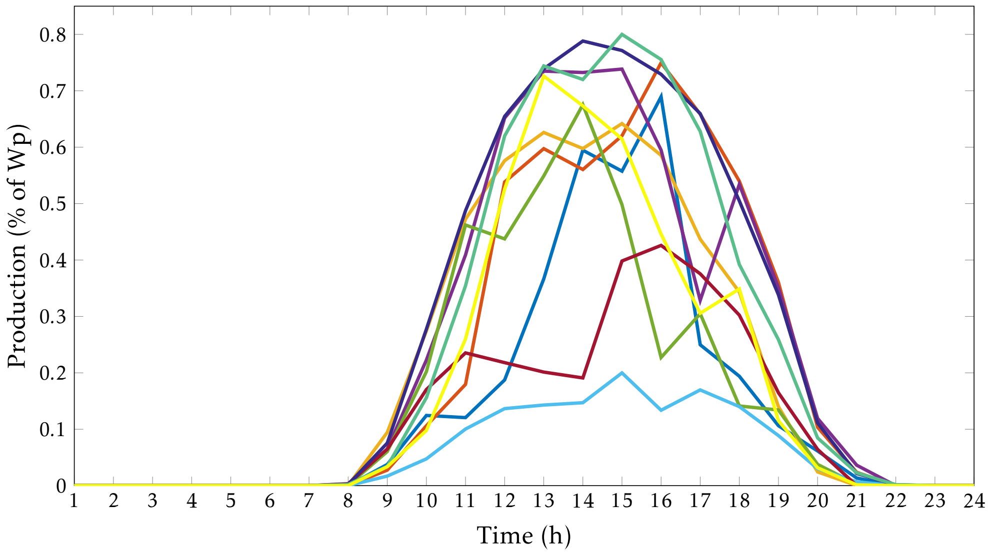


Figure 6.3: Example – 10 Scenarios for PV Production Over a Day

There are three ways to generate scenarios for uncertain input variables. The first is by eliciting the opinions of experts on the evolutions of uncertain variables in the future. The second is by through statistical representation of the probability distributions describing the outcomes of the uncertain variables. The third is by directly measuring the outcomes of the uncertain variables and grouping them based on different criteria. The generated scenarios are then given probabilities of occurrence, as is the case for probability distributions. Whatever the method followed, the generation of scenarios is generally difficult because they require a mastery of the understanding of the behaviour of the uncertain variables. King and Wallace [KW12] argue that the generation of scenarios from distributions and from measured data requires some care, as it can affect the optimal results of the stochastic formulations that use the scenarios.

Discrete stochastic optimisation[2] is an optimisation technique that considers the scenarios for uncertain variables and optimises an expected value of the objective function over all these scenarios. If the optimisation decisions have to be made before the realisation of the uncertainty is known (one decision for all uncertainty realisations), this is called a single stage stochastic problem. If a few decisions have to be made without the knowledge of the uncertainty, and if the remaining decisions can be made with respect to each of the scenarios, this is called a two-stage stochastic problem. Other, multi-stage stochastic problems exist, where several decisions reversals or recourse actions are made as more and more information on the uncertainty becomes available.

[2]The term discrete indicates the nature of the input uncertainty – scenarios – and has nothing to do with the nature of the optimisation problem itself.

A two-stage stochastic problem can be formulated as follows:

$$\min \qquad \sum_{t \in T} \Big(f(x_{0t}) + \sum_{s \in S} \pi_s \cdot g(x_{1t}^s) \Big) \tag{6.7}$$

Here, $f(x_0)$ and $g(x_{1s})$ are arbitrary functions of the decision variables x_0 and x_{1s} whose values are independent and dependent on each scenario s respectively. π_s is the probability of occurrence of each scenario. As can be seen, the optimisation minimises the expected value of the objective function across scenarios, and not for any particular scenario. This means that the decisions for scenarios are not optimal for each scenario, but for an ensemble of scenarios. The constraints applied to the a discrete stochastic formulation are the same as for a deterministic formulation, with one difference. All the variables whose values depend on scenarios have to be calculated for each of these scenarios. This means that the constraints containing these variables have to be declared across all scenarios.

Discrete stochastic optimisation has been successfully applied to OPF and OP formulations, especially in transmission networks, for the unit commitment and economic dispatch problems (see Chapter 4, Section 4.2.2). Wu et al. [WSL07] were among the first to formulate a security-constrained stochastic unit commitment model, using random disturbances and load forecast inaccuracies. Constantinescu et al. [CZR+11] studied the impact of a massive penetration of Wind power on the unit commitment problem using scenarios for wind power forecasts. It is to be noted that the number of scenarios chosen for a particular optimisation influences the characteristics of the formulation like the tractability, scalability, and accuracy (see Section 6.2.3.1). Some of the recent approaches have therefore worked stochastic OPFs using scenario-reduction techniques (see Section 6.2.3.3).

Other research in unit commitment has expanded on to stochastic unit commitment for multi-area systems [PO13], or concentrate on solution techniques to the formulation like parallelisation [WF16]. Recently, Nick et al. [NCP14] have cast the distribution network OP problem under uncertainty in a stochastic formulation, with the use of OLTC and battery systems. They consider a simplified representation of the OLTC with 10 taps, with each tap providing a 1% voltage regulation. Gemine et al. [GEC16] have also developed a stochastic MISOCP formulation for distribution network operational planning. Like their other formulations, the mixed-integer component of their formulation arises solely out of the discrete activation signals for load modulation. They do not consider OLTCs or reconfiguration.

In the next section, other approaches to formulating optimisation problems under uncertainty are discussed and reviewed. These formulations are different from the formulations in this section in the sense that they use bounds for representing uncertainty.

6.2.2 Formulations with Bounds for Uncertainty

Approaches to modelling uncertainties without the use of probabilistic information exist in literature. These approaches are especially useful when the information available with respect to the uncertainty is scarce. The scarcity of this information means that the characterisation of the form that the uncertainty can take becomes unknown. In most cases, only the ranges that these uncertainties can take are known. This was one of the reasons that motivated researchers to develop optimisation methods where uncertainty is represented as ranges or bounds rather than probability distributions. Other reasons do exist for this motivation. In situations where enough information is available with respect to the uncertainty is sufficient, probability distributions can be constructed. However, there are issues with respect to the accuracy of these distributions in representing the spatial and temporal correlation in the behaviour of the uncertainty (see Section 6.2.3.2 for more).

Approaches to handling uncertainty under lack of information include Robust Optimisation [AA98], Interval Optimisation [Ton94], and Information-Gap Decision Theory (IGDT) [Yak06] based optimisation among others. They are discussed in the sections below.

6.2.2.1 Robust Optimisation Formulations

Robust optimisation represents optimisation problems in which 'robustness' is sought against the uncertain behaviour of variables. Like all the methods that consider bounds for uncertainty, it does not need to know the probability distributions of the uncertainty. It assumes that the uncertain data resides in "uncertainty sets" [GYdH15] that are sometimes symmetrical. Many authors have proposed formulations for robust optimisation problems, like Soyster [Soy73], and Ben-Tal et al. [AA98]. Their formulations consider the worst case uncertainty and protects the optimisation against it. Bertsimas and Sim [BS04] subsequently formulate an LP robust optimisation problem with a budget of uncertainty. This budget of uncertainty allows the optimisation to choose the degree of conservativeness with respect to the behaviour of the uncertain variable. This is illustrated in Fig. 6.4.

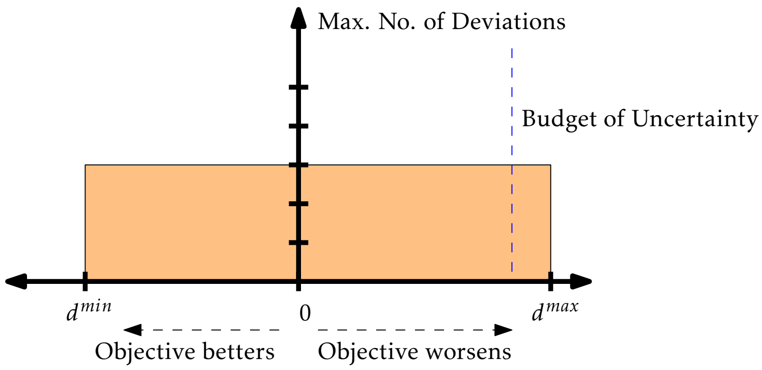


Figure 6.4: Uncertainty Set and Budget of Uncertainty

In the figure, the uncertainty set is represented by the bounds d_{min} and d_{max}. There is no representation of the behaviour of the uncertainty inside the set. For LP problems, the direction of the objective function can be identified based on the deviation of the uncertainty, and this is used to select the worst case uncertainty for the robust optimisation problem. The figure also shows the budget of uncertainty developed in Bertsimas and Sim's formulation. Mathematically, their formulation is represented as follows:

$$max \qquad \sum_{j \in J} c_j x_j \tag{6.8}$$

Subject to:

$$\sum_{j\in J} \tilde{a}x + \Gamma_i w_i + \sum_{j\in J} z_{ij} \le b \qquad \forall i \in I \tag{6.9}$$

$$w_i + z_{ij} \ge d_{ij}^{max} x_j \qquad \forall i \in I, \forall j \in J \tag{6.10}$$

$$w_i \ge 0 \qquad \forall i \in I \tag{6.11}$$

$$z_{ij} \ge 0 \qquad \forall i \in I, \forall j \in J \tag{6.12}$$

$$x_j \ge 0 \qquad \forall j \in J \tag{6.13}$$

Here, the nomenclature used differs from the nomenclature in this thesis. In this formulation, x_j represents the decision variables, a_{ij}, b_i, c_j the coefficients, d_{ij}^{max} is the maximum uncertainty in the direction where the objective worsens, w_i and z_{ij} are dummy variables for the reformulation, and Γ_i is the budget of uncertainty.

Although robust optimisation studies were first published as early as the 1970s, it has been actively developed only since the early 2000s [GYdH15]. The same reference also cites research that shows its applications in finance, energy, supply-chain management, healthcare and marketing among others. Robust optimisation problems have also been formulated for OPF problems, with applications in unit commitment. Saric et al. [SS09] have developed a MILP robust formulation for Volt-VAr control. They employ OLTCs, capacitor banks, and reactive power compensation from generators. Zhao and Zheng [ZZ12] formulate a two-stage robust SCUC problem considering uncertainty in wind power production. Jiang et al. [JWG12] then use the Bertsimas and Sim formulation with uncertainty budgets to develop a robust unit commitment formulation with uncertain wind power. Bertsimas et al. [BLS+13] develop an adaptive robust SCUC problem employing outer approximation and Benders decomposition.

Büsing and D'Andreagiovanni [BD13] have extended the robust optimisation problem to a multi-band robust optimisation problem, where the uncertainty is represented as multiple bands. They take advantage of the fact that inaccurate probability distributions may still provide valuable information on the approximate values of uncertain variables, which can then be grouped into bands. An illustration of these bands is shown in Fig. 6.5. This, according to them, provides finer control over the representation of uncertainty, while still maintaining a bound-based approach. They argue that the conservativeness of the optimisation is reduced as a result. Their approach has also been applied to unit commitment problems by Dai et al. [DWW16] Hu and Wu [HW16] who prove that this approach provides reduced expenditures, while maintaining the same solution robustness.

While robust optimisation problems are computationally tractable, they provide conservative solutions. Their suitability for power system optimisation problems is discussed in Section 6.2.3.5, as a part of a discussion of the challenges to formulating OP problems under uncertainty.

6.2.2.2 Interval Optimisation Formulations

Interval optimisation formulations for OPFs are similar to discrete stochastic formulations, except for a few things. First, instead of using a number of scenarios with probabilities, the interval optimisation formulation uses only 3 scenarios. There is one scenario for the central forecast (CF), and two for lower and upper bounds (LB & UB)

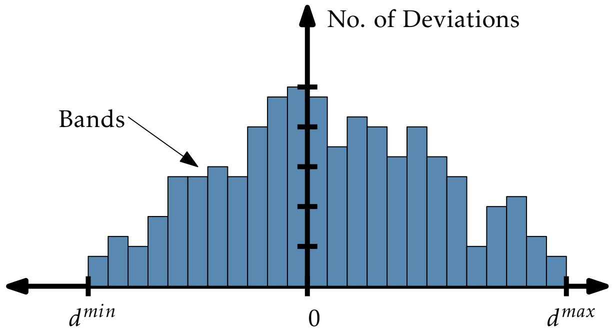


Figure 6.5: Multiple Bands for Uncertainty

on the forecast respectively. The central forecast can be compared to a scenario that presents the "best guess" for a given uncertain variable, while the upper and lower bounds represent the uncertainty spectrum. Second, the formulation does not optimise the expected value of the objective function across scenarios. Instead, it optimises the central forecast, while ensuring feasibility across the bounds. This is done as follows.

Consider the illustration in Fig. 6.6 for two time periods t and $t+1$ of a particular interval optimisation problem:

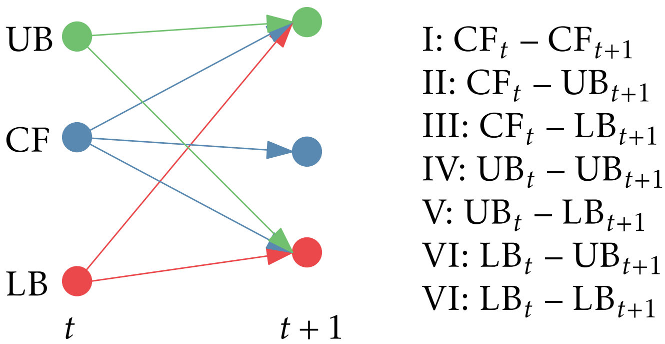


Figure 6.6: Interval Programming and Associated Constraints

An interval optimisation problem for the above figure is formulated as follows:

$$\min \quad \sum_{t\in T}\Big(f(x_{0t}) + g(x_{1t}^{cf})\Big) \tag{6.14}$$

Subject to, $\forall t \in T$:

$$x_{1t}^{cf} - x_{1t+1}^{cf} \le \overline{\Delta x_{1t}} \tag{6.15}$$

$$x_{1t}^{cf} - x_{1t+1}^{ub} \le \overline{\Delta x_{1t}} \tag{6.16}$$

$$x_{1t}^{cf} - x_{1t+1}^{lb} \le \overline{\Delta x_{1t}} \tag{6.17}$$

$$x_{1t}^{ub} - x_{1t+1}^{ub} \le \overline{\Delta x_{1t}} \tag{6.18}$$

$$x_{1t}^{ub} - x_{1t+1}^{lb} \le \overline{\Delta x_{1t}} \tag{6.19}$$

$$x_{1t}^{lb} - x_{1t+1}^{ub} \le \overline{\Delta x_{1t}} \tag{6.20}$$

$$x_{1t}^{lb} - x_{1t+1}^{lb} \le \overline{\Delta x_{1t}} \tag{6.21}$$

If a parallel were to be drawn between interval optimisation and discrete stochastic optimisation, it would be that the central forecast represents the scenario with the highest probability, and that the upper and lower bounds represent the envelopes for all the scenarios (shown in orange in Fig. 6.7). It can be seen that the objective function (6.14) optimises the central forecast. The seven additional constraints to be added to the problem are (6.15)–(6.21), as proposed by the original authors. It is clear that three of these constraints (6.15)–(6.17) are redundant, and can be dropped. When casting an interval optimisation formulation, the deterministic formulation can be kept, with the values for the central forecast substituting the values of the uncertain parameters. The objective function has to be modified, and the interval constraints are the only ones to be added to the problem. This method is simple to achieve, but promises a great improvement in performance under uncertainty.

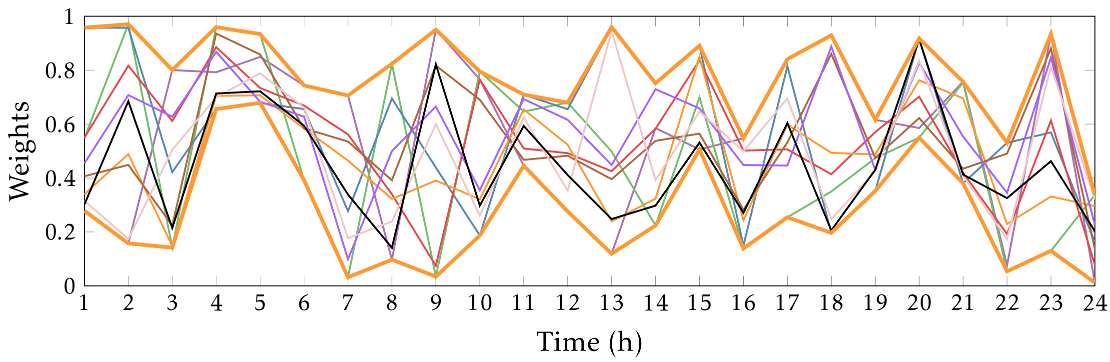


Figure 6.7: Envelopes for Scenarios

Like discrete stochastic programming, interval programming formulations have also successfully been applied to short-term power system studies. Wang and Alvarado [WA92] were among the first to treat the traditional linearised power flow problem using interval arithmetic. Das [Bis02] then analysed power flow calculations in radial power systems using interval analysis for uncertainties. Saric and Stankovic [SS06] formulated an economic dispatch problem for the electricity market where they considered uncertainties not in generation, but in values for physical network parameters[3]. Wang et al. [WXK11] solved the unit commitment problem in transmission networks considering intervals for volatile node injections (net values of loads and generators). Wu et al. [WSL12] then performed a comparative study of scenario-based stochastic and interval optimisation techniques for the security constrained unit commitment (SCUC). They concluded that interval optimisation required less computation time, but that its optimal solution was very sensitive to the chosen uncertainty intervals, meaning that it was not suitable for simulating random outages of generators and power lines.

Other researchers have improved the interval formulation for unit commitment. Dvorkin et al. [DPOVK15] propose a hybrid stochastic / interval unit commitment method for transmission networks. They argue that some advantage can be take from the fact that forecast techniques are more accurate for the first few time periods of the optimisation as these periods are closer to the time at which optimisation is performed. According to them, discrete stochastic optimisation can therefore be employed, with a switch to interval optimisation for later periods. Pandzic et al. [PDQ+16] propose the

[3] In some research works, the term “economic dispatch” has been loosely used for OPF problems with an economic objective function. Therefore, this does not mean that technical network parameters are ignored.

relaxation of the bound constraints described in (6.18)–(6.21), as they argue that these constraints are almost never enforced due to low probabilities of occurrence.

In the next section, a third approach to formulating uncertain optimisation problems under severe lack of information, is outlined. This approach is based on information-gap decision theory (IGDT).

6.2.2.3 Information-Gap Decision Theory (IGDT) based Formulations

Information-Gap Decision Theory (IGDT) is an approach to handling of uncertainties that focuses on the disparity between what is actually known about the uncertainty and what could be known [ZCCM10]. It is a way to look at the uncertainty from the other side of the table.The question to be asked for formulating uncertain problems is not "What do I do when I cannot account for some uncertain behaviours?" It is rather, "If I can only deviate so much from my deterministic objective, how much uncertainty can I accept?" IGDT can be an useful approach when there is severe lack of knowledge about the uncertainty, to an extent that deterministic bounds may not be set. This also means that approaches to solving problems using IGDT cannot be implemented directly, but can only serve as a means to acquire information about the effect of uncertainty on a particular optimisation problem.

IGDT is based on the pioneering work conducted by Ben-Haim [Yak06]. It has been applied to problems in power systems only quite recently. We can cite for example [ZCCM10] for research on a bidding strategy for large consumers on day-ahead markets under uncertain market prices. Murphy et al. [MSK16] present an IGDT based method to manage voltage congestions for distribution networks in the presence of DRES. O'Connell et al. [OCSK16] then formulate an OPF based on IGDT to experimentally calculate robustness and opportuneness in distribution networks under uncertain power injections. Ben-Haim defines robustness in IGDT as a means to protect against changes in the objective of optimisation problems when it worsens. In the same vein, opportuneness is defined as the benefit that can be extracted by having a better objective value with uncertainty. In the context of the work done by O'Connell, this relates to the increase and decrease respectively in DSO expenditures with uncertainty.

6.2.3 Challenges to Modelling Uncertainty in OP

The addition of uncertainty in any optimisation problem is a challenge. The various approaches to adding uncertainty to OPF problems presented in literature have shown as much. In this section, we analyse the different challenges that formulating and solving operational planning problems under uncertainty. Such an analysis is challenging in itself, because of the multitude of factors that affect the performance of these formulations. Any practical optimisation problems under uncertainty have to deal with trade-offs. This is analysed in Section 6.2.3.1.

An analysis of the advantages and disadvantages of using probabilistic information is done in Section 6.2.3.2. This is followed by an analysis of the effect of scenarios on discrete stochastic formulations, in Section 6.2.3.3. The challenges in modelling recourse actions for the approaches discussed above are outlined in Section 6.2.3.4. Recourse actions are defined as follows. Approaches to optimising under uncertainty like discrete stochastic optimisation and interval optimisation possess certain common characteristics. Both contain certain decision variables that are independent of the uncertainty realisation (x_0), and other decision variables that are dependent on these realisations (x_1). Fine-tuning actions for the latter kind of variables are therefore necessary once these realisations become known. These actions are called recourse actions.The final challenge, related to the suitability of robust optimisation to the OP formulation is analysed in Section 6.2.3.5.

6.2.3.1 Trade-Offs for Formulations

Many approaches to optimising under uncertainty were discussed in the previous sections. All these approaches have different performances. The three major performance criteria for these approaches are the tractability, scalability, and accuracy[4] (Fig. 6.8). Unfortunately, all the approaches can only perform well across, at most, two of these criteria. This means that for any algorithm we choose to model our operational planning formulation under uncertainty, we will have to make trade-offs. While performing this analysis, one has to ignore the challenges / problems associated with the modelling of input uncertainties. These trade-offs are therefore purely based on the performance of the approaches.

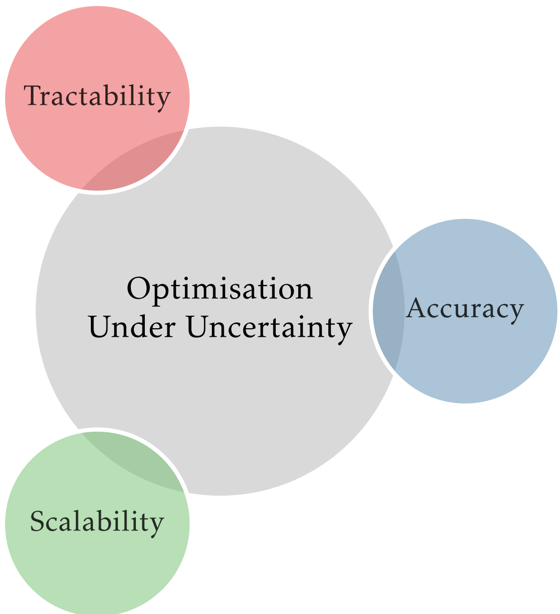


Figure 6.8: Trade-offs in Approaches to Optimisation under Uncertainty

Depending on the solution techniques adopted, probabilistic OPF P-OPF formulations can be the most accurate. However, their tractability and scalability leave a lot to desire. While approximate solution methods increase the tractability of the P-OPF, there is a corresponding decrease in accuracy. Discrete stochastic OPF formulations generally execute and scale better than P-OPFs. They are also accurate, to the extent of the scenarios chosen and the probabilities associated with each scenario. They do suffer from scalability issues, especially with respect to the number of scenarios. The reader may refer to Section 6.2.3.3 for more.

With the same uncertain inputs represented as bands instead of distributions, robust optimisation formulations have the highest tractability and scalability. However, the

[4] Accuracy in this context refers to the cost or optimality of the solution for the same input uncertainty.

solution conservativeness means that the accuracy of the formulation is among the lowest. Interval optimisation formulations sacrifice some of the tractability and scalability for a higher accuracy. By optimising the central forecast while ensuring feasibility across uncertainty bounds, interval formulations provide relatively better solutions. Interval optimisation formulations also exhibit better scalability and tractability than discrete stochastic formulations for the same uncertain input, albeit with a lower solution accuracy [WSL12]. For each execution of the formulation, IGDT-based formulations present the same tractability and scalability as robust optimisation problems. However, solution accuracy is not an element that can be used to describe these formulations, typically because of the exploratory nature of these problems.

Table 6.1 presents a summary of the performances of the different approaches discussed. This table can be found below.

Table 6.1: Trade-offs on Approaches to Optimisation under Uncertainty

Approach	Criterion		
	Tractability	Scalability	Accuracy
P-OPF – MCS	−−−	−−−	++
P-OPF – Analytical	−−	−−	+++
P-OPF – Approximate	−−	−−	+
Discrete Stochastic	+	−	++
Interval	++	++	+
Robust	+++	+++	−−
IGDT	+++	+++	−−

6.2.3.2 Can Probabilistic Information be Trusted?

Probability distributions are rarely accurate representations of uncertainty. They are, at best, a very good approximation of the historical measurements. Different probability distributions for PV and Wind power uncertainties have been explored in literature. Representing the uncertainty using each of these distributions, its advantages, and its disadvantages, have been studied by researchers. Probabilistic OPFs (P-OPF) that rely on these distributions as inputs provide results that are largely influenced by the quality of the distributions. This means that the precision of these distributions has to be spot-on. This is a challenge that has been addressed in relatively few research works in power systems. The use of probability distributions, and consequently a P-OPF formulation for operational planning of distribution networks entails the following challenges.

In order for the behaviour of each of the MV DRES in distribution networks to be characterised correctly, the spatial nature of the network has to be taken into account. This means that probability distributions for all the DRES in the network (even of the same type) are not the same. Different distributions may have to be constructed for different DRES. This conclusion is supported by research. To cite a few, Drobinski and Coulais [DC12] have found that the characteristics of wind in certain areas of France, like the Rhône valley, may not be accurately described by a single Weibull distribution. Abdulkarim et al. [AAJM15] show that distributions represent to various levels of accuracy the behaviour of PV and Wind power in different parts of the world.

Another challenge is that the probability distributions among different production uncertainties in networks show correlations. Models that take this into account are difficult to formulate [Sex12]. The use of marginal distributions for uncertainties ignoring the interdependency provokes inaccuracies.

Two other challenges are put forward for PV power by Ren et al. [RYZ+14]. First, probability distributions do not represent the correlation of PV power between adjacent moments. Second, they do not model the uncertainty of occurrence of the start and end moments of the PV power during a day. They are consequently unsuitable for use in operational planning, and are useful only in long-term planning studies. The first condition can easily be extended to wind power as well, meaning that the distributions for wind power cannot be used in operational planning either.

To summarise the issue with probability distributions, they are approximations of the behaviour of the uncertainty. It is very difficult to represent correlations between the various uncertainties through distributions. Finally, they are also unsuitable for operational planning due to their inability to provide time-correlated information on the behaviour of the uncertainty.

6.2.3.3 Scenario Reduction

Discrete stochastic OPF formulations are more tractable and scale better compared to P-OPF formulations. However, their scalability is highly dependent on the number of scenarios they evaluate. With a high number of scenarios, the execution time of these formulations explodes. On the other hand, a lower number of scenarios also means that the behaviour of the uncertainty may not be captured exactly.

To overcome this issue, scenario reduction techniques, ranging from simple methods like *k-means*, to reduction techniques that statistically represent the information in the original scenario set like fast-forward selection and submodular optimisation exist [FR13], [DWPK14], [WLK16]. With these techniques, these OPF formulations are shown to perform better. However, choosing the best scenario reduction technique is often a very difficult exercise. The submodular optimisation technique developed in [WLK16] not only offers the advantage of reducing scenarios, it also optimises the number of scenarios. This may be suitable when the right choice of the number of scenarios is unclear.

One advantage of using scenarios is that unlike probability distributions, scenarios can capture the correlations of uncertainty between adjacent moments. However, if the scenarios for different types of uncertainty do not have the same probability of occurrence, the number of scenarios increases exponentially, despite scenario reduction techniques. This is detrimental to the solution time of these formulations.

6.2.3.4 What About Recourse Actions?

The choice of decision variables that depend on uncertainty – and therefore that need recourse actions – depends entirely on the physical characteristics of the decision variables and the system being optimised, and on the preferences of the user. This choice is challenging for Mixed-Integer Programming (MIP) problems as it can affect their tractability. While formulating the OP problem for distribution networks, these characteristics were taken into account in order to choose decision variables whose value would depend on the uncertainty, and would therefore need recourse actions. Table 6.2 presents a summary of the same.

It is to be noted that the recourse actions in discrete stochastic optimisation are performed in the second stage of the optimisation itself, while there is no explicit recourse action stage defined in interval optimisation. This stage has to therefore be implemented separately, usually at the hour-ahead stage, for a day-ahead interval optimisation problem.

Table 6.2: Recourse Actions for Flexibilities

Flexibility	Recourse Action	Constraints
OLTC	No	—
Reconfiguration	No	—
Load Modulation Types 1 & 2	No	—
Load Modulation Type-3	Yes	$\forall a_t^{act} = 1$
Battery System	Yes	(4.95) – (4.98)
DRES Curtailment	Yes	$P^{fg} \leq \overline{P^{fg}}$
DRES Q Compensation	Yes	$\underline{Q^{fg}} \leq Q^{fg} \leq \overline{Q^{fg}}$

The physical characteristics of distribution network and the flexibilities used in the optimisation mean that discrete, global flexibilities like the OLTC and reconfiguration are chosen to be independent of the uncertainty. This choice is realistic for the following reasons. Firstly, this tremendously increases the tractability of the OP problem. Secondly, and more importantly, both these flexibilities affect the entire system, as opposed to other flexibilities whose effects are local(ised). In practice, potentially changing the system configuration or the OLTC tap for every realisation of uncertainty may be difficult to achieve for the DSOs, given their current capabilities.

The choice to omit load modulation of types 1 and 2 was also inspired by the nature of these flexibilities – they are assumed to be purchased on the day-ahead market. Recourse actions can however be performed on load modulation of type-3. This is limited to the periods when the modulation has already been activated, and has to respect the constraint on reserved capacity. The equalisation or the rebound can however not be guaranteed on the recourse action. DRES curtailment and reactive power compensation are also included in the recourse actions taking into account their continuous nature and the ease of practical implementation.

6.2.3.5 Robustness for NLPs with Equality Constraints

Robust Optimisation is revolutionary in terms of tractability. Using the Bertsimas and Sim [BS04] formulation to formulate robust optimisation problems entitles only one deterministic optimisation to be run for each budget of uncertainty. Indeed, robust optimisation problems provide conservative solutions. This is the reason for the interest in multi-band robust optimisation, which provides less conservative solutions.

However, is robust optimisation really suitable to operational planning for distribution networks? There are two reasons why this may not be the case. The first has to do with the presence of equality constraints in the problem. The uncertain variable – the DRES production – is represented in equality constraints in the OP formulation. This means that any robust optimisation is not automatically valid for other realisations of uncertainty that are in the uncertainty set. One of the major advantages of robust optimisation is that despite its conservativeness, there is no need for recourse actions. This nullifies that advantage, effectively rendering any robust formulation of the OP problem useless. All the research work on robust, and IGDT based optimisation for

OPFs deal with equality constraints for power balance, meaning that they will also have to use recourse actions.

The second, bigger issue, is the non-linearity of exact operational planning problems. For non-linear problems, the behaviour of the objective function with respect to the change in uncertainty is not linear. This means that an assumption of the worst uncertainty realisation cannot be made. Consequently, it is impossible to choose a value of uncertainty against which the robust formulation can protect the system being optimised. This renders the robust formulation unsuitable for our OP formulation. A detailed illustration that elaborates further the two reasons outlined above can be found in Appendix A.

Given all these issues and challenges, is there an ideal approach to OP under DRES uncertainty? To answer this, a discussion with a specific emphasis on OP formulations for distribution networks ensues in the next section.

6.2.4 An Ideal Approach to OP under Uncertainty?

The choice of an approach to OP under uncertainty depends on several factors. These factors are intricately linked to each other. Firstly, there is the challenge of ascertaining and characterising the uncertainty to be handled. This depends on the amount of information available on this uncertainty. Since the characterisation of uncertainty directly affects accuracy of the solution, the lack of information can do so as well. If solution accuracy is the foremost factor for choosing an approach, information related to the uncertainty is of utmost importance. However, in certain cases, such information is lacking, and means that a highly accurate solution cannot be obtained. Instead, an appropriate formulation will have to be chosen depending on other factors.

Secondly, the suitability for operational planning in distribution networks has to be analysed. The suitability for operational planning is affected by the scalability and tractability of the formulations, while the suitability for distribution networks is in-turn affected by their physical characteristics. P-OPF formulations have the lowest tractability and scalability in general, along with other inabilities in terms of uncertainty characterisation for OP (see Section 6.2.3.2). They are therefore unsuitable for operational planning. IGDT and Robust formulations suffer from their inability to handle non-linear equality constraints without the need for recourse actions. They are therefore unsuitable for distribution networks.Thirdly, the trade-offs between accuracy, scalability and tractability themselves has to be taken into account. They do affect the other two factors. However, when taken separately, they also provide a measure of the performance of each of the approaches (see Section 6.2.3.1).

In this thesis, we first emphasise on the information available on the uncertainty and the suitability for OP in distribution networks. We then analyse the trade-offs for each of the approaches. This is because the major constraints on the OP formulation under uncertainty are imposed by these two factors. Fig. 6.9 illustrates this analysis.

From this analysis, it is clear that discrete stochastic OP and interval OP formulations offer the best in terms of suitability, tractability, scalability, and accuracy. They are therefore the best candidates for approaches to uncertainty. These approaches are characterised by very high and low amount of information on the uncertainty respectively. This augurs well, providing a means to formulate different approaches . However, at

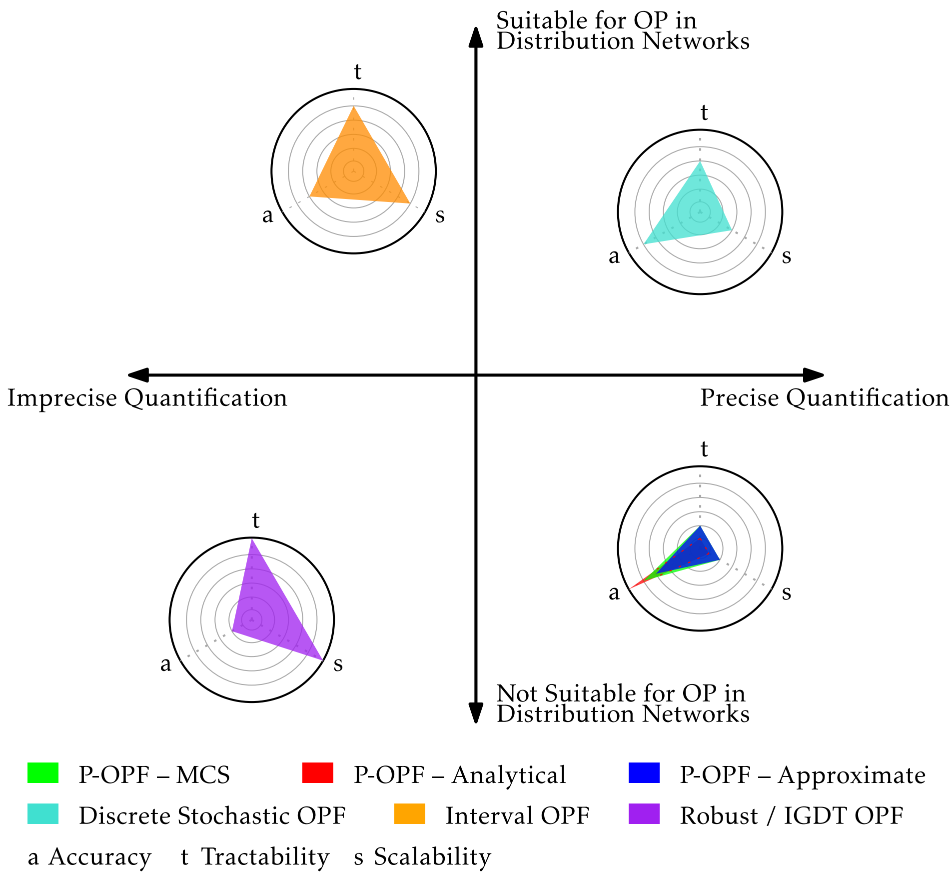


Figure 6.9: Characteristics of Various Approaches to OP under Uncertainty

this juncture, another question arises: "can uncertainty be handled using multiple deterministic optimisation stages?" This is certainly a valid and an interesting question. Literature shows that multiple deterministic optimisations have been explored before [BBG+10], even if they were not explicitly to treat uncertainty. Therefore, apart from interval and discrete stochastic optimisation formulations, we also formulate a two-stage deterministic OP formulation in the next section. All these formulations are extensions of the novel OP formulation in Chapter 4, and use the SOC relaxation to achieve exact formulations that provide the best solutions for the considered uncertainty.

6.3 NOVEL AND EXACT FORMULATIONS FOR OPERATIONAL PLANNING UNDER UNCERTAINTY

A review of the various approaches to optimisation under uncertainty, followed by an analysis of challenges facing OPF and OP formulations under uncertainty was done in the previous sections. The choice of an ideal approach for OP under uncertainty was discussed in Section 6.2.4. Based on this discussion, we formulate three different approaches to OP for distribution networks under uncertainty. These formulations are extensions of the novel op formulation presented in Chapter 4. They are: (1) a two-stage deterministic formulation, (2) a two-stage stochastic formulation, and (3) a two-stage interval formulation. The modelling of these formulations considers that the operational planning under uncertainty is a multi-stage process, in line with the trends in current literature [PO13]. These formulations have been developed with an intention to test and compare their performances against one another. In addition to the assumptions made for the original formulation, we make the following assumptions for these formulations:

1 The uncertainty in the formulations is caused by DRES. The way the uncertainty is characterised by the formulations is different, but the underlying uncertainty is assumed to be the same.

2 The recourse actions allowed across the three formulations are considered to be the same. This means that the actions allowed in the hour-ahead stage of the deterministic formulation are the same as the actions that differ based on the uncertainty in the stochastic and interval formulations. This is done in order to enable a comparison of the three approaches in Chapter 7. The available recourse actions are shown in Table 6.2.

3 The rebound effect for type-3 load modulation, modelled in Chapter 4 through equations (4.59)–(4.61) cannot be achieved in two-stage formulations. This is because any recourse actions performed on this modulation will effectively nullify these constraints. Therefore, we consider type-3 load modulation without rebound in these formulations.

6.3.1 A Two-Stage Deterministic OP Formulation

The first of the three formulations for OP under uncertainty is the two-stage deterministic OP formulation. The idea behind this approach is to perform a first, deterministic optimisation on the day-ahead stage, based on day-ahead forecasts for loads and DRES, in order to acquire flexibilities on the day-ahead market. We remind the reader that flexibilities like types-1 and 2 load modulation, which are thus acquired, do not have recourse actions. The second deterministic optimisation is done on the hour-ahead stage, and optimises recourse actions and purchases on the hour-ahead market based on hour-ahead DRES forecasts. An illustration of this approach is shown in Fig. 6.10.

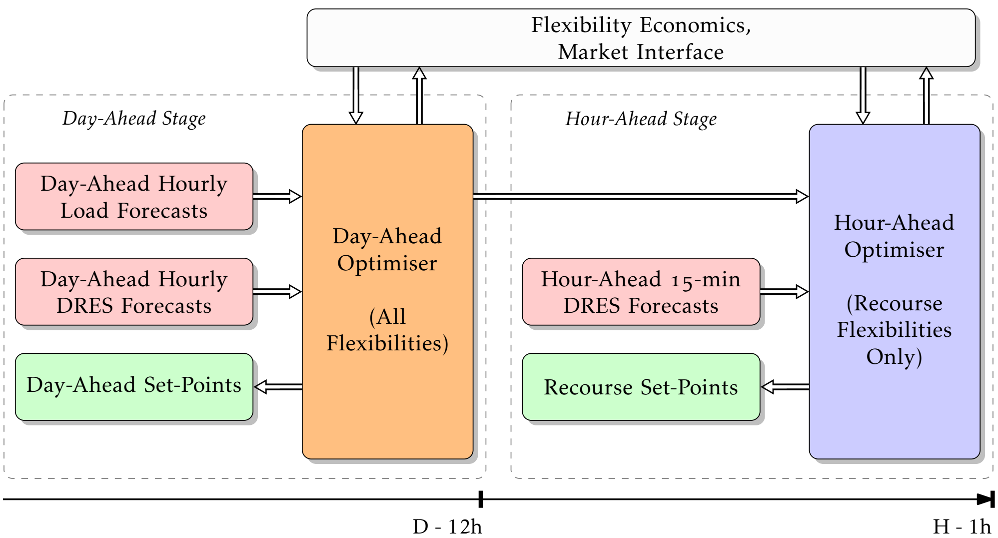


Figure 6.10: Functional Diagram of the Two-Stage Deterministic OP

6.3.1.1 The Day-Ahead Stage

The first stage of this formulation is the day-ahead stage, which, in keeping with the current trend in deregulated power systems, is executed before the gate-closure of the day-ahead market (12 hours before midnight on day D of the optimisation). The day-ahead DRES and load forecasts are for 1-hour time periods. This stage is similar to the OP formulation developed in Chapter 4 and uses the same objective function and different power flow constraints depending on the final problem. We present the objective function once again for ease of reading. The power flow constraints imposed on this optimisation stage are listed in Table 6.3.

$$\begin{aligned}\min \sum_{(i,j)\in\Omega}\sum_{t=1}^{24}&\left(\rho^{l}\cdot r_{ij}\cdot l_{ijt}\right)+\left(\rho_1^{oltc}+\rho_2^{oltc}\cdot\Delta w\right)+\left(\rho_1^{rec}+\rho_2^{rec}\cdot\Delta e\right)\\
&+\sum_{i}\sum_{t=1}^{24}\left[\left(\rho_t^{cur}\cdot P_{it}^{fg}\right)+\left(\rho_t^{ch}\cdot P_{it}^{bat,in}\right)+\left(\rho_t^{dc}\cdot P_{it}^{bat,out}\right)\right.\\
&\left.+\left(\rho^{lcup}\cdot P_{it}^{fcup}\right)+\left(\rho^{lcdn}\cdot P_{it}^{fcdn}\right)+\left(\rho^{act}\cdot a_{it}^{act}\cdot \overline{P_{it}^{fcact}}\right)\right]\end{aligned}$$

Table 6.3: Constraints for the Day-Ahead Stage of the Deterministic OP

Description	**Constraints**
DistFlow	(4.26) – (4.33)
Reconfiguration	(4.34) – (4.38)
Voltage and Current Constraints	(4.45) – (4.52)
Load Modulation (Types 2 & 3)	(4.54) – (4.58)
OLTC	(4.62) – (4.78)
Reconfiguration & OLTC Registers	(4.85) – (4.89), (4.90) – (4.94)
Battery Systems	(4.95) – (4.98)
DRES & Load Power Factor	(4.99) – (4.102)
SOCP Relaxation	(4.104)

6.3.1.2 The Hour-Ahead Stage

The day-ahead stage of the optimisation communicates pertinent results to the hour-ahead stage of the optimisation. This stage is executed one hour before the actual hour to be optimised. In this stage, the DSO is able to perform certain recourse actions for the flexibilities contracted on the day-ahead stage. This could be provoked by new information regarding the uncertainty becoming available, possibly causing constraint violations with the day-ahead solution. In this stage, we deal with forecasts of a higher resolution, given that the time horizon is that of an hour. This stage is therefore formulated with 15-minute time periods, and hence with four such periods for every hour. The objective function of the hour-ahead stage is as follows:

$$\min \sum_{(i,j)\in\Omega}\sum_{h=1}^{4}\left(\rho^{l}\cdot r_{ij}\cdot l_{ijh}\right)+\sum_{i}\sum_{h=1}^{4}\left[\left(\rho_h^{cur}\cdot P_{ih}^{fg}\right)+\left(\rho_h^{ch}\cdot P_{ih}^{bat,in}\right)+\left(\rho_h^{dc}\cdot P_{ih}^{bat,out}\right)\right] \quad (6.22)$$

The hour-ahead optimisation is formulated for performing recourse actions, and only the flexibilities with additional costs of utilisation are included in the objective function. The flexibilities on which recourse actions can be performed do not entail expenditures and are not in the objective function. Other flexibilities are constrained to their day-ahead values through the following constraints. In constraints (6.23), (6.24), the reconfiguration variable and the tap choice are set to the variables from the day-ahead optimisation for the hour in which the 15-minute time periods are considered. Constraint (6.25) imposes the use of the reserved capacity of type 3 load modulation only for the hours during which it was activated in the day ahead-stage.

$\forall (i,j) \in \Omega$ and $\forall h \in H$:

$$e^{ha}_{ijh} = e^{da}_{ij} \tag{6.23}$$

$$w^{ha}_{qijh} = w^{da}_{qijt} \tag{6.24}$$

$\forall i \in \Gamma_{act}$ and $\forall h \in H$:

$$P^{fcup}_{it} \leq a^{act,da}_{it} \cdot \overline{P^{fcact}_{i}} \tag{6.25}$$

Apart from these constraints, a combination of the power flow constraints from the day-ahead stage are also imposed. These constraints are listed in Table 6.4. The reconfiguration and OLTC constraints, the type-2 load modulation constraints, the type-3 load modulation activation constraints, and the linearised register variable constraints do not appear in the hour-ahead stage. They are replaced by the constraints (6.23) – (6.25). This is because these are the flexibilities that have a limited applicability in the recourse stage of the optimisation.

Table 6.4: Constraints for the Hour-Ahead Stage of the Deterministic OP

Description	Constraints
DistFlow	(4.26) – (4.33)
Voltage and Current Constraints	(4.45) – (4.52)
Hour-Ahead Constraints	(6.23) – (6.25)
Battery Systems	(4.95) – (4.98)
DRES & Load Power Factor	(4.99) – (4.102)
SOCP Relaxation	(4.104)

6.3.2 A Stochastic OP Formulation

The second of the three formulations developed is the discrete stochastic OP formulation, based on the principles presented in Section 6.2.1.2. This formulation adopts a two-stage strategy, where the flexibilities without recourse actions are optimised in the first stage, while the flexibilities with recourse actions are optimised in the second. It is to be noted that since the stochastic optimisation explicitly describes discretised scenarios, there is no guarantee that network constraints will not be violated when the uncertainty behaves in a manner not described by scenarios, even if it is within the scenario envelope (see Fig. 6.7).

The two-stage discrete stochastic OP formulation developed in this thesis optimises the expected cost incurred by DSOs over scenarios contained in a scenario set S. The objective function of the formulation is shown in equation (6.26). The probability associated to each scenario is represented by the parameter π_s.

$$\min \left(\rho_1^{oltc} + \rho_2^{oltc} \cdot \Delta w\right) + \left(\rho_1^{rec} + \rho_2^{rec} \cdot \Delta e\right) + \sum_i \sum_{t=1}^{24} \Big[\left(\rho^{lcup} \cdot P_{it}^{fcup}\right) + \left(\rho^{lcdn} \cdot P_{it}^{fcdn}\right) + \left(\rho^{act} \cdot a_{it}^{act,s} \cdot \overline{P_{it}^{fcact}}\right)\Big] + \sum_{s \in S} \pi_s \sum_{t=1}^{24} \Bigg(\sum_{(i,j)\in\Omega} \left(\rho^{l} \cdot r_{ij} \cdot l_{ijt}^{s}\right) + \sum_i \Big[\left(\rho_t^{cur} \cdot P_{it}^{fg,s}\right) + \left(\rho_t^{ch} \cdot P_{it}^{bat,in,s}\right) + \left(\rho_t^{dc} \cdot P_{it}^{bat,out,s}\right)\Big]\Bigg) \tag{6.26}$$

Given that some of the decision variables depend on the scenarios $s \in S$, the constraints imposed on the problem may change with respect to the original deterministic OP formulation. Some of the constraints remain the same, while others take an extra index, that of the scenario s. This means that constraints of the latter kind are imposed on every individual scenario. Table 6.5 provides a summary of all these constraints. The constraints that change are rewritten for ease of understanding.

Table 6.5: Constraints from Deterministic OP for Discrete Stochastic OP

Constraints	Description	New Constraints
Constraints that do not change		
(4.39) – (4.40), (4.43)	Reconfiguration	NA
(4.54) – (4.55), (4.58)	Load Modulation Type-2	
(4.62) – (4.70), (4.72), (4.78)	OLTC	
(4.85) – (4.89)	Reconfiguration Register	
(4.90) – (4.94)	OLTC Register	
Constraints where P, Q, l and v are imposed an index $s \in S$		
(4.26) – (4.33)	*DistFlow*	(6.27) – (6.34)
(4.41) – (4.42)	Reconfiguration	(6.35) – (6.36)
(4.47) – (4.52)	Power Flow and Limits	(6.37) – (6.42)
(4.56) – (4.57)	Load Modulation Type-3	(6.43) – (6.44)
(4.71), (4.73) – (4.75)	OLTC	(6.45), (6.46) – (6.48)
(4.95) – (4.98)	Battery System	(6.49) – (6.52)
(4.99) – (4.102)	DRES and Power Factor	(6.53) – (6.56)
(4.104)	SOCP Relaxation	(6.57)

Constraints that change ($\forall s \in S$, $\forall t \in T$, $\forall i \in \Gamma$, $\forall ij \in \Omega$ and $\forall q \in \Psi_{ij}$ unless specified):

DistFlow Constraints:

$$P_{it}^{G,s} = \sum_{i\in\Omega} P_{ijt}^{s} \qquad \forall j \in \Gamma^d(i) \tag{6.27}$$

$$Q_{it}^{G,s} = \sum_{i\in\Omega} Q_{ijt}^{s} \qquad \forall j \in \Gamma^d(i) \tag{6.28}$$

$$P_{jt}^{s} = \sum_{i\in\Gamma^u(j)} (P_{ijt}^{s} - r_{ij} l_{ijt}) - \sum_{k\in\Gamma^d(j)} P_{jkt}^{s} \tag{6.29}$$

$$Q^s_{jt} = \sum_{i\in\Gamma^u(j)} (Q^s_{ijt} - x_{ij} l_{ijt}) - \sum_{k\in\Gamma^d(j)} Q^s_{jkt} \tag{6.30}$$

$$P^s_{jt} = \sum_{i\in\Gamma^u(j)} \left(P^s_{ijt} - r_{ij} \sum_{q\in\Psi_{ij}} d_{qij}\delta_{qijt}\right) - \sum_{k\in\Gamma^d(j)} P^s_{jkt} \tag{6.31}$$

$$Q^s_{jt} = \sum_{i\in\Gamma^u(j)} \left(Q^s_{ijt} - r_{ij} \sum_{q\in\Psi_{ij}} d_{qij}\delta_{qijt}\right) - \sum_{k\in\Gamma^d(j)} Q^s_{jkt} \tag{6.32}$$

$$P^s_{jt} = P^c_{it} - P^{g,s}_{it} - P^{fcup,s}_{it} + P^{fcdn,s}_{it} + P^{fg,s}_{it} \tag{6.33}$$

$$Q^s_{jt} = Q^c_{it} - Q^{g,s}_{it} - Q^{fcup,s}_{it} + Q^{fcdn,s}_{it} + Q^{fg,s}_{it} \tag{6.34}$$

Reconfiguration Constraints: $\forall ij \in \Omega$ and $\notin \xi$:

$$-e_{ij}\underline{P_{ij}} \le P^s_{ijt} \le e_{ij}\overline{P_{ij}} \tag{6.35}$$

$$-e_{ij}\underline{Q_{ij}} \le Q^s_{ijt} \le e_{ij}\overline{Q_{ij}} \tag{6.36}$$

Voltage Constraints:

$$v^s_{jt} \le v^s_{it} - 2(r_{ij}P^s_{ijt} + x_{ij}Q^s_{ijt}) + l^s_{ijt}(r^2_{ij} + x^2_{ij}) + M(1 - e_{ij}) \tag{6.37}$$

$$v^s_{jt} \ge v^s_{it} - 2(r_{ij}P^s_{ijt} + x_{ij}Q^s_{ijt}) + l^s_{ijt}(r^2_{ij} + x^2_{ij}) - M(1 - e_{ij}) \tag{6.38}$$

Voltage and Current Limits:

$$v^s_{it} \le \overline{v_i} \tag{6.39}$$

$$v^s_{it} \ge \underline{v_i} \tag{6.40}$$

$$v^s_{it} = (V^G_t)^2 \tag{6.41}$$

$$l^s_{ijt} \le \overline{I^2_{ij}} \tag{6.42}$$

Load Modulation Constraints ($\forall i \in \Gamma_{act}$):

$$P^{fcup,s}_{it} \ge a^{act}_{it} \cdot \epsilon \tag{6.43}$$

$$P^{fcup,s}_{it} \le a^{act}_{it} \cdot \overline{P^{fcact}_i} \tag{6.44}$$

OLTC Constraints ($\forall ij \in \kappa$):

$$l^s_{ijt} - \overline{(I_{ij})}^2(1 - w_{qijt}) \le \delta_{qijt} \le l^s_{ijt} \tag{6.45}$$

$$v^s_{it} - \overline{V^2_i}(1 - w_{qijt}) \le \gamma_{qijt} \le v^s_{it} - \underline{V^2_i}(1 - w_{qijt}) \tag{6.46}$$

$$v^s_{jt} \le \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P^s_{ijt} + x_{ij} \cdot Q^s_{ijt}) + M(1 - e_{ij}) \tag{6.47}$$

$$v^s_{jt} \ge \sum_q \frac{\gamma_{qijt}}{d^2_{qijt}} + (r^2_{ij} + x^2_{ij}) \sum_q d^2_{qijt} \cdot \delta_{qijt} - 2(r_{ij} \cdot P^s_{ijt} + x_{ij} \cdot Q^s_{ijt}) - M(1 - e_{ij}) \tag{6.48}$$

Battery System Constraints ($\forall i \in \Gamma_{bat}$):

$$E_{it}^{soc,s} = E_{i,t-1}^{soc,s} + \eta_i^{in} \cdot P_{it}^{bat,in,s} - \eta^{out} \cdot P_{it}^{bat,out,s} \tag{6.49}$$

$$\underline{E_i^{soc}} \leq E_{it}^{soc,s} \leq \overline{E_i^{soc}} \tag{6.50}$$

$$P_{it}^{bat,in,s} \leq \overline{P_i^{bat}} \tag{6.51}$$

$$P_{it}^{bat,out,s} \leq \overline{P_i^{bat}} \tag{6.52}$$

DRES Constraints ($\forall i \in \Gamma_g$):

$$P_{it}^{fg,s} \leq \overline{P_{it}^{fg,s}} \tag{6.53}$$

$$\underline{Q_{it}^{fg,s}} \leq Q_{it}^{fg,s} \leq \overline{Q_{it}^{fg,s}} \tag{6.54}$$

Load Power Factor Limits ($\forall i \in \Gamma_{act}$):

$$Q_{it}^{fcup,s} = P_{it}^{fcup,s} \cdot tan(\phi) \tag{6.55}$$

$$Q_{it}^{fcdn,s} = P_{it}^{fcdn,s} \cdot tan(\phi) \tag{6.56}$$

SOCP Relaxation:

$$4(P_{ijt}^s)^2 + 4(Q_{ijt}^s)^2 + (l_{ijt}^s - v_{it}^s)^2 - (l_{ijt}^s + v_{it}^s)^2 \leq 0 \tag{6.57}$$

It is to be noted that the constraints related to type-3 load modulation apply only to nodes where such modulation is possible (Γ_{act}). Further, the constraints (6.55) and (6.56) do not depend on the scenario s for all nodes i that do not belong in the type-3 load modulation set Γ_{act}.

6.3.3 *An Interval OP Formulation*

The third formulation developed is the interval OP formulation, based on the principles of interval optimisation presented in Section 6.2.2.2. The scenario set S in the formulation contains three scenarios (for lack of a better word) for DRES: the central forecast (CF), the lower bound (LB), and the upper bound (UB). The objective function of the interval OP formulation is presented in equation (6.58). The objective function minimises the cost of the flexibilities that do not have recourse actions. It also minimises the cost of the flexibilities that have recourse actions, but only for the central forecast.

$$\begin{aligned} \min \ & \left(\rho_1^{oltc} + \rho_2^{oltc} \cdot \Delta w\right) + \left(\rho_1^{rec} + \rho_2^{rec} \cdot \Delta e\right) + \sum_i \sum_{t=1}^{24} \left[\left(\rho^{lcup} \cdot P_{it}^{fcup}\right) + \left(\rho^{lcdn} \cdot P_{it}^{fcdn}\right)\right] \\ & + \sum_{t=1}^{24} \Bigg(\sum_{(i,j)\in\Omega} \left(\rho^l \cdot r_{ij} \cdot l_{ijt}^{cf}\right) + \sum_i \Bigg[\left(\rho_t^{cur} \cdot P_{it}^{fg,cf}\right) + \left(\rho^{act} \cdot a_{it}^{act} \cdot \overline{P_{it}^{fcact}}\right) \\ & + \left(\rho_t^{ch} \cdot P_{it}^{bat,in,cf}\right) + \left(\rho_t^{dc} \cdot P_{it}^{bat,out,cf}\right)\Bigg]\Bigg) \end{aligned} \tag{6.58}$$

As outlined in Section 6.2.2.2, additional constraints have to be imposed in order to ensure that the inter-temporal transitions for flexibilities whose values change in the scenarios do not violate their ramp limits. These flexibilities, namely DRES curtailment, load modulation type-3, and battery systems are imposed the additional constraints expressed below.

$\forall i \in \Gamma, \forall t \in T$:

$$P_{it}^{fg,ub} - P_{it-1}^{fg,cf} \leq \overline{\zeta(P_i^{fg})} \quad (6.59)$$

$$P_{it-1}^{fg,cf} - P_{it}^{fg,lb} \leq \overline{\zeta(P_i^{fg})} \quad (6.60)$$

$$P_{it}^{fg,ub} - P_{it-1}^{fg,lb} \leq \overline{\zeta(P_i^{fg})} \quad (6.61)$$

$$P_{it-1}^{fg,ub} - P_{it}^{fg,lb} \leq \overline{\zeta(P_i^{fg})} \quad (6.62)$$

$\forall i \in \Gamma_{act}, \forall t \in T$:

$$P_{it}^{fcact,ub} - P_{it-1}^{fcact,cf} \leq \overline{\zeta(P_i^{fcact})} \quad (6.63)$$

$$P_{it-1}^{fcact,cf} - P_{it}^{fcact,lb} \leq \overline{\zeta(P_i^{fcact})} \quad (6.64)$$

$$P_{it}^{fcact,ub} - P_{it-1}^{fcact,lb} \leq \overline{\zeta(P_i^{fcact})} \quad (6.65)$$

$$P_{it-1}^{fcact,ub} - P_{it}^{fcact,lb} \leq \overline{\zeta(P_i^{fcact})} \quad (6.66)$$

$\forall i \in \Gamma_{bat}, \forall t \in T$:[5]

$$P_{it}^{bat,ub} - P_{it-1}^{bat,cf} \leq \overline{(P_i^{bat})} \quad (6.67)$$

$$P_{it-1}^{bat,cf} - P_{it}^{bat,lb} \leq \overline{(P_i^{bat})} \quad (6.68)$$

$$P_{it}^{bat,ub} - P_{it-1}^{bat,lb} \leq \overline{(P_i^{bat})} \quad (6.69)$$

$$P_{it-1}^{bat,ub} - P_{it}^{bat,lb} \leq \overline{(P_i^{bat})} \quad (6.70)$$

The ramp rate of DRES inverters can go up to 1200% of their rated power per minute [SMA17], and the ramping of loads is instantaneous, given their switch-on / switch-off nature. This means that in terms of ramping between the scenarios, these flexibiltiies have more than sufficient ramping capabilities. For battery systems, the ramp rate is fixed by the maximum power that the battery can deliver.

Apart from the equations (6.59) – (6.70), the following equations used in the discrete stochastic OP formulation can be employed, and are shown in Table 6.6. For equations containing scenarios, $S = \{lb, cf, ub\}$.

6.3.4 Comparing the Performance of the Formulations

The performance of the three formulations developed in Sections 6.3.1, 6.3.2 and 6.3.3 has to be based on various criteria to determine which among them perform better under different conditions. A framework to perform such a comparison is presented in this section.

The idea behind this comparison is the following. All the three formulations have day-ahead stages. On one hand, the stochastic OP formulation provide recourse action set-points for flexibilities for each input scenario. This means that if the realisation of the uncertainty is not part of a scenario, a deterministic optimisation needs to be run to obtain the new recourse action set-points. On the other hand, the interval OP

[5] In these equations, $P^{bat} = P^{bat,out} - P^{bat,in}$

Table 6.6: Constraints for Interval OP

Description	Constraints
DistFlow	(6.27) – (6.34)
Reconfiguration	(4.39) – (4.40), (4.43), (6.35) – (6.36)
Voltage and Current Constraints	(6.37) – (6.42)
Load Modulation (Types 2 & 3)	(4.54) – (4.55), (4.58), (6.43) – (6.44)
OLTC	(4.62) – (4.70), (4.72), (4.78), (6.45), (6.46) – (6.48)
Reconfiguration & OLTC Registers	(4.79) – (4.84), (4.90) – (4.94)
Battery Systems	(6.49) – (6.52)
DRES & Load Power Factor	(6.53) – (6.56)
SOCP Relaxation	(6.57)

formulation chooses the flexibilities that can satisfy network constraints for all realisations of uncertainties within predefined bounds. When the actual realisation of the uncertainty becomes known, a deterministic optimisation has to be run to find the final recourse cation set-points. This deterministic optimisation routine, and its function, seems familiar. This is because it is. The hour-ahead stage of the deterministic two-stage OP formulation is intended to perform the same function as the deterministic optimisation routine that provides recourse action set-points for the other two formulations. Consequently, the hour-ahead stage of the two-stage deterministic OP formulation can be integrated to the other two formulations as well. The framework for comparing the three formulations is illustrated in Fig. 6.11.

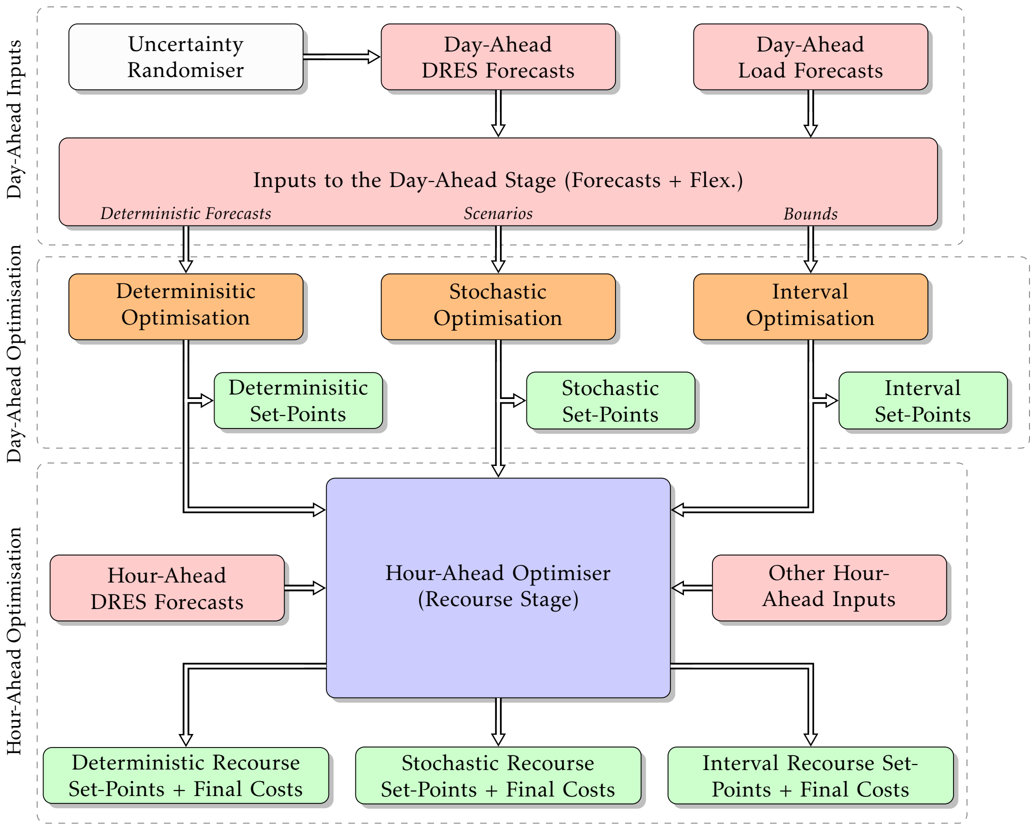


Figure 6.11: Framework for Comparing the OP Formulations under Uncertainty

In the day-ahead stage, a randomiser generates disturbances to create uncertainty in the day-ahead DRES forecasts. The inputs to the day-ahead stage of the three formulations also contain load forecasts. The three day-ahead stages then optimise the the given distribution network based on these forecasts, and provide day-ahead set-points with their associated costs. The results are also transmitted to the hour-ahead stage, which optimises the recourse actions for the choice of flexibilities made by each of the three formulations. This optimisation accepts 15-minute DRES forecasts for which there are no uncertainties. The day-ahead load forecasts considered constant over the 15-minute periods in an hour, considering that this framework is made only for comparison. The final set-points and costs are then obtained for the three formulations, for analysis and comparison.

6.4 CONCLUSIONS

In this chapter, the need for considering uncertainty in optimisation was first underlined using a simple example. This example showed how solutions to deterministic optimisation problems can be infeasible when the input parameters to the optimisation become uncertain. This was followed by a discussion and review of the characterisation of uncertainty, and the various approaches in literature to solving optimisation problems under these characterisations of uncertainty. The two major characterisations explored were the probabilistic characterisation and the characterisation using bounds. Two approaches were reviewed as a part of the first type of characterisation: the probabilistic OPF (P-OPF) and the discrete stochastic OPF, while three approaches were reviewed as a part of the second: the interval OPF, robust OPF, and the IGDT OPF. This review presented the recent and important work in these approaches.

An analysis of the challenges to modelling distribution network operational planning formulations using these approaches was then presented. As a part of this analysis, the advantages and disadvantages of each of these methods were explored. Specific emphasis was applied on the application of these methods to distribution network operational planning. A summary at the end of this analysis identified two different methods, the discrete stochastic OPF and the interval OPF. A third, simpler way of handling uncertainty, using a two-stage deterministic approach was also chosen.

The three approaches were then used to cast the distribution network operational planning problem, with uncertainty in the DRES forecasts. The formulations were derived from the deterministic OP formulation developed in Chapter 4 and tested in Chapter 5. The two-stage deterministic OP formulation relies on a day-ahead and an hour-ahead stage, both employing deterministic OP formulations. The stochastic OP formulation considers discrete scenarios to characterise the uncertainty in DRES. The interval OP formulation treats the same uncertainty via a central forecast and bounds. To enable a comparisonof the performances of these three methods, a comparison framework was developed and presented. In the next chapter, results of the tests on these three formulations are presented, and their performances are analysed with respect to various factors.

7 Operational Planning under Uncertainty – Results

« Errors using inadequate data are much less than those using no data at all. »
- Charles Babbage

7.1 Introduction

7.1.1 Context

The novel OP formulation for distribution networks developed in Chapter 4 was extended to create three formulations that handle uncertainty in Chapter 6. The three formulations are a two-stage deterministic formulation, a stochastic formulation, and an interval formulation. A framework to compare the performance of these formulations was also developed in the same chapter.

In this chapter, the results of the tests on the three operational planning formulations under uncertainty are presented. The results of the comparison of the three formulations, using the framework developed in Section 6.3.4, are also presented. The tests are performed on the day-ahead and hour-ahead stages, with uncertainty in DRES production. For the comparison framework, a total of 1000 DRES production scenarios are generated to test the performance of the three formulations. The main contribution of this chapter to the thesis is (numbering consistent with the contributions listed in Chapter 1):

C12 Tests on the different formulations developed for operational planning under uncertainty. A comparison and analysis for the performance of the different formulations for different realisations of uncertainty.

The tests on the different formulations allow us to show that they are effectively able to handle uncertainty in DRES forecasts, presented in three different forms: deterministic forecasts, scenarios, and bounds. The results of tests using the comparison framework serve to show how the formulations perform when the actual realisations of the uncertainty become known in the hour-ahead stage. To perform these tests, we use the parameters and conditions described in the next section.

7.1.2 Test Parameters and Conditions

7.1.2.1 Test Network

To test the three formulations and the comparison framework, the test network employed is the Baran Test Network. The network consists of 33 nodes, with 37 lines (32 NC and 5 NO). The characteristics of this network have already been presented in Chapter 5. Additional details for this network are also presented in Appendix B. For ease of reading, we present the main characteristics of the Baran network once again in Table 7.1.

Table 7.1: Baran Test Network – Main Characteristics

Characteristics	Value			
Nodes	33 (1 Slack, 32 PQ)			
Lines	37 (32 NC, 5 NO, All Manoeuvrable)			
Connected Load	3.71 MW (4.37 MVA)			
OLTC	5 Taps, 0.025 pu per tap			
DRES (20 %)	Wind		PV	
	Node	W_p	Node	W_p
	4	0.423 MW	26	0.417 MW
			27	0.273 MW

7.1.2.2 Forecasts & Uncertainty Generation

We recall that the uncertainty in our OP problem arises from the DRES forecasts. This means that the DRES forecasts considered in Chapter 5 are not valid for the tests of the OP formulations under uncertainty. To test these formulations, the DRES forecasts must include a way to represent uncertainty. We remind the reader that the representation of the forecasts depends on the formulation it is used in.

For the two-stage deterministic OP formulation, the day-ahead and hour-ahead DRES forecasts are all deterministic. For the stochastic OP formulation, these forecasts are represented as scenarios. And for the interval OP formulation, this is a central forecast with the bounds on uncertainty. To generate these DRES forecasts, we rely on the random uncertainty generator from the comparison framework presented in Fig. 6.11.

In this chapter, we test and present the results of the formulations for an instance of the uncertainty generated by this random uncertainty generator. We consider an insertion rate of 20 % for generating DRES forecasts. The type, size, and location of DRES corresponding to this insertion rate have already been presented in Table 7.1. These forecasts are illustrated for each formulation in their respective sections.

As for the load forecasts, in the context of this thesis, we consider that there is no uncertainty. This means that the load forecasts used in Chapter 5 can be reused for all the tests in this chapter. We recall that there are three types of loads: residential, commercial, and industrial. The load and net load profiles for the Baran network can be found in Appendix B.

7.1.2.3 Flexibility Limits

Among the flexibilities available, the flexibilities without recourse actions (choice independent of uncertainty) are that of the OLTC, reconfiguration, and type-2 load modulation. Type-3 load modulation is constrained with respect to the activation hours across the uncertainty realisations. However, the actual load reduction can vary depending on the uncertainty realisation. The other flexibilities whose set-points can be changed depending on the uncertainty realisation are those of DRES curtailment and batteries. Overall, the numerical limits imposed on the flexibilities in the tests are shown in Table 7.2.

A specific point to be noted is with respect to the nodes where type-2 and type-3 load

Table 7.2: Flexibility Limits for Tests under Uncertainty

Flexibility	Limits	
	Description	**Constraints**
OLTC	Register	$\Delta w_{ij} \leq 24$
DRES Curtailment	Maximum Limit	$\overline{P_{it}^{fg,s}} = P_{it}^{g,s}$
DRES Q-Compensation	Injection Limit	$\overline{Q_{it}^{fg,s}} = 0.4 \cdot (P_{it}^{g,s} - P_{it}^{fg,s})$
	Consumption Limit	$\underline{Q_{it}^{fg,s}} = -0.35 \cdot (P_{it}^{g,s} - P_{it}^{fg,s})$
Battery	Maximum Ramping	$\overline{(P_i^{bat})} \leq 0.25\,\mathrm{MW/h}$
	State of Charge	$\overline{E_i^{soc}} = 0.8 E_i^{bat}$
	State of Charge	$\underline{E_i^{soc}} = 0.2 E_i^{bat}$

modulations are available. In the absence of type-1 load modulation, the nodes, where it was available, are converted to one of the other two types. All the odd-numbered nodes in the network are thus considered for type-2 load modulation, while the even-numbered nodes are considered for type-3 load modulation.

7.1.2.4 Cost Parameters

The cost parameters used in the formulations under uncertainty is the same as the cost parameters used in the novel OP formulation. This has been presented in Section 5.1.3.5 of Chapter 5. For convenience, these parameters are presented again in this section, in Table 7.3.

Table 7.3: Test Parameters – Flexibility Costs

Flexibility		Cost
OLTC		14.21 € per day + 11.875 € per tap change
Reconfiguration		0.898 € per day + 4.5 € per switching action
Active Power Losses		50 € per MWh
Load Modulation	Types 1 & 2	Day-Ahead Market Price
	Type-3	18 € per MWh for every activation
Battery	Charge	-522.81 to -507.22 € per MWh
	Discharge	563.19 to 578.78 € per MWh

7.1.3 Test Environment

The General Algebraic Modelling System (GAMS) [GAM13] with a Matlab® interface is once again used to model the different formulations developed in Chapter 6. The Branch-and-Cut method in the IBM CPLEX® solver is used to solve the models. All the tests for which the results are presented in this chapter and in Appendix B have been carried out on a computer with an 80-core Intel® Xeon® E5-2698 v4 processor and 96 GB of RAM, running Windows Server 2016.

7.1.4 *Organisation of Results*

The results presented in this chapter are organised as follows. The main test results for the two-stage deterministic OP formulation are presented in Section 7.2. This is followed by the presentation of the results for the stochastic OP formulation in Section 7.3. The results for the interval OP formulation are presented in Section 7.4. Additional results for the formulations can be found in Appendix B of this thesis.

The comparison framework is used to test the effectiveness of the three formulations. Tests using this framework are done for two different levels of uncertainty, and the main results from these tests are presented in Section 7.5. An analysis on the performances of the different formulations along with the conclusions to the chapter are finally presented in Section 7.6.

7.2 THE TWO-STAGE DETERMINISTIC OP FORMULATION

7.2.1 *Original Conditions*

The deterministic day-ahead and hour-ahead forecasts generated by the random uncertainty generator are illustrated in Fig. 7.1 and Fig. 7.2 respectively. We remind the reader that for a DRES insertion rate of 20 %, the tests in Chapter 5 were done with a wind power generator of 0.423 MW at node 4, and PV generators of 0.417 and 0.273 MW at nodes 26 and 27 respectively.

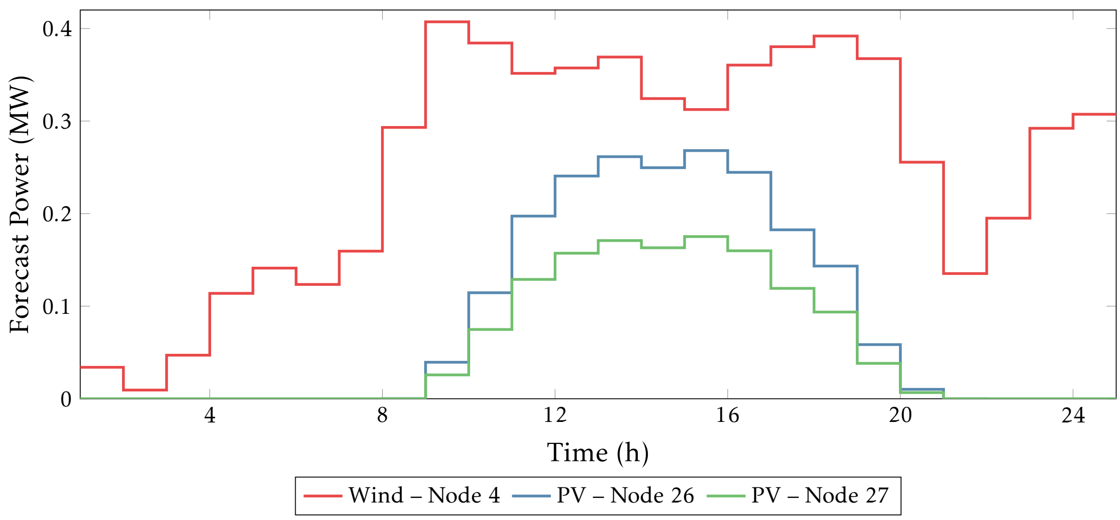


Figure 7.1: Two-Stage Deterministic OP Formulation – Day-Ahead DRES Forecasts

The original conditions for this test case in the day-ahead stage have already been evaluated. This can be found in Section 5.2.1 of Chapter 5. For ease of reading, we remind the reader that the network suffers from under-voltage issues in this test case, with a lowest observed voltage of 0.875 pu. The total DSO expenditures without the optimisation stand at 428 990.9 €.

7.2.2 *Results for the Day-Ahead Stage*

In the day-ahead stage, the two-stage deterministic OP formulation has access to all flexibilities available for optimisation. This includes reconfiguration, OLTC, types 2 and

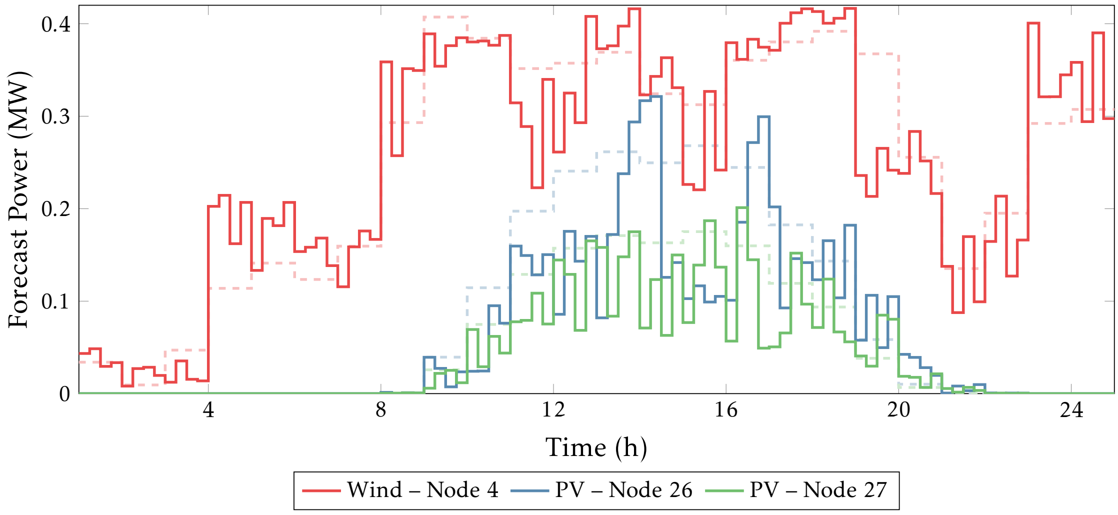


Figure 7.2: Two-Stage Deterministic OP Formulation – Hour-Ahead DRES Forecasts

3 load modulation, DRES curtailment and Q-compensation, and battery systems. The main results obtained for this stage of the OP formulation are outlined in Table 7.4.

Table 7.4: Two-Stage Deterministic OP Formulation – Results for the Day-Ahead Stage

Description	**Value**	
DSO Expenditures (Objective)	310.66 €	
Execution Time	66.67 seconds	
Active Losses	4.52 MWh	
Tap Setting	4 (Hours 1–24)	
Open Switches	C1 (Hours 1–24)	
Load Modulation (kWh)	Type-2: 46.93	Type-3: 375.28
DRES Curtailment	—	
DRES Reactive Compensation	3.775 MVArh (Injection)	
Average Relaxation Error	0.07 VA^2	

The major difference between this test and the test case *OP−etol3a* in Chapter 5 is the absence of type-1 load modulation. Despite this absence, the optimal DSO expenditures are the same, and stand at 310.66 €. In fact, results obtained for this stage are almost similar in all respects with those obtained for the test case *OP−etol3a*. The lack of type-1 load modulation is compensated for with a higher use of type-2 load modulation. In fact, the total used type-2 modulation in this test case (46.93 kWh) is very similar to the total of the used types 1 and 2 load modulation (46.86 kWh) in the test case *OP−etol3a*. All the other results are similar, leading to the same final expenditures (accurate to 1 c€) for the DSO. The configuration C1 corresponds to the configuration with the same name in Chapter 5, illustrated in Appendix B.

The optimised network voltages are shown in Fig. 7.3. We conserve the colour-space from Fig. 5.6 in Chapter 5 for uniformity. The minimum and maximum voltages in the optimised network are 0.95 pu and 1.0454 pu respectively.

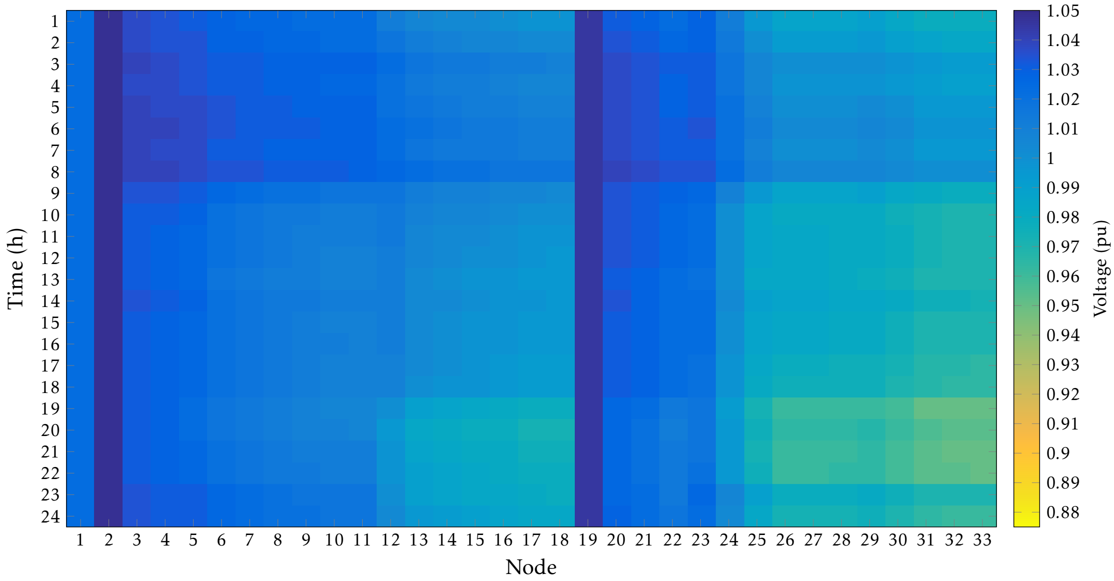


Figure 7.3: Two-Stage Deterministic OP Formulation – Optimised Network Voltages

Nodes 31 and 33 are chosen for type-2 load modulation, while nodes 26, 28, and 30 are chosen for type-3 load modulation. The total reduced load amounts to a meagre 0.38 % of the total load in the network. The DSO spends a total of 8.28 € towards the utilisation of load modulation in this stage.

7.2.3 *Results for the Hour-Ahead Stage*

In the hour-ahead stage, new 15-minute DRES forecasts are available to the DSO. When the flexibility set-points provided by the day-ahead formulation are applied to the network with these new DRES forecasts, additional violations of the network constraints may occur.

We observe two voltage violations in the network when the day-ahead solution is applied with the new hour-ahead forecasts. These violations occur in nodes 32 and 33 during hour 19. This is due to the following reasons. In the day-ahead solution, the voltages at these nodes were 0.9504 and 0.95 pu respectively, meaning that they were close to the lower limit of the allowed voltage. The power injection from DRES in the nodes 26 and 27 during this hour were 0.058 and 0.038 pu respectively. However, the new DRES power injections in these nodes during the first 15' of the hour are lower than the day-ahead forecast values, at 0.0577 and 0.037 pu respectively. This causes the voltages downstream (nodes 32 and 33) to drop below the permissible limits, to 0.9499 and 0.9496 pu respectively (see Fig. 7.4).

By applying the hour-ahead formulation for each hour, we find that corrective actions are taken during hour 19. This eliminates the voltage violations. The results obtained for this stage are presented below, in Table 7.5.

Hour 19 is the only hour where recourse actions that result in additional DSO expenditures are made. During the other hours, the only recourse actions made are that for type-3 load modulation and DRES reactive power compensation. During hour 19, the battery in node 28 injects 35.64 kWh, improving the voltage downstream, and contributing to the elimination of the under-voltages in nodes 32 and 33.

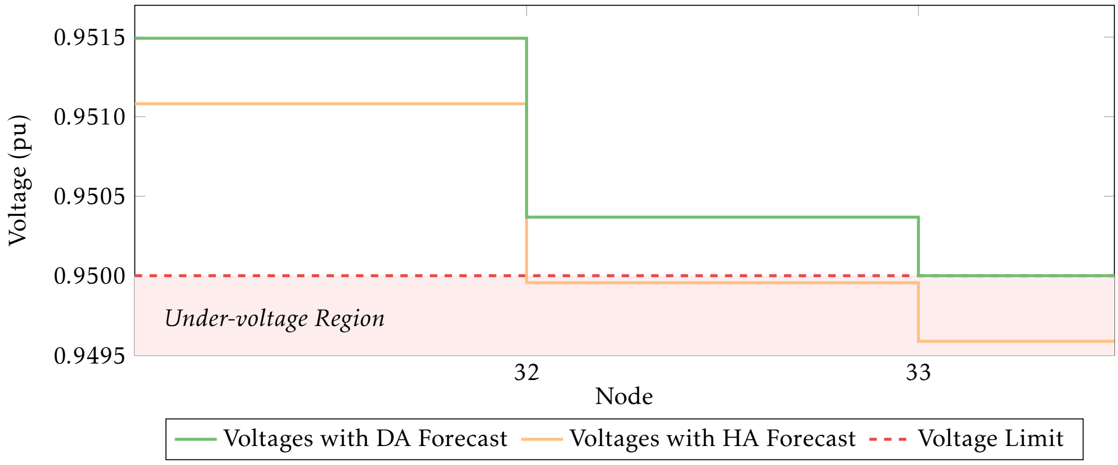


Figure 7.4: Voltage Violations with Hour-Ahead Forecasts

Table 7.5: Two-Stage Deterministic OP Formulation – Results for the Hour-Ahead Stage

Description	**Value**
DSO Expenditures (Objective)	232.86 €
Execution Time	226.3 seconds
Active Losses	4.62 MWh
Type-3 Load Modulation (kWh)	375.3
DRES Curtailment	—
Battery	35.64 kWh (Injection)
DRES Reactive Compensation	3.453 MVArh (Injection)
Average Relaxation Error	0.16 VA^2

The actualised operational cost for DSOs is the cost incurred for the flexibility chosen on the day-ahead stage and the total DSO expenditures on the hour-ahead stage. We recall that the flexibilities chosen on the day-ahead stage are reconfiguration, OLTC, and load modulation types 2 and 3. In this test case, the actualised operational costs are therefore 317.57 € (84.71 € on the day-ahead stage). Fig. 7.5 shows the operational costs incurred for each hour.

Some additional results for the hour-ahead stage are presented in Appendix B. It is to be noted that the results presented here are for an example of the hour-ahead forecasts. Additional tests that compare the performance of the two-stage deterministic OP formulation with the other formulations are done for 1000 different sets of hour-ahead forecasts. The results of these tests are presented in Section 7.5.

7.3 THE STOCHASTIC OP FORMULATION

7.3.1 *Original Conditions*

The stochastic OP formulation requires discrete scenarios to represent the uncertainty in DRES forecasts. In this test case, the random uncertainty generator generates 10 scenarios for the DRES present in the network, in nodes 4, 26, and 27. The generated scenarios are shown in Fig. 7.6. Each of these scenarios is also associated a probability of occurrence by the random uncertainty generator. These probabilities are listed in Table

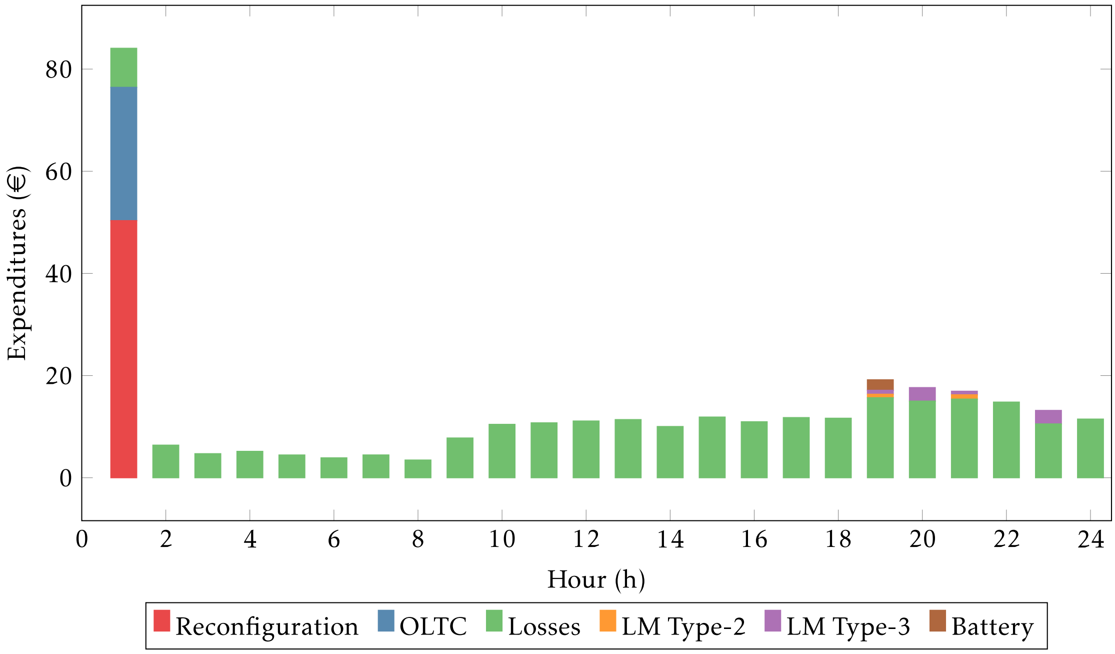


Figure 7.5: Two-Stage Deterministic OP Formulation – Hourly DSO Expenditures

7.6. Scenario 3 has the highest probability of occurrence at 24.06 %. The scenario with the lowest probability of occurrence is scenario 4, with a 2.26 % probability.

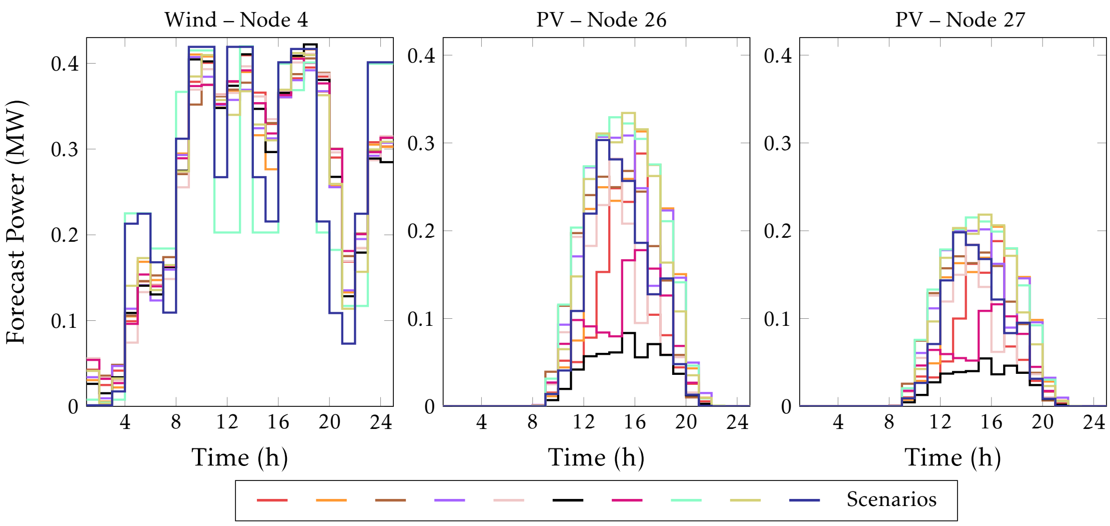


Figure 7.6: Stochastic OP Formulation – DRES Forecast Scenarios

Table 7.6: Stochastic OP Formulation – Scenario Probabilities

Scenario	1	2	3	4	5
Probability (%)	4.51	5.26	24.06	2.26	9.02
Scenario	6	7	8	9	10
Probability (%)	14.29	6.02	21.80	9.02	3.76

Across the scenarios, the unoptimised network shows only under-voltage violations. The voltage profiles in the network for the scenarios are shown in Fig. 7.7.

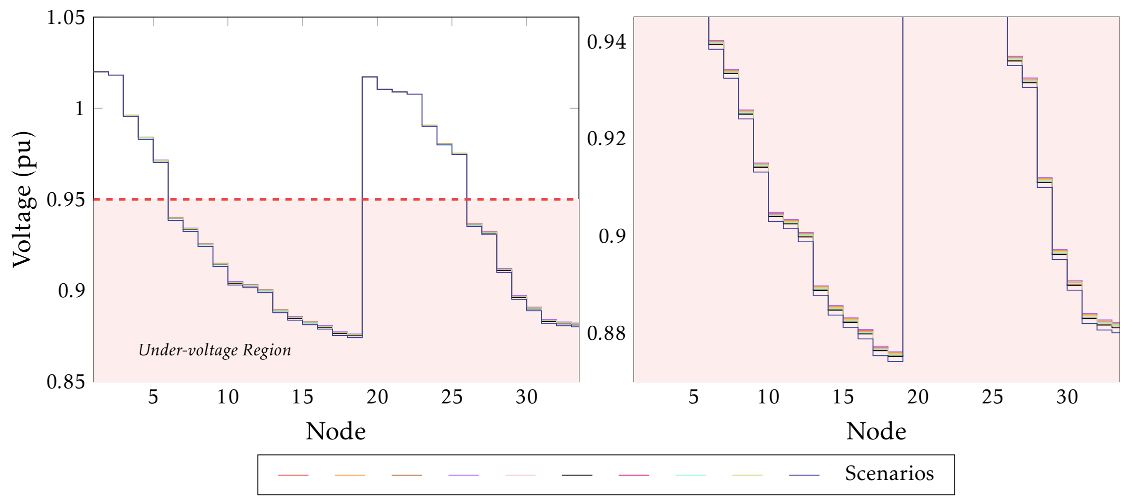


Figure 7.7: Stochastic OP Formulation – Minimum Unoptimised Network Voltages

The lowest observed voltage across all the scenarios is 0.8741 pu, occurring in node 18 with scenario 10. Since the stochastic OP formulation provides an expected value of DSO expenditures, the hypothetical DSO expenditures without optimisation are also presented as an expected value. We remind the reader that these expenditures are calculated with respect to the losses and the energy not distributed, and outlined in Section 4.5.12 in Chapter 4. To ascertain this, we compute the DSO expenditures in each scenario, and multiply the obtained value with the associated probability. This expected value amounts to 432 937.09 €.

7.3.2 *Results with the Stochastic OP Formulation*

We run the stochastic OP formulation on the Baran network with the given input conditions and scenarios. The main results obtained from the formulation are presented in Table 7.7 in Page 158. These results include the DSO expenditures (objective value), the active losses, the load modulation, the battery use, and DRES reactive power compensation for each scenario. The expected value of the DSO expenditures with the given scenarios amounts to 450.57 €.

An interesting aspect of the results for this formulation is the difference between the losses in the original and the optimised network as shown in the Table. In 7 of the 10 scenarios, the losses in the optimised network are higher than that of the original network. The losses are not the only objective of the optimisation. However, this alone cannot explain the increase, given that the results presented for deterministic formulations have always provided lower losses. The additional reason is that the stochastic OP formulation optimises network expenditures across a set of scenarios in a combined manner.

In the formulation, the network configuration, the OLTC tap setting, and the load modulation are constant across scenarios. Type-3 load modulation is used to the maximum available extent, subject to the activation constraints. This is the reason why its value is constant across scenarios. DRES curtailment is not used in any of the scenarios. Battery systems are used in 4 of the 10 scenarios. In particular, the battery systems in nodes 18, 26, 28, and 32 inject a total of 355.7 kWh in scenario 10. They help improve the voltages in the peripheral nodes of the network. Their injection patterns are shown in Fig. 7.8 in Page 158.

Table 7.7: Stochastic OP Formulation – Results Across Scenarios

Result \ Scenario		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Objective (€)		414.94	465.67	463.82	481.58	428.71	338.16	395.16	486.56	481.31	654.54
Execution Time (sec)		120963.8									
Active Power Losses (MWh)	Original	6.95	6.83	6.85	6.80	6.92	7.09	6.98	6.78	6.80	6.91
	Optimised	6.55	7.60	7.57	7.85	6.78	5.05	6.19	8.02	7.92	7.29
Tap Setting		4 (h1–24)									
Open Switches		C1: {6-26, 8-21, 9-15, 11-12, 18-33}									
DRES Q Compensation (MVArh)		3.383	3.831	3.802	3.930	3.472	2.746	3.265	3.912	3.936	3.598
Load Modulation (kWh)		444.9 (Type-2: Nodes 31 & 33; Type-3: Nodes 26, 28, & 30)									
Battery (Injection) (kWh)		3.46	—	—	6.68	7.88	—	—	—	—	355.7
Average Relaxation Error (VA²)		1.29									

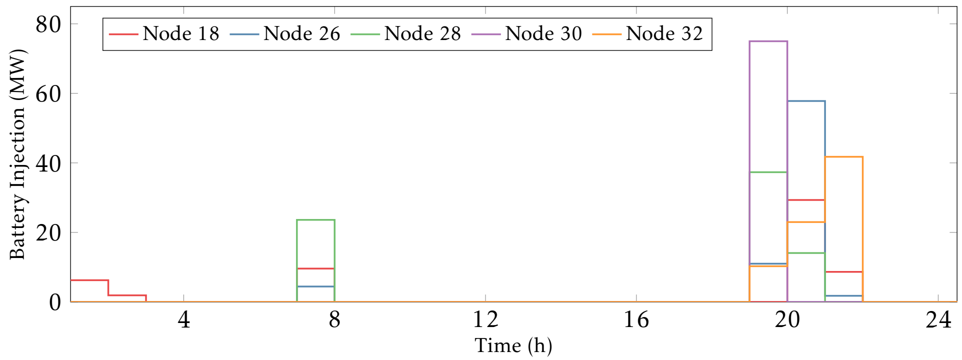


Figure 7.8: Stochastic OP Formulation – Battery Injection in Scenario 10

The original and optimised voltages in the network across the tested scenarios are shown in Fig. 7.9. There is a marked improvement in the voltages in the optimised network. The median voltage in the optimised network is 1.009 pu, while that of the unoptimised network is 0.957 pu. The minimum and maximum voltages in the optimised network across all scenarios are 0.95 and 1.045 pu, while those of the unoptimised network are 0.874 and 1.02 pu respectively.

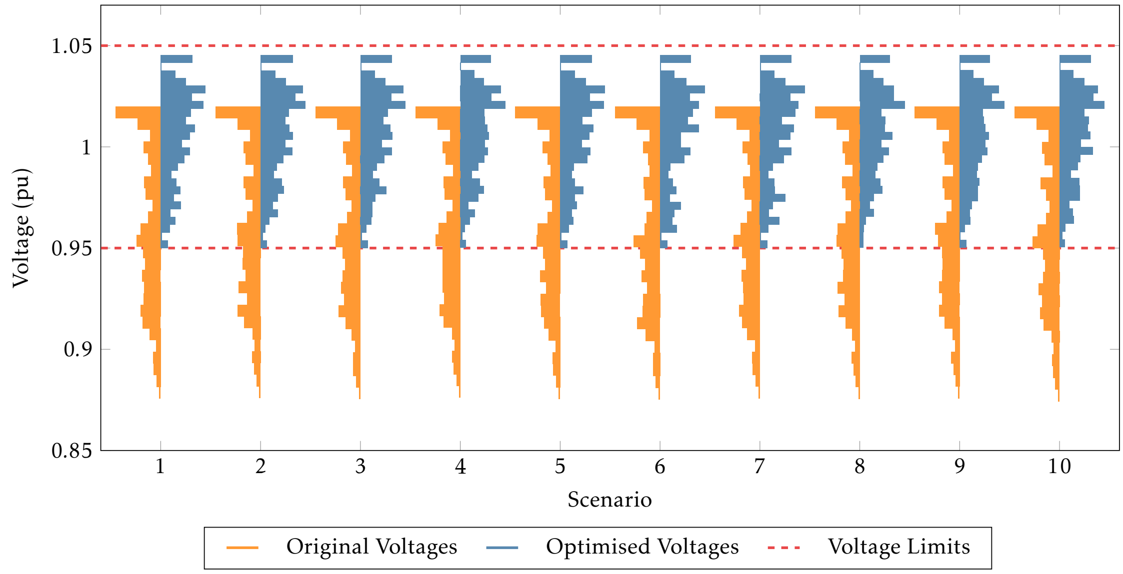


Figure 7.9: Stochastic OP Formulation – Original and Optimised Network Voltages across Scenarios

Load modulation is utilised in nodes 26, 28, 30, 31 and 33. In nodes 31 and 33, this corresponds to type-1 load modulation, while in the other nodes, it corresponds to type-2 load modulation. The total load reduction achieved via load modulation across scenarios stands at 444.9 kWh. The aggregated load curves, presented in Fig. 7.10, illustrate the reduction in the loads before and after load modulation. It can be seen that the modulation is achieved during hours 19, 20, 21 and 23.

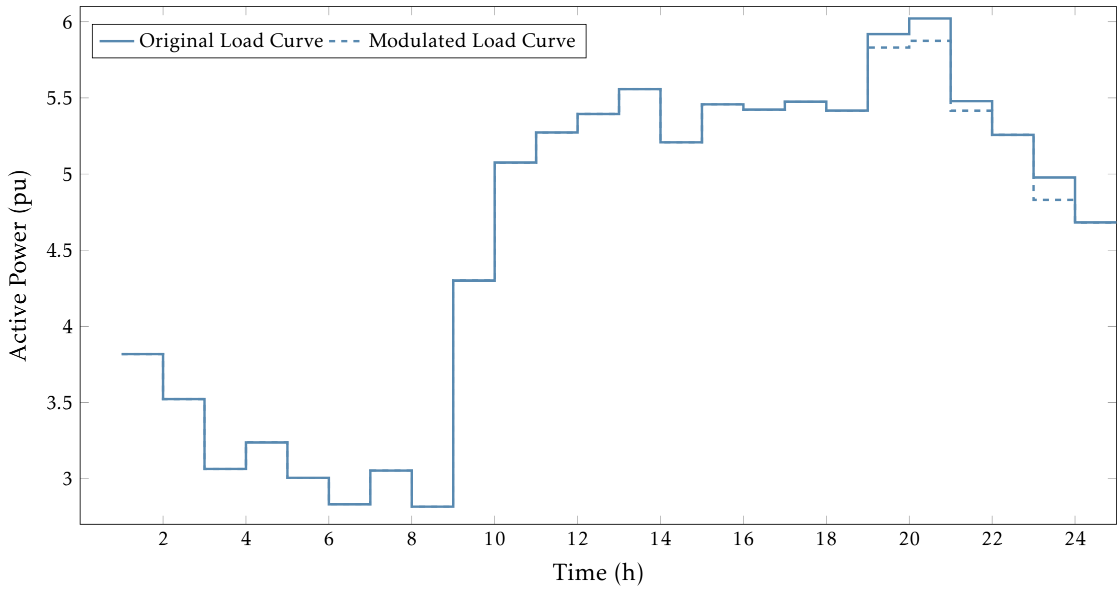


Figure 7.10: Stochastic OP Formulation – Aggregated Load Curves Before and After Load Modulation

In node 31, type-1 load modulation is used during hours 19 and 21, and corresponds to a total load reduction of 25.98 kWh. During hour 19, a total load of 25.3 kWh is reduced, while during hour 21, the load reduction is 0.68 kWh. The voltages in node 31 range between 0.8923 and 0.8963 pu during hour 19 and between 0.889 and 0.8898 pu during hour 21 across the tested scenarios. This load modulation helps improve these voltages, and is illustrated in Fig.7.11.

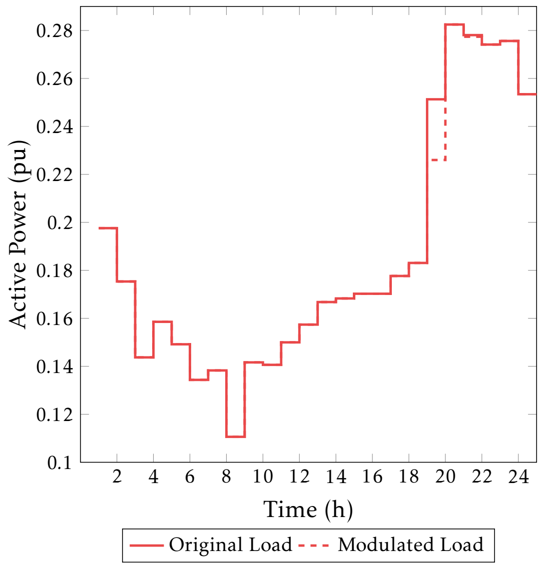


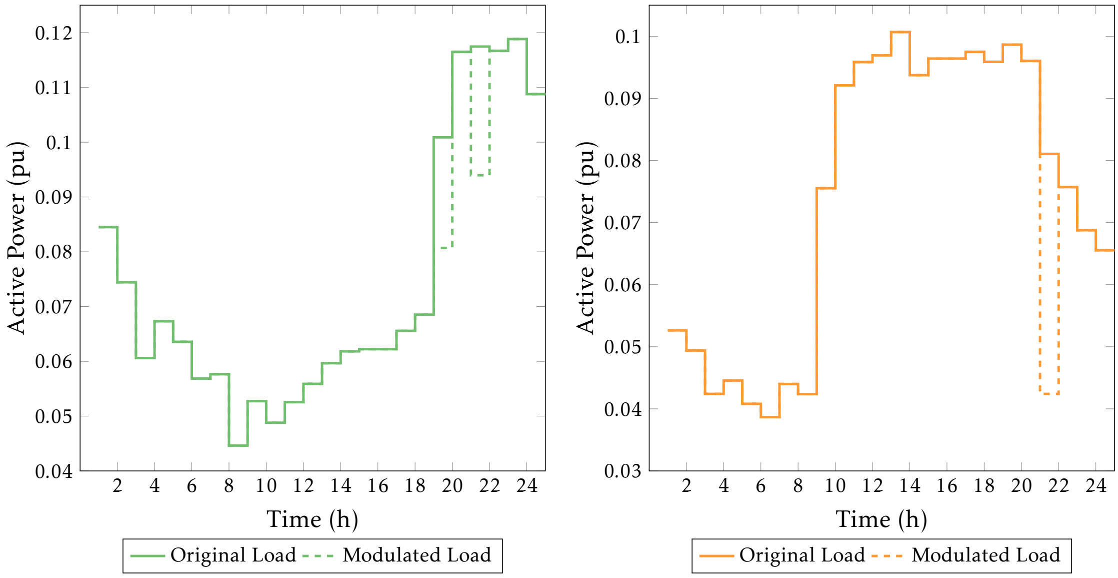
Figure 7.11: Stochastic OP Formulation – Type-1 Modulation (Node 31)

The other node with type-1 load modulation, node 33, sees total load reduction of 43.67 kWh, also during hours 19 and 21. The reduction during hour 19 corresponds to 20.17 kWh and the reduction during hour 21 to 23.5 kWh. This helps improve the original voltages in the node, which ranged between 0.8905 and 0.8945 pu during hour 19 and between 0.887 and 0.8879 pu during hour 21. This load modulation is illustrated in Fig. 7.12a. With the given cost parameters, the DSO spends a total of 2.26 € to achieve this load modulation.

Type-2 load modulation employed in nodes 26, 28 and 30 contribute to a load decrease of 375.27 kWh, at a total cost of 6.75 € to the DSO. In node 26, it is used for a reduction of 38.65 kWh during hour 21, improving voltages ranging from 0.9409 to 0.9417 pu. This is illustrated in Fig. 7.12b. In node 28, it is used for a reduction of 42.92 kWh during hour 19, improving voltages ranging from 0.9177 to 0.9216 pu. This is illustrated in Fig. 7.13a. In node 30, it is used for a reduction of 146.85 kWh during hours 20 as well as 23. This improves voltages in the node, which are between 0.8888 and 0.8909 pu during hour 20 and between 0.9049 and 0.9056 pu during hour 23. This load modulation is illustrated in Fig. 7.13b.

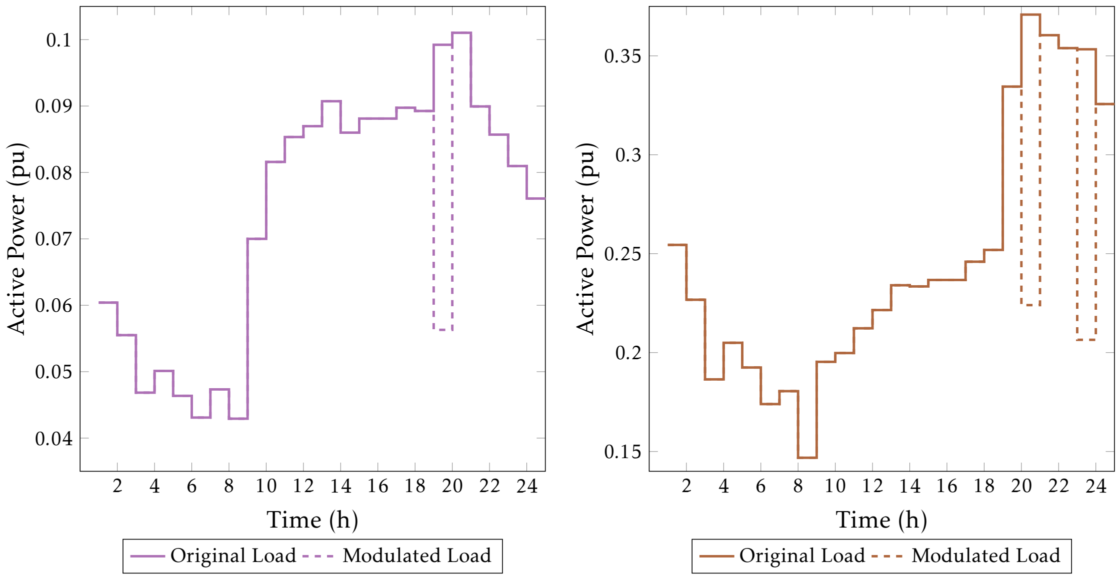
A break-up of the DSO expenditures as provided by the stochastic OP formulation is presented in Fig. 7.14. It is to be noted that the results provided are expected values. However, we know for sure that network reconfiguration, OLTC, and load modulation are constant across scenarios. This means that only the cost of losses and battery use are presented as expected values.

The stochastic OP formulation is able to optimise the network over a set of 10 DRES scenarios, providing feasible results for all scenarios, and an optimal expected value of DSO expenditures across the scenarios. Additional tests on the stochastic OP formulation are performed in Section 7.5, where the formulation is compared with the other formulations under uncertainty. In the next section, the results of the interval OP formulation are presented.



(a) Type-1 – Node 33 (b) Type-2 – Node 26

Figure 7.12: Stochastic OP Formulation – Load Modulation Types 1 & 2



(a) Node 28 (b) Node 30

Figure 7.13: Stochastic OP Formulation – Type-2 Load Modulation

7.4 THE INTERVAL OP FORMULATION

7.4.1 *Original Conditions*

The interval OP formulation requires a central forecast and bounds for the uncertainty. To ensure homogeneity, we consider the following with respect to DRES forecasts for the interval OP formulation:

1 The scenario with the highest probability in the stochastic OP formulation becomes the central forecast for the interval OP formulation.

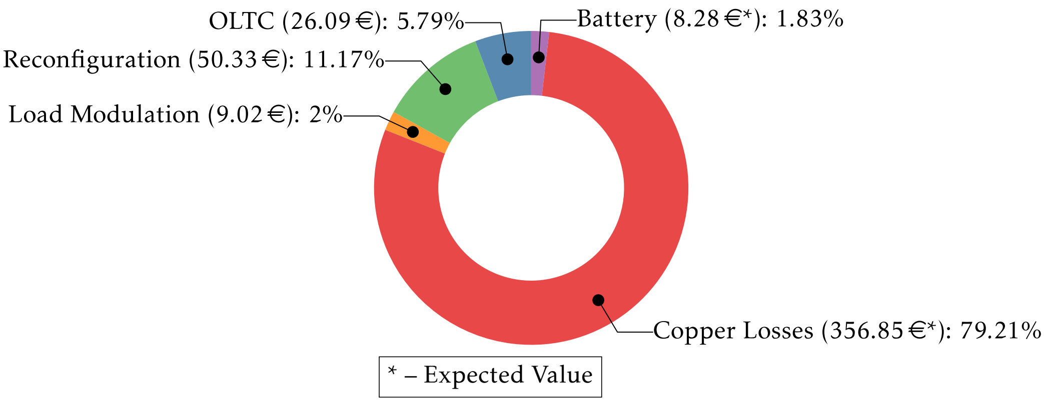


Figure 7.14: Stochastic OP Formulation – Break-up of DSO Expenditures

2 The upper and lower bounds for the forecasts required by the interval OP formulation are envelops of the 10 scenarios in the stochastic OP formulation.

This homogeneity allows us to compare the results obtained with the two formulations as the underlying uncertainty is The DRES forecasts is retained across formulations. The DRES forecasts thus obtained are illustrated in Fig. 7.15. The central forecast for the DRES is shown as a continuous line, the lower bound as a dotted line, and the upper bound as a dashed line.

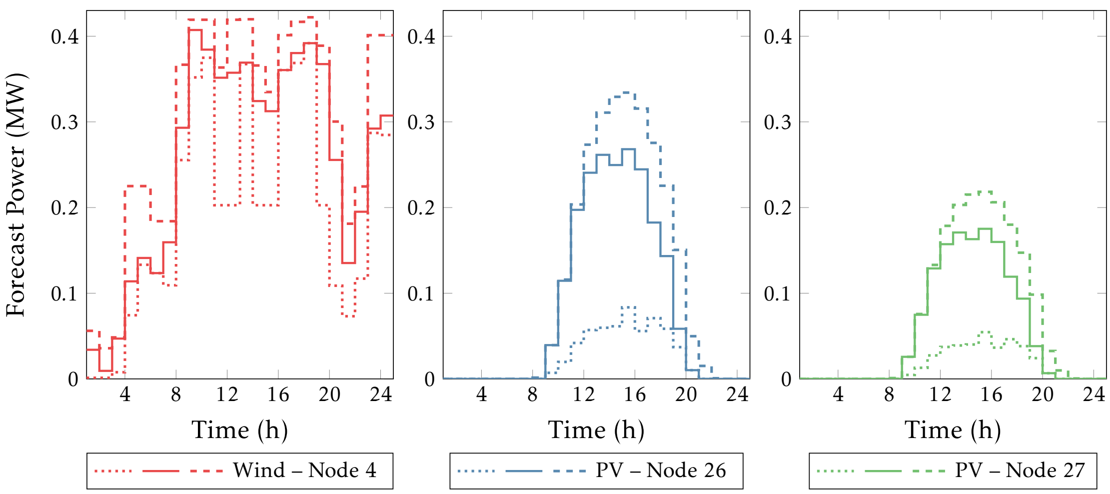


Figure 7.15: Interval OP Formulation – DRES Forecasts with Bounds

The minimum voltages in the original, unoptimised network are shown, for each node and for each hour in Fig. 7.16. There are a total of 326 voltage violations for the central forecast. For the lower and upper bounds of the forecasts, the voltage violations stand at 338 and 321 in number respectively. The lowest observed voltages for the three DRES *scenarios* all occur at node 18 during hour 20. They are 0.875 pu for the central forecast, 0.8741 pu for the lower bound, and 0.8763 pu for the upper bound. The total hypothetical baseline DSO expenditures stand at 428 990.90 € for the central forecast, and at 452 393.22 € & 418 086.96 € for the lower and upper bounds respectively.

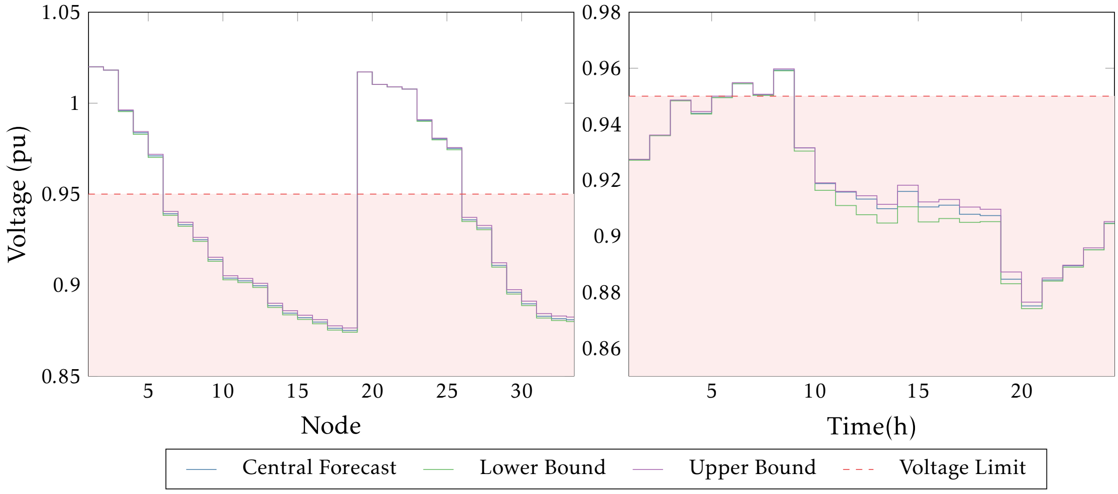


Figure 7.16: Interval OP Formulation – Minimum Network Voltages across Nodes and Hours

7.4.2 *Results with the Interval OP Formulation*

Unlike the stochastic OP formulation, the interval OP formulation optimises the network for the central forecast only, while ensuring feasibility across the bounds.[1] The main results from the interval OP formulation are presented in Table 7.8.

The total DSO expenditures with the formulation stand at 453.62 €. This is higher than the expected value obtained with the stochastic OP formulation for the following reasons:

1 DRES uncertainty realisations with the lowest probabilities (at the bounds) are as likely to occur as that of the realisations with the highest probabilities. This is because the interval OP formulation treats the uncertainty as bounds.

2 The interval OP formulation forces feasibility of inter-hour transitions with low probabilities (see equations (6.59) – (6.70) in Chapter 6) at all costs.

Table 7.8: Interval OP Formulation – Main Results

Description	**Value**
DSO Expenditures (Objective)	453.62 €
Execution Time	34655.03 seconds
Active Losses	6.99 MWh
Tap Setting	4 (Hours 1–24)
Open Switches	C2[2](Hours 1–24)
Load Modulation (kWh)	Type-2: 281.9 Type-3: 1544.2
DRES Curtailment	—
DRES Reactive Compensation	3.262 MVArh (Injection)
Average Relaxation Error	0.29 VA^2

[1] For solution feasibility, the losses in the bounds are optimised, as required by the SOCP relaxation. The cost of losses at the bounds are subsequently removed from the objective function in final result.

[2] See Appendix B for details on the network configuration C2.

The formulation takes a significant amount of time for a solution. However, it is faster than the stochastic OP formulation. This is primarily owing to the need to optimise only the central forecast, and the reduced number of *scenarios* in the formulation. Similar to certain scenarios in the stochastic OP formulation, the losses in the optimised network are higher for the central forecast as compared to those in the original network. This increase is explained by the fact that the solution found has to be feasible for the bounds of DRES production.

The load modulation activated by the interval OP formulation amounts to 1.826 MWh in terms of the load reduced in the network. This is around 1.66 % of the total energy consumed by the loads in the network. The DSO expenditures towards load modulation are 36.64 €. The total modulated load is shown in Fig.7.17.

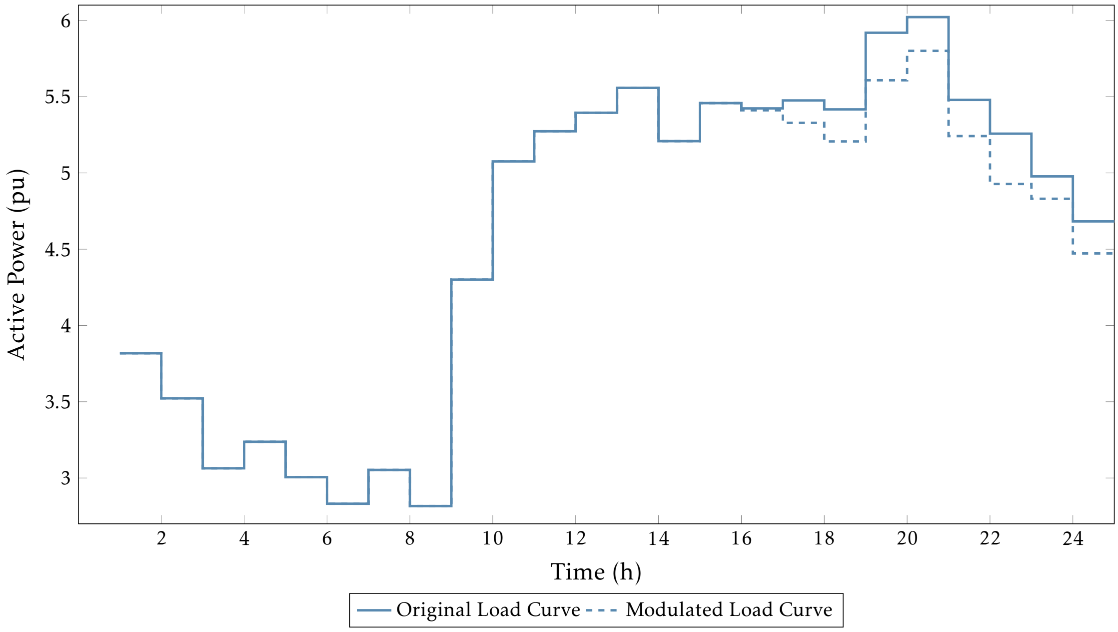


Figure 7.17: Interval OP Formulation – Aggregated Load Curves Before and After Load Modulation

Type-2 load modulation is activated in 3 nodes 29 (hours 19 & 22; 62.1 kWh), 31 (hours 19-22; 117.1 kWh) and 33 (hours 16 & 19-22; 102.7 kWh). Type-3 load modulation is activated at 6 different nodes. Table 7.9 summarises the load modulation in these nodes. They are further illustrated in Appendix B.

The original and optimised voltages in the network for the central forecast and the bounds are shown in Fig. 7.18. Once again, there is a marked improvement in the voltages in the optimised network. The median voltage in the central forecast in the optimised network is 1.0064 pu, as compared to the median voltage of the central forecast in the original network, which is 0.9579 pu.

The interval OP formulation is able to optimise the network for the central DRES forecast, while ensuring feasibility across its bounds. When compared to the stochastic OP formulation, the interval OP formulation provides a higher value of the objective (DSO expenditures). However, it should technically be able to provide lower recourse costs than either the deterministic or the stochastic OP formulations. To verify this aspect of the formulations, we compare their performances for a large number of scenarios of DRES forecasts, in the next section.

Table 7.9: Interval OP Formulation – Load Modulation

Type	**Node**	**Hour**	**Reduction (kWh)**	**Type**	**Node**	**Hour**	**Reduction (kWh)**
Type-2	29	19	25.7	Type-3	8	22	133.8
		22	36.4		10	20	42.9
	31	19	50.3		26	19	38.7
		20	8.2			22	
		21	3.7		28	19	25.7
		22	54.8			22	36.4
	33	16	12.4		30	17	146.9
		19	20.2			20	
		20	23.3			23	
		21	23.5		32	18	210.02
		22	23.3			21	
Type-3	8	19	133.8			24	

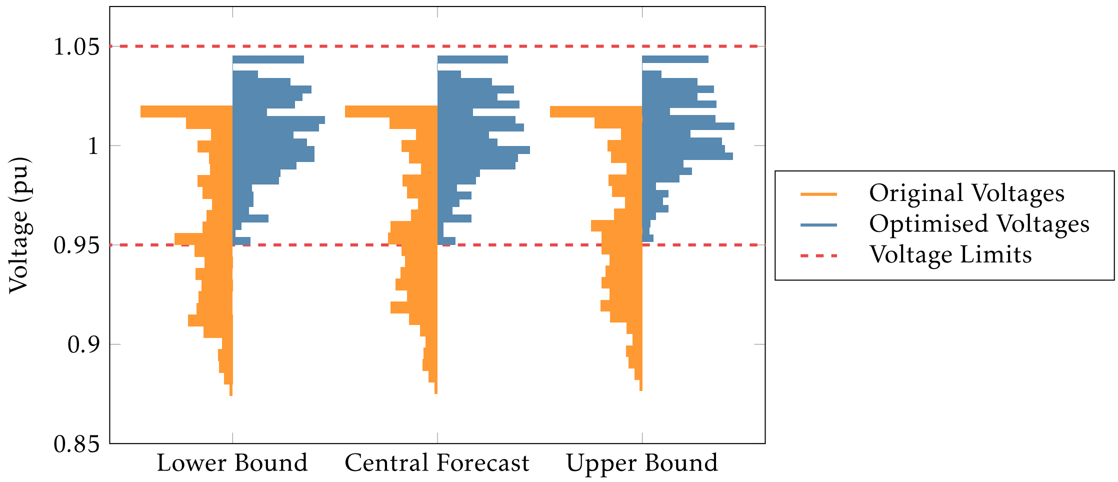


Figure 7.18: Interval OP Formulation – Original and Optimised Network Voltages across Scenarios

7.5 RESULTS FROM THE PERFORMANCE COMPARISON FRAMEWORK

The two-stage deterministic OP formulation (day-ahead stage), the stochastic OP formulation, and the interval OP formulation provide set-points for flexibilities on the day-ahead stage. Their solutions differ from each other, owing to the difference in the way the uncertainty in the DRES is characterised. The deterministic OP formulation provides the lowest objective value, while the interval OP formulation provides the highest objective value.

In this section, we test the performance of these formulations for various realisations of uncertainty. We use the framework presented in Section 6.3.4 of Chapter 6 for this comparison. The randomiser generates total of 1000 scenarios for DRES production for each hour of the day-ahead stage. These scenarios have 15-minute intervals, and there consequently exists four DRES production values for each hour. They are generated from a normal distribution bounded by the DRES forecast bounds. Then, for the day-ahead results obtained with each formulation, the hour-ahead optimisation routine is executed with these new forecasts. The flexibilities with recourse actions are then allocated new set-points in this stage if need be. A total of 24000 such executions are done (one test for each hour and for each scenario). Table 7.10 summarises the main results obtained.

Table 7.10: Performance of the Formulations – Main Results

Result	Deterministic OP	Stochastic OP	Interval OP
Average Daily Objective (€)	231.29	230.18	223.57
Average Losses Cost (€)	230.20	230.01	219.96
Recourse Activations (No.) *	615	394	2578
DRES Curtailment (No.)	1	1	0
Battery Actions (No.)	614	393	2578
Infeasibility	0	0	0

*: Recourse Actions that cost money

Out of the 24000 executions, none were infeasible. This first means that the recourse flexibilities available were sufficient to offset the changes in the network conditions provoked by the different uncertainty realisations of the DRES. On an average, the lowest objective with recourse actions was provided by the flexibility set-points of the interval OP formulation. This is the case in spite of the fact that on 2578 out of the 240000 tests, there was a need for recourse flexibility that cost money (as opposed to DRES Q-Compensation, which is free recourse flexibility). This is primarily because the cost for losses, which makes up a major part of the objective, is lower for the interval OP formulation. Battery systems were the recourse flexibility that was the most used, with an average total usage cost of 1.77 €, 0.44 €, and 1.40 € for the three formulations.

A plot of the recourse actions that cost money to the DSO for the three formulations is shown in Fig. 7.19. All the recourse flexibility activations that cost money to the DSO were made between hours 19 and 22 for the three formulations. The interval formulation made 513, 563, 530, and 972 activations respectively during these hours.

We analyse the reason why these activations were made. To do so, we observe the network voltages before the hour-ahead routine is run. These are the network voltages when the flexibility set-points from the formulations are applied and when the network is simulated with the 1000 scenarios for DRES. The only voltage violations encountered in the network occur in node 33. Fig. 7.20 shows the distribution of voltages in node 33 for the hours 19–22 across scenarios when the interval OP formulation's flexibility set-points are applied. It is clear that the number of voltage violations each hour corresponds more or less to the number of recourse flexibility activations solicited during the hour-ahead stage.

We know that the interval OP formulation provides the cheapest recourse actions on an average, even though such actions are more in number. In Fig. 7.21, the probability distributions of the recourse action costs for the three formulations are presented. The CDFs are shown in bold lines, while the PDFs are shown in dotted lines. It is clear from these distributions that the interval OP formulation outperforms the other two

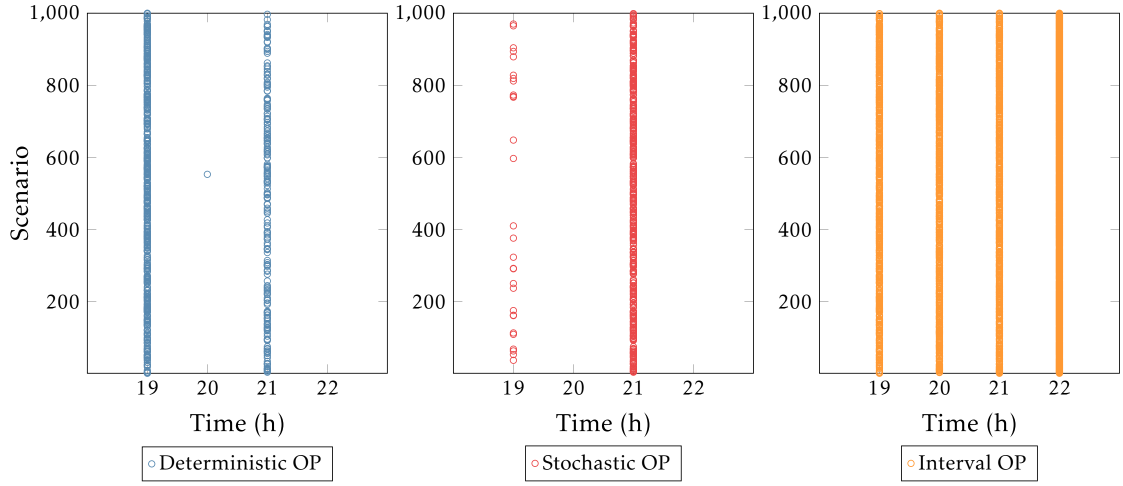


Figure 7.19: Recourse Actions for the OP Formulations

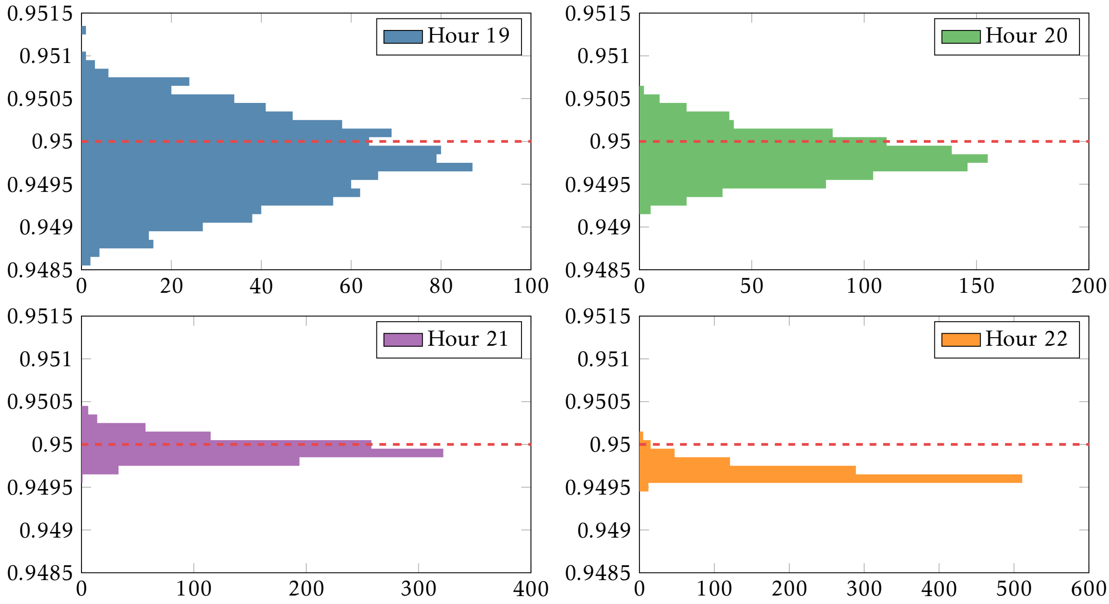


Figure 7.20: Voltages at Node 33 with the Interval OP Formulation Results and 1000 DRES Scenarios

formulations across all scenarios. However, the distribution suffers from a rather large tail. This is also the case with the deterministic OP formulation. The stochastic OP formulation has a tight distribution of the recourse action costs.

The day-ahead costs of the formulations, which comprise the cost of reconfiguration, OLTC and load modulation, are not integrated in this illustration. These costs amount to 84.71 € for the two-stage deterministic OP formulation, 85.44 € for the stochastic OP formulation, and 104.07 € for the interval OP formulation. When these costs are integrated to the recourse action costs for the formulations, we obtain the actual DSO expenditures for optimising their networks. The distributions of these actual expenditures are presented in Fig. 7.22.

The distribution shows that the interval OP formulation is not the cheapest in terms of the actual DSO expenditures. In fact, it is by far the most expensive of the three formulations. This makes it uninteresting, and is a direct result of the enforcement of

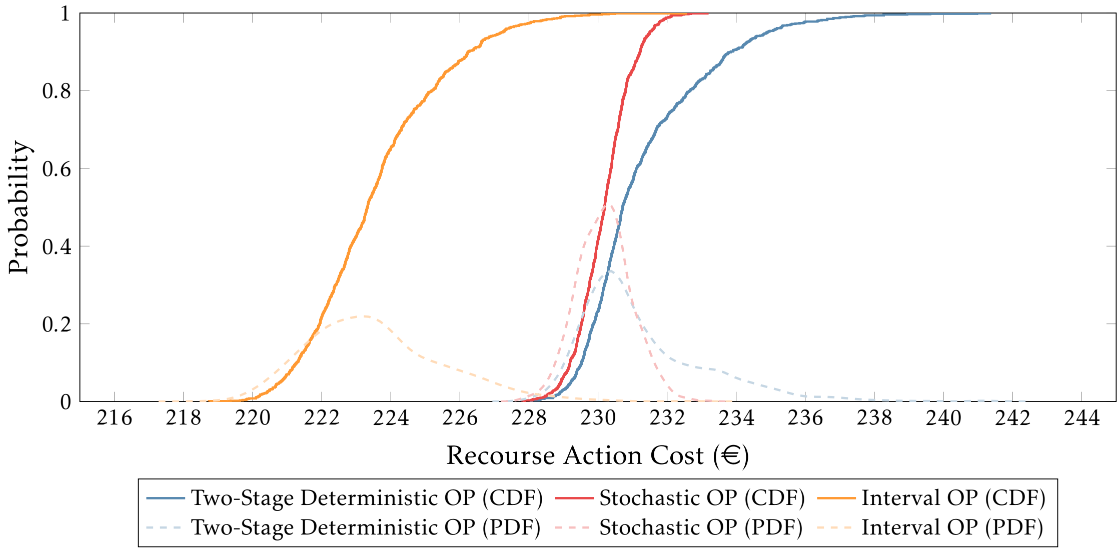


Figure 7.21: Probability Distributions of Recourse Action Costs for 1000 DRES Scenarios

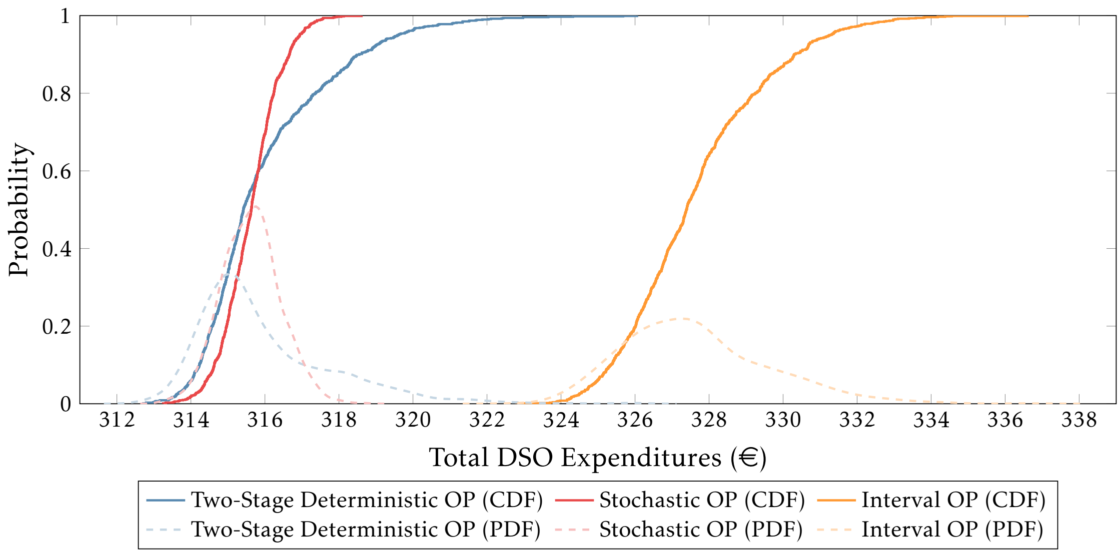


Figure 7.22: Probability Distributions of Total DSO Expenditures for 1000 DRES Scenarios

transitions with low probabilities, translating to a high day-ahead cost. This overestimation permits the DSO to spend less on recourse actions, but the high day-ahead costs offset this advantage.

The stochastic and two-stage deterministic OP formulations show interesting characteristics. There is a 59.2 % probability that the two-stage deterministic OP formulation performs better than the stochastic OP formulation. The average difference in the DSO expenditures, in this case, is around 0.31 €. However, when the stochastic OP formulation performs better, it does so with a much higher difference in resultant DSO expenditures. The difference is around 1.35 € on an average. This is evidenced by the long tail that the probability distribution of the two-stage deterministic OP exhibits, as opposed to the tighter shape of the probability distribution of the stochastic OP formulation.

The stochastic OP formulation provides average total DSO expenditures of 315.62 € as opposed to the two-stage deterministic OP formulation, for which the average DSO expenditures are 315.99 €. The stochastic OP formulation performs marginally better. However, it comes at a large computational cost. The average execution time for the stochastic OP formulation, combined with the hour-ahead optimisation routine, is observed to be around 121 032 seconds or 1 day, 9 hours, 37 minutes, and 12 seconds. Using a more powerful computer, decreasing the number of scenarios, or employing mathematical decomposition techniques may improve solution time. However, even a 50 % improvement in solution time brought about by these techniques may not be sufficient. As it stands, it is therefore unrealistic to use the stochastic OP formulation on a day-ahead basis, primarily because it takes more than a day to solve the problem. On the other hand, the two-stage deterministic OP formulation executes with a much lower average time of 135 seconds.

The choice between the three formulations in terms of performance, based on the results of this test case, is clear. The interval OP formulation performs the best when the day-ahead costs are ignored, but becomes the most expensive formulation when the actual DSO expenditures are considered. The stochastic OP formulation performs marginally better than the two-stage deterministic OP formulation, which suffers from rather large expenditure differences in certain scenarios. The two-stage deterministic OP formulation is however the most computationally tractable of the three formulations. In the next section, we will present concluding remarks on the results obtained for tests on the different formulations and the comparison of the performances.

7.6 CONCLUSIONS

The treatment of uncertainty is a necessary step in operational planning. In Chapter 6, we developed three different formulations to perform operational planning under uncertain DRES production. In this chapter, we tested the three formulations. The tests showed that these formulations were all able to optimise the network with their respective uncertainty characterisations. Owing to the difference in these characterisations, the feasible and optimal results they provided were different as well.

Firstly, the two-stage deterministic OP formulation showed that it was possible to first optimise the network with deterministic DRES forecasts on the day-ahead stage, followed by a second, hour-ahead optimisation using recourse flexibilities when accurate DRES forecasts became available. The effectiveness of this formulation lay in its computational tractability. However, the uncertainty in DRES forecasts was not factored into the formulation. Therefore, there could be cases where the recourse flexibilities do not suffice when the actual uncertainty realisations become known in the hour-ahead stage.

Secondly, the stochastic OP formulation showed that it was possible to optimise the network across a set of scenarios for DRES forecasts. By explicitly considering uncertainty in the DRES production, the formulation produced results that could be guaranteed as feasible when the actual uncertainty realisations became known, albeit with the use of recourse flexibilities. However, the construction of scenarios often requires expert knowledge of the uncertainty. This is an issue that merits consideration, as constructing scenarios for the sake of exercise may not work in the real-world. Further, the tractability of the stochastic OP formulation is the lowest of the three formulations. Where more powerful computational resources are unavailable, further work in this regard would need to focus on mathematical decomposition techniques. Scenario reduction, as discussed in Section 6.2.3.3 of Chapter 6, would help increase tractability, but may pose other problems related to the accuracy of the representation of uncertainty.

Thirdly, the interval OP formulation optimised the network using a central forecast and bounds for DRES forecasts. The bounds were obtained from the stochastic DRES scenario envelopes, in order to ensure homogeneity between the results. The central forecast was the scenario with the highest probability, which was also the day-ahead forecast for the two-stage deterministic OP formulation. Tests on this formulation showed that the DSO expenditures were the highest. The tractability of the formulation was better than that of the stochastic OP formulation, but worse than that of the deterministic OP formulation.

Finally, the comparison of the performances of the three formulations was also done. A total of 1000 DRES scenarios were constructed based on a normal distribution within the bounds of the interval OP to test optimise the network using recourse flexibilities. The day-ahead flexibility set-points of the three formulations were applied to each of the scenarios, and the additional cost to optimise the recourse flexibilities, if needed, were computed. A total of 24000 tests were thus done (one test for each hour and for each scenario) for each formulation, and the results show that the interval OP formulation performed the best when recourse action costs were considered. However, owing to a high day-ahead cost, the total operational cost of this formulation was the highest, making it an uninteresting option. The two-stage deterministic OP and the stochastic OP formulations had comparable performances. The two-stage deterministic OP formulation performed slightly better than its stochastic counterpart for 59.2 % of the scenarios tested. However, in the rest of the scenarios, the stochastic OP formulation performed much better.

The main issue of the stochastic OP formulation was its computational tractability. If this can be improved, either through the use of more powerful computers, or through mathematical decomposition techniques, the stochastic OP formulation would be the best choice. In the lack of such options, the two-stage deterministic OP formulation, which provides no guarantee for feasible hour-ahead solutions using recourse flexibilities, would be the best choice.

Part IV of this thesis follows this chapter, and focuses on the conclusions, perspectives, references, and a summary of the thesis in French. It begins with Chapter 8, where the general conclusions of the work done in this thesis, along with the perspectives for future work are outlined.

PART IV

CONCLUSIONS, PERSPECTIVES, REFERENCES & SUMMARY (IN FRENCH)

8 Conclusions & Future Work

The rising shares of DRES in power systems, more particularly in distribution networks is one of the main challenges for power systems. This, combined with deregulation, presents two challenges that DSOs, among others, will have to face. Both these challenges affect the status-quo of distribution network planning and operation, which can be considered passive for most DSOs today. Intermittent DRES renders planning and operation techniques adopted today infeasible or sub-optimal. The new deregulated environment forces DSOs to interact with new actors, provide new services, and take up new responsibilities. In this context, the various achievements of this thesis are presented in the following sections. The work done was composed of different contributions, listed in Chapter 1, and together lead to the achievements of this thesis.

8.1 Achievements of this thesis

The problems posed by the integration of intermittent DRES and the new challenges that DSOs face in a deregulated environment underlined the need to rethink the planning and operation of distribution networks. The concepts of Active Distribution Networks (ADN) and the associated Active Network Management (ANM) were presented in the thesis as a potential means to overcome these challenges.

In the ADN context, DSOs will take up new and innovative roles and offer new services. This will allow them to plan, operate, and maintain their networks in a cost-effective, a more flexible, and a more intelligent manner. The improvement in network observability and controllability brought about by ADN, along with services like flexibility available in the deregulated environment, will allow them to achieve this evolution. The ability of DSOs to optimally use flexibility in operational planning (OP) of their networks is arguably one of the keys to this evolution.

Operational planning (OP) of active distribution networks, taking place in the short-term (usually day-ahead) time-frame is a preparatory step in the operation of these networks. Adverse network conditions like voltage and current constraints, provoked by intermittent DRES, foreseen through forecasts in OP. The goal of the OP is then to use flexibilities in an optimised manner to mitigate these adverse network conditions. To achieve this, the flexibilities used must be modelled.

In this thesis, these flexibilities were first modelled accurately or by using practically adopted DSO methodologies, depending on the level of detail available for each of them. This allowed for a realistic technical representation of these flexibilities in the operational planning formulations and was contribution C1 of the thesis. In a competitive environment, DSOs should have to contract and use these flexibilities in an unbiased manner. This allows them to be cost-effective and allow for the choice of the best flexibilities. The economic models developed for the flexibilities, resulting in the computation of utilisation costs, facilitates this choice. In this context, the economic modelling of these flexibilities done as a part of this thesis was a significant step. These models were derived for short-term time-frame, with a specific emphasis on the total cost of operation, including especially in the case of endogenous flexibilities like reconfiguration and OLTCs. This was contribution C2 of the thesis.

Currently, there is a lack of methods and tools in OP for distribution networks. This hinders the adoption of operational planning. In order to overcome this, an analysis of the literature in optimal power flows and operational planning allowed us to identify the best approaches to operational planning for distribution networks. The mixed-integer second-order cone programming (MISOCP) approach to the OPF was chosen as the best approach, primarily owing to its exactness in modelling the OPF problem and its accuracy in capturing the physical characteristics of distribution networks. This approach was employed to develop a novel OP formulation for distribution networks. The aim of this OP formulation was to use DRES and load forecasts to decrease day-ahead DSO expenditures on flexibilities and losses in the network.

The biggest challenge to developing the novel OP formulation was the non-linearity of the OPF equations and the flexibility models used. The first achievement (contribution C3) of the development was the reformulation of flexibility models, both technical and economic, resulting in exact linearisation of these models. The second, related achievement concerned the reformulation of the OPF equations. Different exact reformulation techniques, both continuous and discrete, were used to integrate the OPF equations into the novel OP formulation (contribution C4).

The SOCP relaxation of the power flows allowed the transformation of the mixed-integer non-linear non-convex OP into a mixed-integer convex OP. This meant that for the first time, an exact operational planning formulation for distribution networks, integrating discrete flexibilities like reconfiguration and OLTCs, and providing a guaranteed optimal solution was created. This meant, in addition, that the solution allowed DSOs to contract and use flexibilities in a cost-effective manner, and maintain good operating conditions in their networks.

The SOCP relaxation is guaranteed to hold only under certain conditions, one of which the novel OP formulation does not conform to. The challenge then was to develop an algorithm that would guarantee globally optimal solutions to the OP problem even in the event of the failure of the relaxation. This was achieved through the development of a dichotomic solution recovery and search heuristic, relying on constraint transformation, and achieving a globally optimal solution via an iterative procedure (contribution C6).

The novel OP formulation was then tested on two distribution networks using different test cases, and for a range of DRES insertion rates (contribution C5). For the Baran network, the results of these tests showed that the formulation could solve all constraint violations that arose in the network using the cheapest set of flexibilities. For the PREDIS network, the SOCP relaxation did not hold, as evidenced by an abnormally high relaxation error. The dichotomic solution recovery search heuristic was then employed, and as a result, globally optimal solutions to the OP problem for the PREDIS network were also found. A discussion on the use of flexibility in operational planning, based on these results, provided insights into the use of endogenous and exogenous flexibilities in operational planning, and the reasons why certain flexibilities were used often, and others sparingly. This was contribution C7 of the thesis.

The novel OP formulation considered deterministic DRES and load forecasts. Any changes in these forecasts, in intermittent DRES for example, brought the risk of solution infeasibility. The main challenge was to develop OP formulations capable of handling uncertainty. The achievements of this thesis in operational planning under uncertainty consist of the following. First, an analysis of the best approaches to operational planning under uncertainty was done. This analysis highlights the drawbacks of some commonly used methods like robust optimisation in handling parametric uncertainty in OPF and OP problems. This was contribution C8 of the thesis. The other achievement of the thesis was the development of three different approaches to OP under uncertainty, based on this analysis. These approaches each model the uncertainty in DRES differently.

The two-stage deterministic OP formulation considered deterministic forecasts for DRES over two stages, a day-ahead stage and an hour-ahead recourse stage (contribution C9). The stochastic OP formulation considered scenarios for DRES forecasts (contribution C10). And the interval OP formulation modelled the DRES uncertainty in terms of a central forecast and bounds (contribution C11). In order to compare the performance of the three formulations, a comparison framework was also developed. The three formulations were tested on the Baran network with uncertain renewable production. The comparison framework used 1000 different scenarios for DRES, and performs a total of 24000 tests (one per hour of the day and per scenario). Through the use of recourse flexibilities, the framework optimises the network for each of the scenarios. This was contribution C12 of the thesis.

In the next section, perspectives for future work in the field are discussed. These perspectives include further developments that can be done on the achievements in this thesis, as well as other avenues for the development of methods for operational planning.

8.2 FUTURE WORK PERSPECTIVES

In terms of the work done towards the analysis and modelling of flexibilities in active distribution networks, the following future work can be envisaged. The technical modelling of flexibilities has been done with a consideration on their accuracy and the realistic nature. The economic models derived have been done with the short-term usage in mind. Future work in flexibilities could be done in integrating additional flexibilities, like CHPs and capacitor banks among others. The modelling of CHPs consists of multi-physical phenomena, necessitating the introduction of thermal comfort and other related multi-temporal constraints, and in general resulting in an increased problem size.

As for economic modelling of flexibilities, we have made certain assumptions to arrive at the economic models and utilisation costs of flexibilities. These models could be revised / refined based on real-world data from DSOs (which is usually confidential). While the economic models developed in this thesis allowed us to execute the OP formulations, higher precision in utilisation costs of flexibilities could result in higher solution quality.

The novel OP formulation developed in the thesis worked with the SOCP relaxation of the OPF. This relaxation is shown to fail for one of the two networks tested in this thesis. The dichotomic solution recovery search heuristic is able to find the globally optimal solution even with this relaxation fails. However, it is significantly slower than the novel OP formulation. The number of iterations required for it to recover globally optimal solutions are high. Two future prospects could be foreseen in this area. The first lies in the development of algorithms that perform better, resulting in accelerated solution times. The second lies in the development of parallelised search heuristics to overcome the physical limitations of the calculation routines, allowing multiple instances of the problem to be executed in tandem.

The SOCP relaxation is one of the many relaxations like the Quadratic Convex (QC) relaxation and the Semi-definite Programming (SDP) relaxation. One of the future developments envisaged could be the development of OP formulations using these relaxations, in order to compare their performances.

In terms of handling uncertainty in operational planning, future development could concentrate on two distinct areas. The first area is the improvement of the performance of the formulations. In particular, interval and stochastic OP formulations have been shown to take a significant amount of time to solve the operational planning problem under uncertainty. Mathematical techniques like decomposition could be employed to improve their performance.

The second area for development is the integration of other types of uncertainty. In all our tests under uncertainty, we considered only DRES forecasts as uncertain. Other parametric uncertainty, like that in load forecasts, was not considered. These uncertainties could be integrated in future. In some formulations like the two-stage deterministic OP and the interval OP, additional sources of parametric uncertainty like that of loads can easily be integrated. This is because the two-stage deterministic OP considers deterministic forecasts, and the uncertainty realisations (also deterministic) are known in the hour-ahead stage. The interval OP formulation models uncertain parameters through bounds, and consequently can also treat additional sources of uncertainty like that of loads easily. The stochastic OP would however scale badly, especially of there is no correlation between load and DRES uncertainty. Simplifications and or better solution methods may be required for such a formulation.

A different approach to operational planning lies organisational structure of the problem itself. Decentralised and heterarchical approaches provide interesting avenues for research. They rely on modelling and solving multiple small problems locally, as opposed to a centralised paradigm, where a single, large problem is formulated and solved. This speeds-up execution, and may provide faster results. Such approaches, which have attracted much interest recently, and can be thought of as alternative ways to simplify the problem, while ensuring optimality.

In general, further tests on each of the formulations developed in the thesis, using real-world distribution networks, would allow a better evaluation of the abilities and practical constraints of the formulations. A field implementation of the formulation will therefore be necessary, and this could be developed in collaboration with a DSO. The comparison of the performance of the OP formulations under uncertainty stand to particularly benefit from such tests.

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Résumé de la Thèse

Il y a deux changements majeurs que subissent les réseaux électriques d'aujourd'hui. Le premier défi est lié au réchauffement climatique, avec comme cause l'industrialisation et la dépendance sur les matières primaires fortes en gaz à effet de serre. Cela a provoqué une augmentation importante des températures terrestres. Les accords internationaux comme ceux de Kyoto [Nat98] et COP21 [Fra16] ont pour but le maintien des températures mondiales en dessous d'une certaine limite par rapport aux celles constatées avant la révolution industrielle. Les efforts menés par ces accords misent notamment sur la réduction des émissions du gaz à effet de serre.

La production de l'électricité à partir des matières primaires fortement polluants est l'une des premiers émetteurs de ces gaz. Cela fait de la production d'électricité un des cibles importants de ces efforts, et on constante aujourd'hui un changement fondamental dans la manière de production d'électricité. En Europe, les directives comme celle de 20/20/20 [Eur12] issues de ces accords provoquent un taux croissant des générateurs d'énergie renouvelables (GED).

Le deuxième défi est lié à la dérégulation du système électrique de ces dernières années a crée de nouveaux acteurs et services. Traditionnellement, le système électrique est un exemple parfait de monopole. Cette infrastructure collective était et financée par les gouvernements, qui investissaient dans des grosses centrales de production centralisées et des réseaux (de transport et de distribution). Dans un premier temps, le taux croissant des GED provoque un changement dans la manière dont l'électricité est produite. Ensuite, la dérégulation vise à démanteler ce monopole, en séparant les activités de production, de transport, et la distribution d'électricité.

En Europe, la directive de la Commission européenne de 1996 pour la dérégulation du marché intérieur de l'électricité [Eur96], parmi la première de nombreuses autres directives émises à l'effet de la déréglementation, de l'efficacité énergétique et de l'accès à l'électricité, a amorcé le démantèlement de ces monopoles. Les nouveaux acteurs créés ont favorisé une concurrence et une complexité accrue de l'ensemble du système électrique.

La problématique

Ces changements touchent le système électrique dans tous les domaines: la production, le transport et la distribution. Dans la production, le taux croissant des GED continuera de changer le mix de production d'électricité et obligera les investisseurs à mettre en place d'autres stratégies d'investissement. En ce qui concerne le transport et la distribution, les gestionnaires n'auront aucun autre choix que de faire face à ces changements grâce à une évolution systématique de leurs pratiques de planification, d'exploitation et de maintenance. Les réseaux de distribution et ses gestionnaires (GRD) en particulier sont les plus touchés.

Traditionnellement, l'électricité provient des générateurs centralisés, transportés via des réseaux de transport, et distribués par des réseaux de distribution. Ce type de fonctionnement a permis aux GRD de dimensionner leurs réseaux en fonction d'un ensemble de règles qui ne considéraient que les scénarios les plus critiques. Cela a entraîné des réseaux nécessitant peu de décisions à court terme (jour-avant et temps réel). Cette approche cessera cependant d'être efficace dans une situation où plus en plus de GED intègrent le réseau. Leur intermittence, la raison principale de cela, peut également provoquer des flux de puissance vers le réseau de transport.

Les réseaux de distribution actifs sont une solution potentielle pour ces problèmes. Le concept de ces réseaux consiste à une planification, maintenance et exploitation plus intelligent, efficace et rentable [Eur13a]. Ces réseaux dépendront d'un concept qui s'appelle la flexibilité. Les GRD bénéficieront potentiellement en rendant leurs réseaux actifs, car ils arbitre leurs décisions d'investissement et d'opération, créant un cadre rentable. Cependant, une telle modification nécessite un effort important et concerté de leurs parts. Les GRD devront évoluer et prendre de nouveaux rôles. Un accent particulier devrait être mis sur leur capacité à contracter et à utiliser la flexibilité, et à gérer leurs réseaux dans le court terme à l'aide d'algorithmes d'optimisation intelligents (gestion prévisionnelle). Cela nécessitera également une modification de la réglementation, sans laquelle les GRD se trouveront incapables de prendre ces rôles.

Dans un scénario où la réglementation permet aux GRD de prendre ces nouveaux rôles, les différents types de flexibilité qu'ils pourront contracter et utiliser devront être caractérisés. Un compromis, concernant les flexibilités, entre celles appartenant aux GRD[1] et celles fournies par des acteurs externes, doit être possible. Enfin, des algorithmes d'optimisation pour la gestion prévisionnelle devront être développés afin que ces flexibilités puissent être utilisées de manière rentable et efficace. Ces algorithmes doivent prendre en compte: (1) les différences dans la modélisation par rapport à la nature (discrète ou continue) des différentes flexibilités, (2) l'aspect temporel des contraintes liées à certaines d'entre elles, (3) les caractéristiques physiques des réseaux de distribution comme leur faible rapport de réactance à résistance (X/R) et (4) l'incertitude dans certains paramètres d'entrée.

De nombreuses recherches ont récemment été menées dans le cadre de la gestion prévisionnelle grâce à des progrès dans des techniques de modélisation et d'exploitation des réseaux. Cependant, la plupart de ces recherches ont des inconvénients. Par exemple, l'inadéquation de la recherche dans un contexte pratique et la qualité de la modélisation mathématique de ces méthodes se traduisent, entre autres, par la qualité des solutions obtenues.

LES CONTRIBUTIONS DE LA THÈSE

Les contributions de cette thèse dans le cadre de la gestion prévisionnelle des réseaux actifs de distribution sont numérotées du C1 au C12. Une partie de cette thèse a été réalisée dans le projet FP7 européen evolvDSO [evo14] ainsi que dans deux groupes de travail sur les pertes techniques et non-techniques et sur la flexibilité.

[1] Cf. chapitre 2, section 2.4.3 pour plus d'informations.

Flexibilité – modélisation et analyse économique

C1 Le développement des modèles techniques des flexibilités. Ces modèles visent à décrire de manière précise / pratique le comportement des flexibilités et sont basés sur ceux dans la littérature ou utilisés par les GRD.

C2 L'analyse économique des flexibilités, avec un accent sur la rationalisation entre le coût d'utilisation des flexibilités internes et externes. Le développement de ces coûts est aussi effectué pour un cas de test particulier, avec pour but l'utilisation dans une optimisation technico-économique.

Gestion prévisionnelle – optimisation convexe

C3 La reformulation des modèles de flexibilité développés dans les contributions C1 – C2 afin d'obtenir des modèles linéaires et exactes.

C4 Le développement d'une formulation de gestion prévisionnelle (Novel Operational Planning (OP) Formulation). Cette formulation utilise la relaxation du cône de second-ordre du calcul de répartition des charges. Cette formulation intègre les modèles de flexibilité obtenus via la contribution C3, et résout le problème avec une optimalité globale.

C5 Tests sur la Novel OP Formulation avec différents réseaux, avec différents taux d'intégration de GED et d'utilisation de flexibilités.

C6 Le développement d'un heuristique capable à résoudre le problème de gestion prévisionnelle avec optimalité dans le cas où la relaxation du cône de second-ordre ne tienne. La convergence de l'heuristique est prouvée de manière empirique.

C7 Une discussion sur l'utilisation des flexibilités dans la gestion prévisionnelle et les effets sur les caractéristiques des solutions obtenues.

Analyse de l'incertitude dans la gestion prévisionnelle

C8 Une analyse de différentes approches pour la gestion prévisionnelle des réseaux de distribution sous incertitude. Cette analyse permet d'identifier les meilleurs approches en fonction de 5 différents critères.

C9 Le développement d'une formulation exacte déterministe de deux étapes pour la gestion prévisionnelle. Cette formulation optimise le réseau pour le jour-avant et l'heure-avant.

C10 Le développement d'une formulation stochastique pour la gestion prévisionnelle. Cette formulation optimise le réseau avec des scénarios pour l'incertitude.

C11 Le développement d'une formulation par intervalles pour la gestion prévisionnelle. Cette formulation traite l'incertitude par intervalles et optimise une prévision centrale, tout en assurant la faisabilité aux extrémités.

C12 Tests sur les trois formulations développés via les contributions C9 – C11. Une comparaison entre la performance de ces formulations pour nombreuses réalisations de l'incertitude.

ORGANISATION / ACCOMPLISSEMENTS DE LA THÈSE

Pour répondre à la problématique, les différentes contributions ont été listées dans la section précédente. Dans cette section, l'organisation de ce manuscrit est décrite. Ce manuscrit est composé de 5 différentes parties, avec 8 chapitres en total.

La partie I de ce manuscrit, composée de chapitres 2 et 3 traite les aspects détailles de l'évolution des réseaux de distribution et les gestionnaires de ces réseaux (GRD). Le problèmes posés par le taux croissant des GED et la dérégulation souligne la nécessité de repenser la planification et l'opération des réseaux de distribution.

A cette fin, le chapitre 2 présente une analyse de l'état actuel technique et réglementaire en ce qui concerne les réseaux de distribution ainsi que les challenges auxquels cet état fait face aujourd'hui. Le concept des réseaux actifs de distribution est ensuite présenté. Dans le contexte des réseaux actifs de distribution, les GRD prendront de nouveaux rôles innovateurs et offriront de nouveaux services. Cela permettra aux GRD de planifier, opérer et faire des travaux dans leurs réseaux de manière rentable, flexible et intelligente. Les améliorations dans l'observabilité et la contrôlabilité dans ce contexte, combiné avec de nouveaux services comme la flexibilité, permettront les GRD à le faire. Or, le GRD doivent être capables d'utiliser la flexibilité de manière optimale. Pour cela, une meilleure compréhension de la flexibilité est requise.

Dans le chapitre 3, la flexibilité dans des réseaux de distribution est décrite et caractérisée. La modélisation technique des flexibilités est faite, dans la mesure du possible, avec précision. Dans le cas où les informations suffisantes manquent, la modélisation est faite en prenant en compte les pratiques adoptées par les GRD. Cette thèse à réussi une telle modélisation des flexibilités à travers la contribution C1. Quant à l'utilisation des flexibilités dans les différents processus d'optimisation des GRD, la modélisation économique est nécessaire. Dans un environnement compétitif, l'approvisionnement des flexibilités est fait via des contrats. L'utilisation de ces flexibilités coûte donc de l'argent pour les GRD. Les flexibilités internes font objet, elles aussi, d'un coût d'utilisation, même si elles ne sont pas «achetées ». Pour assurer, dans un souci de rentabilité, que les GRD utiliseront ces flexibilités de manière optimale, la modélisation économique faite dans cette thèse prend en compte ce fait. La contribution C2 de cette thèse met en place une modélisation réaliste et un arbitrage entre les flexibilités internes et externes.

Parmi les différents outils que les GRD devront utiliser dans le contexte des réseaux actifs de distribution, la gestion prévisionnelle (GP) est une étape préparatoire court-terme (jour J-1). Les violations de contraintes dans les réseaux telles que la tension et le courant, souvent provoquées par les GED intermittents sont d'abord identifiées. Le but de GP est d'ensuite utiliser les flexibilité disponibles pour résoudre ces violations de contraintes. La partie II de cette thèse est dédiée à la gestion prévisionnelle. Dans cette partie, composée de chapitres 4 et 5, le développement d'une méthodologie de gestion prévisionnelle, suivi par des tests de cette méthodologie sont présentés.

Actuellement, il y a un manque d'outils et de méthodologies de gestion prévisionnelle dans des réseaux de distribution. Les problèmes associés à ce manque sont d'abord soulevés dans le chapitre 4. Les caractéristiques idéales d'une méthodologie de gestion prévisionnelle sont ensuite identifiées. Afin de procéder ensuite à la modélisation d'une telle méthode, une analyse bibliographique des méthodes de calcules de répartition de charge et de la gestion prévisionnelle est présentée. L'approche de modéliser notre problème à travers un modèle «*Mixed-Integer Second-Order Cone Programming (MISOCP)* »est ensuite choisie. Ce modèle nous permet de surmonter le problème de non-convexité.

Ce modèle intègre deux contributions différentes. La reformulation des modèles de flexibilités modélisées à travers les contributions C1 et C2 est accomplie dans la contribution C3. Quant au calcul de répartition de charge qui est le cœur de la gestion prévisionnelle, les reformulations mathématiques telles que les linéarisations exactes et aussi la relaxation convexe du cône de second-ordre, les accomplissements de la contribution C4, aident à la convexification du modèle final de gestion prévisionnelle. Ce modèle, qui intègre aussi les flexibilités modélisées dans la contribution C3, est appelé «*Novel OP Formulation* ».

Ce *Novel OP Formulation* offre pour la première fois la possibilité d'obtenir une solution optimale garantie pour un modèle de gestion prévisionnelle intégrant des flexibilités variées, y compris les flexibilités discrètes comme la reconfiguration et les régleurs en charge. Cependant, la relaxation du cône de second-ordre doit tenir pour que les solutions optimales obtenues soient physiquement valables. Si la relaxation ne tient pas, les solutions ainsi obtenues ne seront pas utilisables.

Ce modèle a ensuite été testé sur deux réseaux de distribution dans le chapitre 5 pour un certain nombre de cas d'études et de taux d'insertion des GED. Ces tests font partie de la contribution C5 de cette thèse. Pour le réseau Baran, les résultats montrent que le modèle trouve des solutions optimales pour tous les cas d'études. Pour le réseau PREDIS, la relaxation du cône de second-ordre ne tient pas. Pour retrouver une solution optimale qui soit physiquement valable, la contribution C6 dans le chapitre 4 prévoit un modèle heuristique basé sur la recherche dichotomique. Ce modèle repose sur une méthode de transformation de contraintes, où la fonction objective de l'optimisation gestion prévisionnelle est transformée en fonction objective plus une contrainte. Cette nouvelle fonction objective fait que la relaxation du cône de second-ordre tienne et la solution optimale est retrouvée grâce à la recherche dichotomique qui restreint progressivement la contrainte.

Suite aux tests avec le modèle heuristique, une analyse sur l'utilisation des flexibilités est menée via la contribution C7 dans le chapitre 5. Cette analyse fournit des explications sur les raisons pour lesquelles il existe des différences dans l'utilisation des flexibilités.

La *Novel OP Formulation* ne traitant pas des incertitudes, dans des prévisions par exemple, la partie III est dédiée à son extension pour inclure l'incertitude. Cette partie est composée par les chapitres 6 et 7. Dans le chapitre 6, une analyse des meilleures approches pour la gestion prévisionnelle sous incertitude est menée. Pour une incertitude choisie – celle de la puissance produite des GED – cette analyse fournit les avantages et inconvénients des différentes approches sous incertitude. La contribution C8 est composée de cette analyse et trois formulations différentes sont ensuite choisies pour le développement des méthodes de gestion prévisionnelle sous incertitude.

La «*Two-stage Deterministic OP Formulation* »traite l'incertitude dans la production des GED en considérant des prévisions déterministes sur deux étapes : une première étape au jour J-1 et une deuxième à l'heure H-1. Le développement de son modèle est fait à travers la contribution C9. La «*Stochastic OP Formulation* »considère des scénarios pour la représentation de l'incertitude et compose la contribution C10). Finalement, la «*Interval OP Formulation* »traite l'incertitude à travers une prévision centrale et des bornes supérieures et inférieures. Le développement de ce modèle est fait via la contribution C11.

Dans le chapitre 7, les trois formulations sont testées sur le réseau Baran, pour différents cas d'études et taux d'insertion, et les résultats obtenus sont présentés. Une comparaison des performances des formulations développées est aussi faite pour 1000 scénarios différents, à travers 24000 tests. Tous les travaux de ce chapitre composent la contribution C12 de cette thèse.

La partie IV de cette thèse est composée des conclusions générales et perspectives de cette thèse (chapitre 8), des références bibliographiques et de ce résumé en français. Finalement, les annexes présentées dans la partie V viennent compléter les informations présentées dans cette thèse.

Publications & Communications Related to this Thesis

Conference Publications & Presentations:

1 Bhargav Swaminathan, Vincent Debusschere, and Raphaël Caire. A Dynamic Programming based Approach to Day-Ahead Operational Cost Reduction for DSOs. *CIRED 2015*.

2 Bhargav Swaminathan, Vincent Debusschere, and Raphaël Caire. Intelligent Day-Ahead Scheduling for Distribution Networks with High Penetration of Distributed Renewable Energy Sources. *IEEE PowerTech 2015*.

3 Bhargav Swaminathan, Vincent Debusschere, and Raphaël Caire. Short-Term Operation of Active Distribution Networks with Convex Relaxation of Power Flows. *IEEE PowerTech 2017*.

evolvDSO Project Deliverables:

1 Contributing author. Advanced Tools and Methodologies for Forecasting, Operational Scheduling and Grid Optimisation. *Deliverable 3.2*.

2 Contributing author. Validation of the Methodologies and Tools Developed for DSO. *Deliverable 3.4*.

Working Group Deliverables:

1 Contributing author. Demand Response Status and Initiatives around the World. *Global Smart Grids Federation*.

2 Secretary of WG and contributing author. Reduction of Technical and Non-Technical Losses in Distribution Networks. *CIRED Working Group on Losses Reduction – WG CC-2015-2*.

Other Invited Talks & Presentations:

1 The evolvDSO Solution to Operational Planning. *IEEE PowerTech 2015*.

2 An Overview of Losses - Definitions, Measurement & Regulation. *CIRED 2017*.

PART V

APPENDICES

Appendix to the Operational Planning Models

A

This appendix provides the following additional information to support the work done in this thesis. In Section A.1, the unsuitability of the DC-OPF for distribution networks is illustrated via tests performed on an IEEE test network.

In Section A.2, the initial OP-tool solution developed as a part of this thesis for the evolvDSO project is outlined. In Section A.3, a simple merit-order based congestion management procedure is outlined. This procedure was used in the OP-tool in order to provide feasible initial solutions to a constraint programming optimisation routine in the tool.

In Section A.4, the proof of optimality of the solution obtained to MISOCP problems using the Branch & Cut method is presented. Finally, in Section A.5, the unsuitability of robust optimisation formulations for distribution network OPFs under uncertainty is provied.

A.1 Distribution Networks – Unsuitability of DC-OPF

In order to test the DC-OPF's suitability for distribution networks, a modified version of the well-known IEEE 30-bus system [Ric93] is used. The French DSO Enedis uses certain cross sections (CS) of power cables in its distribution networks [ENE10]: 95, 150, and 240 mm^2 Aluminium (Al.), and 240 mm^2 Copper (Cu.). The resistance and reactance of the lines in test system are modified based on the typical unit values for these cross sections shown in Table A.1.

Table A.1: Typical R and X values for 12 kV Power Cables used by Enedis

Type	CS (mm^2)	R/km	X/km	X/R Ratio
Al.	95	0.32	0.12	0.375
	150	0.206	0.11	0.534
	240	0.125	0.11	0.88
Cu.	240	0.0754	0.1	1.326

The modified network is subject to a total of 1 000 tests. The tests were carried out using the MATPOWER library, and the average error between the DC and the AC load flows in the network were obtained for each of the tests. The results of these tests are shown in Fig. A.1 through a scatter and histogram count plot. They show that the error when using the DC OPF is generally very high, with an average of about 26.6 %. The minimum and maximum errors across all tests are about 13.8 % and 38.9 % respectively. At these levels of losses, one can conclude that the DC OPF is definitely unsuitable for distribution networks.

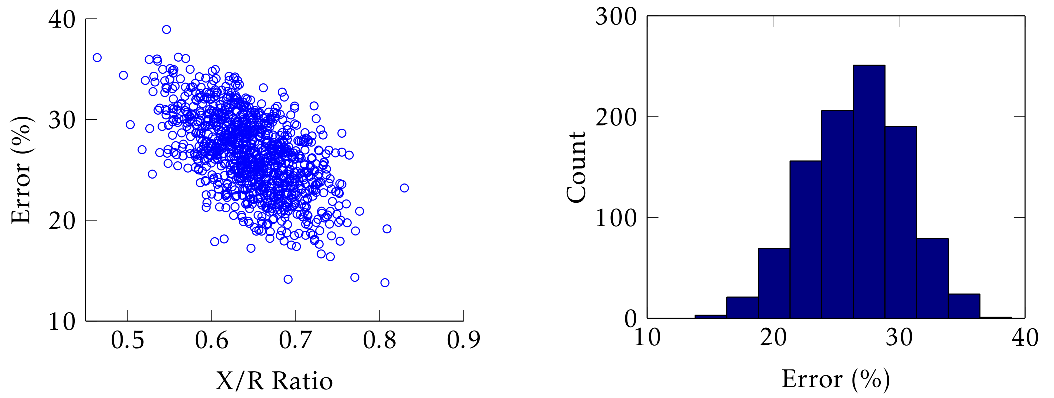


Figure A.1: Errors in the DC Load Flow for Distribution Networks

A.2 EVOLVDSO – THE OP-TOOL AS AN INITIAL SOLUTION

An initial solution to the OP problem partly developed in this thesis and presented in the evolvDSO European project is the operational planning tool (OP-Tool) for distribution networks. The development was carried out by a consortium of three research institutions: RSE SpA from Italy, VITO NV from Belgium, and Grenoble INP from France. The OP-Tool developed by the consortium was the result of an effort to create a modular tool for the short-term planning of distribution networks. The framework of the developed tool is shown in Fig. A.2.

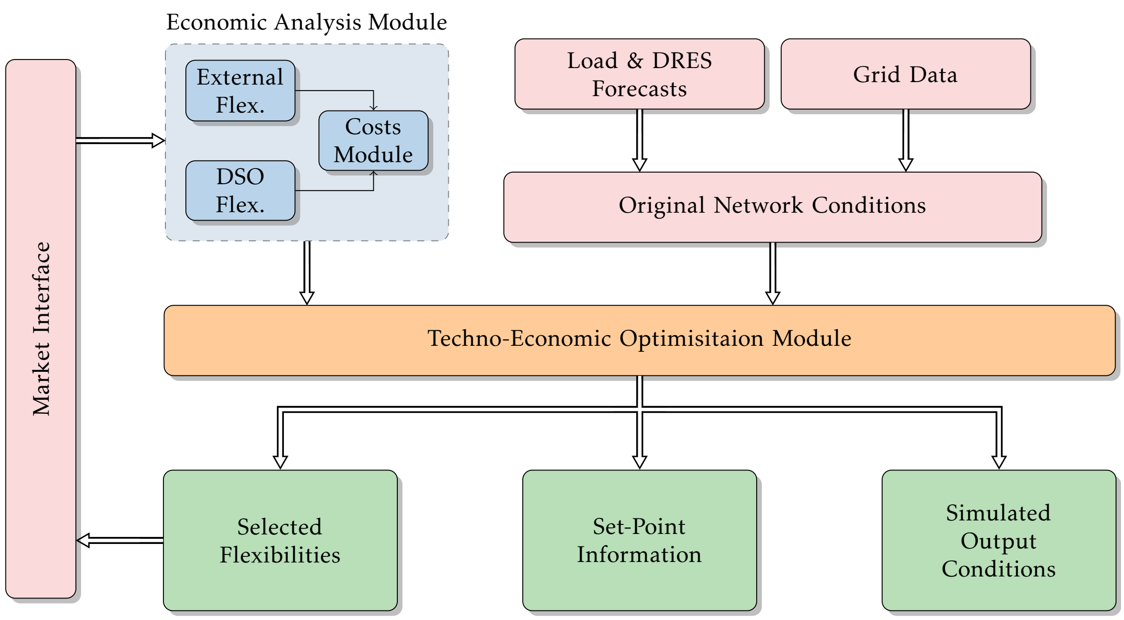


Figure A.2: Framework of the Operational Planning Tool (evolvDSO)

The inputs and interfaces to the framework are represented in red, processes in blue and orange, and outputs in green. A brief description of the main modules that can be found in the framework follows.

The market interface module that is used to collect information related to flexibilities available for use in the distribution network to be optimised, and also to acquire the flexibilities selected by the optimisation. Two input modules that provide data on the network to be optimised, and the load & DRES forecasts in the network, and a third module that aggregates this information and calculates the input network conditions and the constraints violated.

The economic analysis module that sorts flexibilties for use in one of the optimisation approaches developed in the project. This module integrates the work done on the economic analysis of flexibilities in Chapter 3 in to the framework. The module also creates a "merit-order" for flexibilities in the broad sense of the word. An example merit-order methodology developed for active power flexibilities developed as a part of this thesis and used in the evolvDSO project is presented in Section A.3.

The techno-economic optimisation module that combines the inputs and uses two different optimisation approaches in order to alleviate the constraint violations in the network. It consists of two different solvers. The first solver is a constraint programming solver developed by VITO NV. The aim of the constraint programming solver is to find near-optimal solutions to the OPF problems underlying the OP formulation in a timely manner. The solver models the power flow constraints as linear approximations of the power flow equations around a particular operating point. The sensitivity factors for these approximations are calculated analytically. Flexibilities are integrated into the solver as constraints that describe their functional aspects. The solver uses a three-stage search heuristic to guide the overall search process using lower and higher-resolutions of the problems. The second solver, developed by RSE SpA, relies on a MINLP formulation of the OPF.

The flexibilities to be used are modelled as constraints, along with the different constraints for the active and reactive power balance, the voltage and current limits, and battery storage. This solver does not integrate network reconfiguration in the formulation. Three output modules, the first interfacing with the market for acquiring the selected flexibilities, the second providing set-points and other operational information to the DSO, and a third informative module for displaying simulated output conditions after the optimisation. The framework proposed in Chapter 2 closely resembles this framework. For further information, the reader may consult reference [DGR+15].

A.3 CONGESTION MANAGEMENT USING FLEXIBILITY MERIT-ORDER – A SIMPLE EXAMPLE

The economic analysis module in Fig. A.2 is also responsible for generating a hierarchical merit order for active power flexibilities in the network. This is especially useful for the constraint programming solver, whose solution times depend on the initial solutions provided as an input. Apart from speeding up the execution of optimisation solvers which may need initial solutions, this merit order also provides an immediate outlook with respect to the active power flexibilities that can be of interest at different time-frames, in different parts of the network. Of course, these merit orders are not time dependent, meaning that inter-temporal constraints that link certain flexibilities are not described.

We consider a radial distribution network with one substation, two feeders, and seven nodes. This network is illustrated in Fig. A.3. There is a load connected to every node. For a given time minute period, we assume that there is a congestion of 1 MW in Feeder 1, in the line connecting the substation and the first downstream node. Also, there is a 2 MW congestion in the substation, meaning the transformer is overloaded. There are five active power flexibilities A, B, C, D, and E. Each of these flexibilities has their respective availabilities and unit costs as shown.

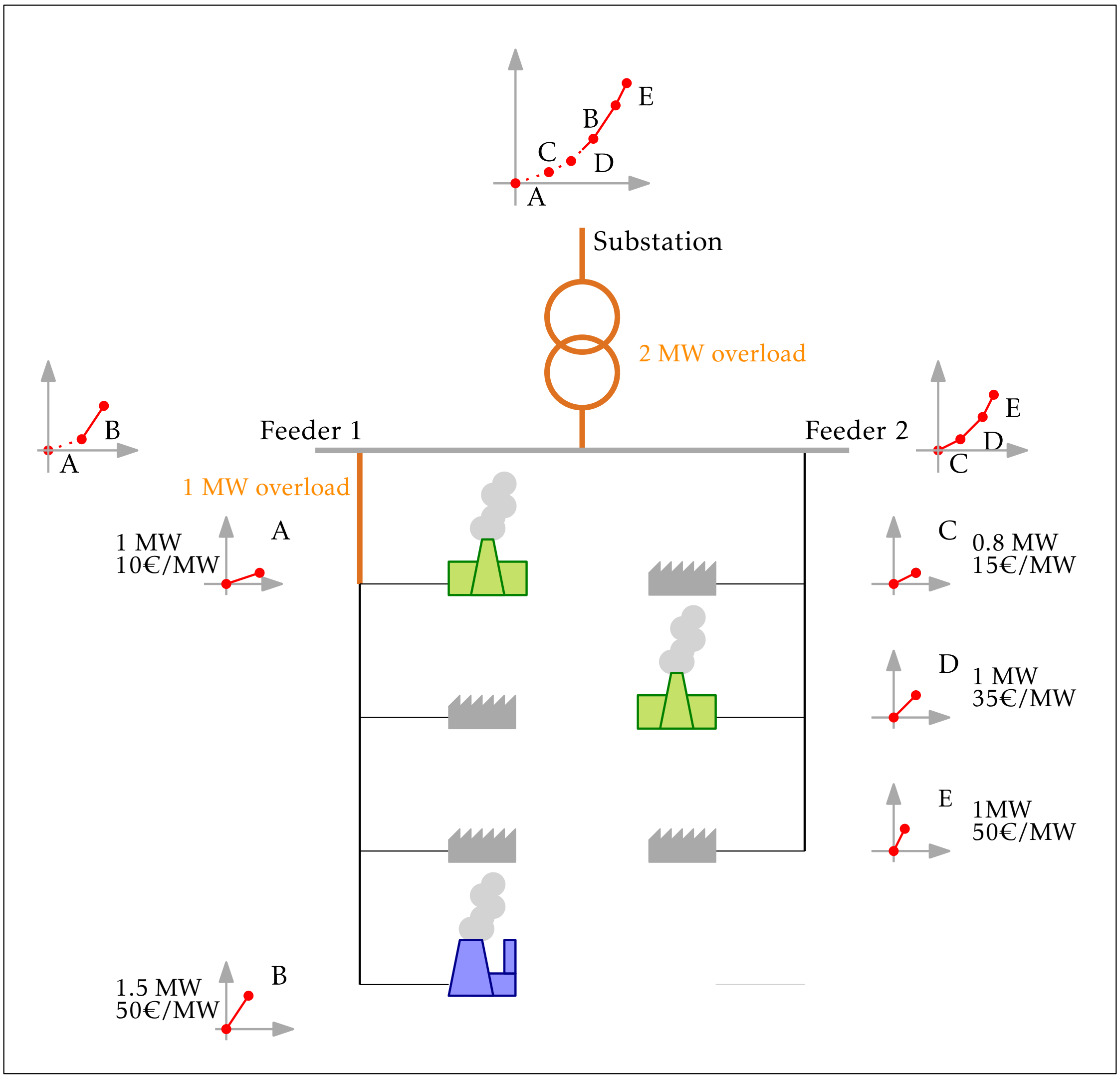


Figure A.3: Hierarchical Merit-Order for Active Power Flexibilities (evolvDSO)

The bottom-up approach to constructing the merit order starts from the nodes furthest from the substation, and checks for a network congestion in the power line immediately upstream. If there is a network congestion present, it aggregates all the available flexibilities and ranks them in an ascending order of their prices. Then, it indicates that the use of certain flexibilities can solve the congestion, and updates their status. This is the case with Feeder 1. The first congestion encountered is that of 1 MW. And there are two flexibilities: A and B available to solve it. By ranking them an indication that flexibility A can solve the congestion is obtained. Only the remaining amount of flexibility A can be used for upstream congestion solving. In this case, this amount is 0 MW. Therefore, flexibility A is used completely to solve the congestion, and is unavailable for exploitation to solve congestions that may be found upstream. This is shown in the aggregated merit order curve for Feeder 1, where A is indicated as used up (in orange). This not only indicatively solves the congestion in the feeder, but also decreases the congestion in the substation by 1 MW. This means that when the next encountered congestion in this case is at the substation, and is only 1 MW (as compared to 2 MW originally). At the substation (node N1), there are now four flexibilities: B, C, D, and E. When a new ranking is done, the indication is to use C to its fullest, and D to the tune of 0.2 MW. This also provides the final merit order, with the indications for flexibility use in the entire network.

This simple case can be extrapolated to a radial distribution network of any size, provided that congestions and active power flexibilities exist. In cases where the available flexibility is not sufficient, merit order routine will still generate one with indications to solve congestions as much as possible (even if it means indicating that all levers in the network should be activated). The merit order generator for active power flexibilities was tested with the operational planning solution developed in the evolvDSO project. The results of these tests, along with those of the OP tool, can be found in [JJR+15].

A.4 THE BRANCH & CUT METHOD AND MISOCP PROBLEMS – OPTIMALITY OF SOLUTIONS

In order to solve the different operational planning formulations developed in this thesis, we rely on the Branch & Cut (B&C) method employed by CPLEX. In Chapter 4, we developed a mixed-integer second-order cone programming (MISOCP) formulation that could guarantee globally optimal solutions to the OP problem for distribution networks. This work would be rendered useless of the solution technique were to provide results without any guarantee on their optimality. Therefore, we set out to prove that the B&C method can gurantee optimal solutions to MISOCP formulations. To this end, we first explain the working of the method, and then explain how this method converges to a globally optimal solution for MISOCP formulations. We rely on the work of Drewes [Sar09] and Touré [Tou14] for this proof.

A.4.1 Branch & Cut Method – Working

Consider a mixed-integer problem Π with a continuous decision variable set C and a discrete decision variable set D. Mathematically, the problem can be represented through the equations (A.1) – (A.4).

$$\min \qquad f_0(x) \tag{A.1}$$

Such that:

$$f_i(x) = b_i \qquad \forall i \in n \tag{A.2}$$

$$f_j(x) \leq b_j \qquad \forall j \in m \tag{A.3}$$

$$x \in C \times D \tag{A.4}$$

A continuous relaxation of the problem Π can be derived by relaxing the integrality constraint of the variables in set D. We obtain the relaxed problem $\underline{\Pi}$ as a result. The decision tree is the result of an iterative process where each tree node is a relaxed sub-problem. A parent node is a node that has sub-problems. The method begins by solving the continuous relaxation $\underline{\Pi}$. If the solution $\overline{x}$ is discrete and feasible, the problem has a solution. Otherwise, the B&C method creates two sub-problems by adding equations

$x \le \lceil \overline{x} \rceil$ and $x \ge \lfloor \overline{x} \rfloor$. The $\lceil\rceil$ and $\lfloor\rfloor$ operators correspond to ceiling and floor functions respectively. The manner in which the Branch & Cut (B&C) method solves the problem is by creating a decision tree of these sub-problems. Each node of the decision tree with a non-discrete solution is a lower bound on the solutions to the sub-problems of the node. In a similar fashion, each discrete solution is an upper bound to the entire problem. Each sub-problem thus adds constraints to either the lower or the upper bounds that, over several iterations, become more restrictive. At a given stage, the lower bound to a sub-problem meets and upper bound of the entire problem, and this is the solution of the problem. To explain the working in another way, we state the three rules that the B&C method uses:

1 If the solution to a node in the tree is feasible and discrete, then any and all soluions to the sub-problems of the node will have a higher objective value. Hence, there is no interest in exploring these solutions.

2 If the solution to a node in the tree is greater larger than the upper bound of the entire tree, any and all discrete solutions to sub-problems of the node will only provide a larger upper bound. There is no need to explore these solutions.

3 If the solution to a node is infeasible, any and all solutions to the sub-problems of the node will be infeasible as well. There is no need to explore these solutions.

We now present an instance of the decision tree to a mixed-integer problem Π in Fig. A.4. To explain the working of this tree, we define a discrete set $J = \{j \mid x \in D\}$, a lower bound LB and an upper bound UB of the problem Π, the optimal solution x_k^* of a node k, and a set N that contains all the cuts, the lower bounds, and upper bounds of the problem at the node k.

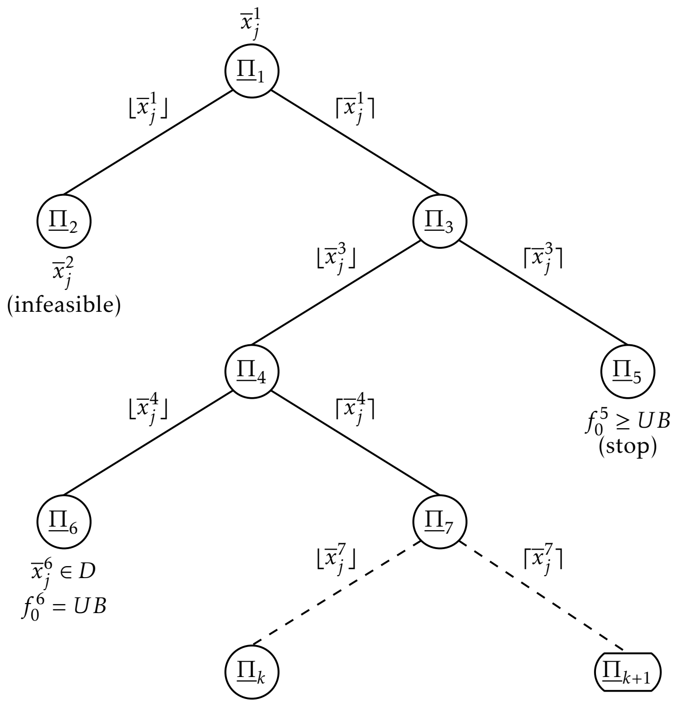


Figure A.4: Illustration of the B&C Decision Tree [Sar09]

In the figure, the problem $\underline{\Pi}_1$ is first evaluated by the algorithm. It is checked for infeasibility. If it is infeasible, then the entire problem is infeasible as well (rule 3). If not, two sub-problems $\underline{\Pi}_2$ and $\underline{\Pi}_3$ are created with the new cuts $x^2 \geq \lfloor \overline{x}^1 \rfloor$ and $x^3 \leq \lceil \overline{x}^1 \rceil$ respectively. At the creation of every sub-problem, it is checked for infeasibility. If it is infeasible as is the case with $\underline{\Pi}_2$, further search in this direction is abandoned. If not, the optimal solution x_3^* is evaluated. If this a non-discreet solution higher than the current lower bound and lower than the global upper bound, a new cut x_3^* is added to the sub-problems of the node. The process continues with the sub-problems $\underline{\Pi}_4$ and $\underline{\Pi}_5$. If the optimal solution to any problem is higher than the global upper bound ($\underline{\Pi}_5$), the search in this direction is stopped (rule 2). Otherwise, new lower bound cuts are added, and sub-problems are generated. If the solution to any sub-problem is a discrete solution, this becomes the new upper bound, and the search in this direction is stopped as well (rule 1). This process of refining the lower and upper bounds continues until there is no difference (or a tolerable difference) between the lower and upper bounds. The node where this result is achieved is the node whose solution is the solution to the problem Π.

A.4.2 Optimality with MISOCP Problems

In order to verify that the solutions to MISOCP problems using the B&C method are optimal, let us consider a MISOCP problem Π. The continuous relaxations of this problem results in a continuous second-order cone programming (SOCP) problem. At a node k, consider two values of the objective functions of the problem f_k^1 and f_k^2, such that $f_k^1 < f_k^2$. If the minimisation of the problem $\underline{\Pi}_k$ provides the objective value of f_k^2, it means that the problem is not convex. In other words, and convex problem $\underline{\Pi}_k$ can only provide one minimum value of its objective function, f_k^1.

In the case of the OP formulation, the discrete variables to be relaxed are that of reconfiguration and OLTCs. The final result of the B&C method consists of finding discrete values for the reconfiguration variables and OLTCs with the least objective value of the continuous relaxations. Since the relaxed problems in each node of the decision always provide optimal solutions to the continuous OP formulation, the final result of the B&C method is the globally optimal solution for the MISOCP problem. In other words, for the B&C method to guarantee a globally optimal mixed-integer solution, the relaxed sub-problems will have to be solved optimally as well. This is the case with SOCPs, and the parent MISOCP problem can therefore be solved with global optimality.

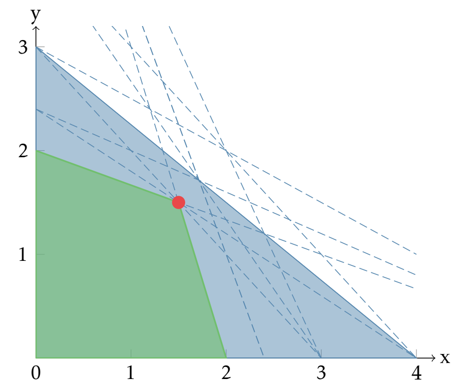
A.5 THE UNSUITABILITY OF ROBUST OPTIMISATION FOR OPF

The concept of recourse actions, and its necessity when optimising under uncertainty was explained in Chapter 6, Section 6.2.3.4. One of the biggest advantages of robust optimisation in general is that the obtained solution is feasible for all realisations of uncertainty that lie within the uncertainty set. This means that for traditional robust optimisation problems, recourse actions are unnecessary for any such realisation of uncertainty.

However, this is untrue for power system optimisation formulations such as unit commitment (UC) and optimal power flow (OPF). The reasons for this, as explained in Chapter 6, Section 6.2.3.5, are two-fold. First, OPF problems with parametric uncertainty have equality constraints. Second, some OPF formulations are non-linear in nature. To better illustrate the issues caused by the non-linearity and equality constraints, we make use of constraint (4.3) in Chapter 4, constraint (6.9) from Chapter 6, and Fig. 6.1(b), also from Chapter 6. For ease of understanding, these constraints and the figure are shown once again. In the following sections, the two issues are further explained with the help of these equations and figure.

$$\sum_{g \in \Upsilon} P_t^g = \sum_{c \in C} P_t^c \qquad \forall t$$

$$\sum_{j \in J} \tilde{a}x + \Gamma_i w_i + \sum_{j \in J} z_{ij} \leq b \qquad \forall i \in I$$



A.5.1 The Presence of Equality Constraints

Robust optimisation treats uncertainty in inequality constraints, as shown via constraint (6.9). The first problem related to the use of robust optimisation in OPFs and OPs is therefore related to the presence of uncertainty in equality constraints. The Constraint (4.3) is a the power balance constraint in Unit Commitment. This is an equality constraint, and it conserves this equality even in OPF formulations (see constraints (4.28)–(4.33) in Chapter 4). If the DRES production (or even the demand) is considered uncertain, it is in this power balance equation that the uncertainty will appear.

A solution obtained with a conservative estimate of the uncertain parameter (DRES production) may therefore not be feasible for other, less conservative, realisations of the parameter. This is because the solution obtained with an equality constraint may be mathematically valid only for the given set of values that variables and parameters take in the equation. This infeasibility can be illustrated with the optimisation problem described by the equations (6.1), (6.4)–(6.6), the presence of an equality in constraint (6.4) would transform the solution space from a 2-D region (shaded in green) into 1-D lines (dotted blue). Recourse actions may therefore be necessary when the actual realisation of the uncertain parameter becomes known. This defeats the original purpose of the robust optimisation, as the solution is technically no longer robust.

This issue may be overcome by using approximations. The power balance equality constraint can be transformed into an inequality constraint via a direct approximation. However, for any solution to be feasible, the inequality must be tight, and such a guarantee cannot be provided in the OP formulation. One or more variables in the equality constraint may be eliminated in order to convert the equality constraint into an inequality constraint. However, these variables have to be state / analysis variables that do not need the compuation of an optimal value [GYdH15], [ALA09]. In any case, an approximation is not guaranteed to produce an optimal, or even a feasible result.

A.5.2 Non-Linearity in the Problem

The presence of non-linear constraints in the robust optimisation problem poses two problems. The first problem is related to the feasibility of recourse actions. In a case where recourse actions are allowed in the robust optimisation formulation with equality constraints, certain decision variables change their values depending on the realisation of the uncertain parameter. However, these actions can be guaranteed as feasible only if the problem is linear. This stems partly from the non-linear behaviour of the system to be optimised with respect to the uncertainty, where certain realisations may not have feasible recourse actions.

The second problem is related to the identification of the worst case scenario, against which the robust optimisation protects the system to be optimised. This identification is easy if the problem is linear, as the behviour of the system with respect to the uncertainty is linear. Evidently, this means that one of the bounds of the uncertainty is the worst-case. However, if the problem is non-linear, this may not necessarily be the case (non-linear convex problems are exempt). The worst-case condition may be caused by a realisation of the uncertainty that could be anywhere in the uncertainty set. It is impossible to evaluate this. Therefore, a robust optimisation problem cannot be formulated.

B

Appendix to the Test Networks and Test Results

This appendix presents the following information. In Section B.1 the technique used to decide the type, size, and location of the DRES in the test networks is presented. Then, in Section B.2, the additional data for the Baran test network, like the line resistances, the line reactances, the load profiles, and additional information on the network characteristics are presented. In Section B.3, similar data is presented for the PREDIS network.

In Section B.4, the additional test results for the novel OP formulation are presented. This includes an illustration of the configurations C1 – C6 chosen by the OP formulations. Finally, in Section B.5, the additional test results for the OP formulations under uncertainty are presented.

B.1 Pseudo-random DRES allocation

The working principle of the technique for deciding the type, size, and location of the DRES in the test cases is described here. It is based on the *MADGIC* method in [AHBG+13] to evaluate the maximum insertion rate of DRES in networks.

To realistically distribute the DRES in a given network, our technique relies on real-world information of the distribution of the type and size of DRES. This information is available in [ENE16], and is synthesised in Table B.1.

Table B.1: Installed Capacities of PV and Wind Power in Enedis MV Distribution Networks [ENE16]

Production Range (MW)	Installed Capacity (MW)			Proportion (%)			
				In Range		In Total Installed	
	Solar	Wind	Total	Solar	Wind	of Range	Cumulative
0.25 – 0.5	73.6	0.5	74.1	99.33	0.67	0.63	0.63
0.5 – 1	175.7	8.2	183.9	95.54	4.46	1.56	2.19
1 – 3	369.8	171.4	541.2	68.33	31.67	4.6	6.8
3 – 7.5	868.05	998.1	1866.15	46.52	53.48	15.87	22.66
7.5 – 10	477.05	2998.4	3475.45	13.73	86.27	29.55	52.22
10 – 12	234.5	4318.1	4552.6	5.15	94.85	38.71	90.93
12 – 14	234.5	669.2	903.7	25.95	74.05	7.68	98.61
14 – 17	0	163	163	0	100	1.39	100

In this table, the installed capacities are first shown in different ranges of rated production. The proportion of PV and wind power in each range is also indicated. This is followed by the indication of the proportion of the capacity in each range as a percentage of the total installed capacity in all ranges. Finally, the cumulative installed capacity taking into account the installed DRES in and below the ranges is calculated.

Based on this data, a new probability distribution is created for the chance of occurrence of DRES in an MV distribution network. This distribution is illustrated in Fig. B.1.

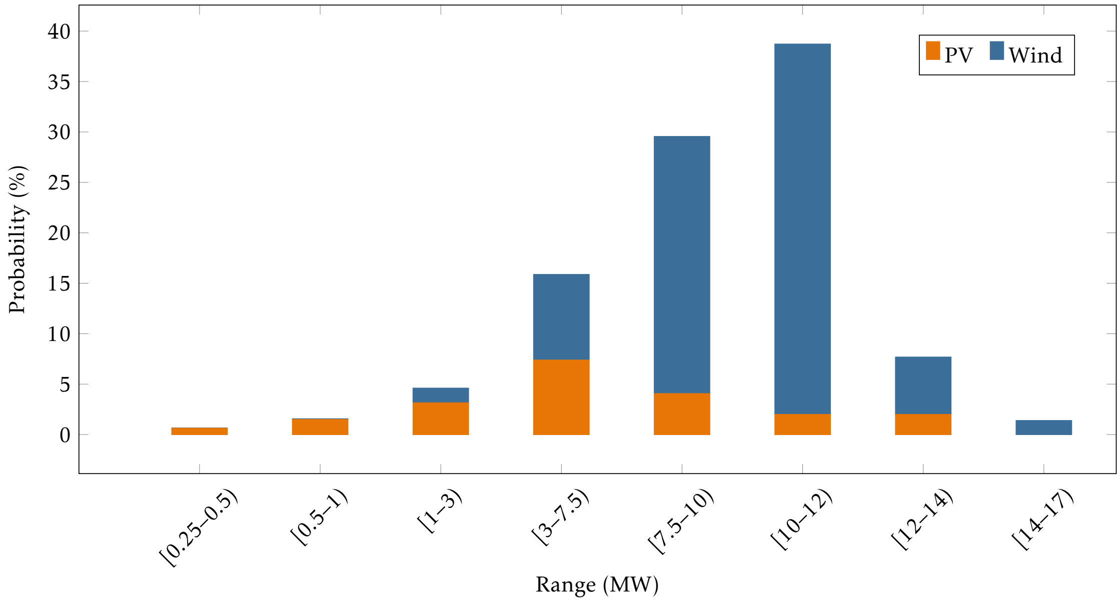


Figure B.1: Probability Distribution (PMF) for DRES Size and Type

The DRES insertion rate τ in a network is the ratio of the maximum power that can be produced by all DRES connected to the network (P^g_{max}) to the connected load in the network (P^c_{max}). It is given by the formula (B.1).

$$\tau = \frac{P^g_{max}}{P^c_{max}} \cdot 100 \tag{B.1}$$

We also define other parameters for this method whose values are extracted from Table B.1. They are the DRES generation P^g, the range of DRES production r^g, the type function of the DRES $type()$, the probability function $prob()$, the allocated power P^{al}, the remaining power P^{rem}, and the iteration register i. Then, we develop the following procedure to pseudo-randomly allocate DRES in the network:

procedure DRESALLOC(P^g)
  $P^{rem} = P^c_{max} \cdot \tau$
  $P^{al} = 0$
  $i = 1$
  while $P^{rem} \geq 0$ **do**
    Select r^g where P^{rem} can lie
    Normalise $prob(r^g)$ for selected ranges
    Select one range from r^g according to $prob(r^g)$
    $P^g_i = rand(r^g)$
    Select $type(P^g(i))$ according to $prob(type(P^g(i)))$
    if $P^g_i > p^{rem}$ **then**
      $P^g_i = p^{rem}$
    end if

$P^{al} = P^{al} + P_i^g$
$P^{rem} = P^{rem} - P_i^g$
Store P_i^g and $type(P_i^g)$
$i = i + 1$
end while
return results
end procedure

In this procedure, the maximum power that can be allocated, based on the DRES insertion rate τ is first ascertained. Then, in an iterative way, the production and the type of DRES are allocated based on the probability laws that govern their occurrence. This is done until no power is left to be allocated. It is to be noted that this procedure does not produce repeatable results, as the range and type of the DRES are decided pseudo-randomly in all iterations.

B.2 ADDITIONAL DATA – BARAN NETWORK

In this section, additional data pertaining to the Baran test network are presented. First, the per-unit resistances and reactances for the Baran test network are presented in Table B.2. These per-unit values are calculated on a base of 12.66 kV and 1 MVA.

Table B.2: Baran Test Network – Line Resistances and Reactances

Node		Resistance (pu)	Reactance (pu)	Node		Resistance (pu)	Reactance (pu)
From	To			From	To		
1	2	0.001	0.293	20	21	2.555	2.985
2	3	3.076	1.567	21	22	4.423	5.848
3	4	2.284	1.163	3	23	2.815	1.924
4	5	2.378	1.211	23	24	5.603	4.424
5	6	5.110	4.411	24	25	5.590	4.374
6	7	1.168	3.861	6	26	1.267	0.645
7	8	4.439	1.467	26	27	1.773	0.903
8	9	6.426	4.617	27	28	6.607	5.826
9	10	6.514	4.617	28	29	5.018	4.371
10	11	1.227	0.406	29	30	3.166	1.613
11	12	2.336	0.772	30	31	6.080	6.008
12	13	9.159	7.206	31	32	1.937	2.258
13	14	3.379	4.448	32	33	2.128	3.308
14	15	3.687	3.282	8	21	12.479	12.479
15	16	4.656	3.400	9	15	12.479	12.479
16	17	8.042	10.738	12	22	12.479	12.479
17	18	4.567	3.581	18	33	3.120	3.120
2	19	1.023	0.976	25	29	3.120	3.120
19	20	9.385	8.457				

The spread of load types in the different nodes in the network is shown in Fig. B.2. The nodes 3, 11, 17, 23, 27 and 32 are chosen for type-1 load modulation, and are assumed to be provided by the industrial loads connected to these nodes. The connected load and load power factor at each of the nodes in the network is shown in Table B.3. The load values have been calculated on a 1 MVA base.

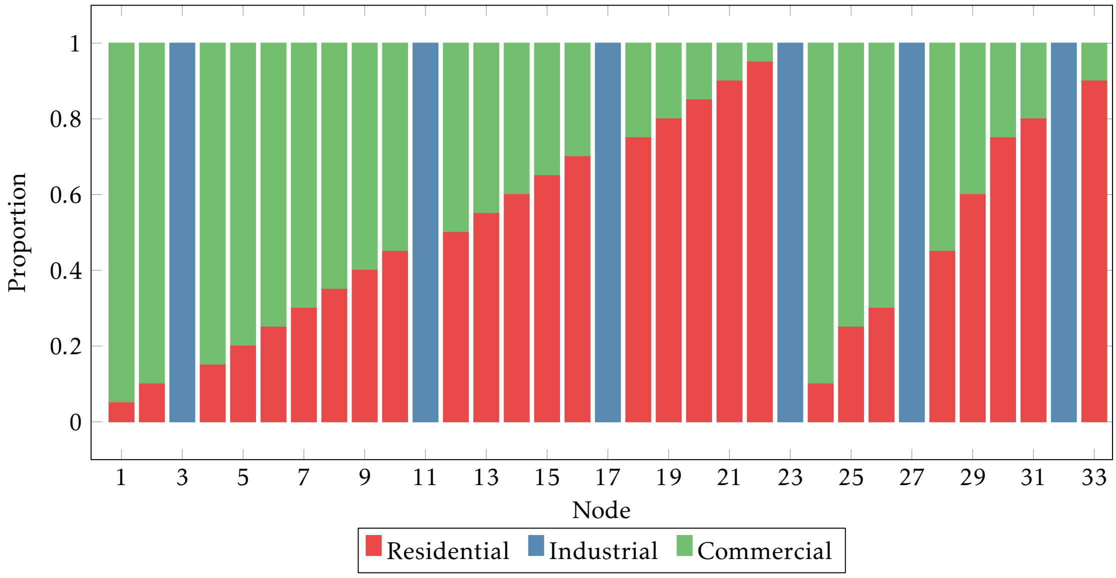


Figure B.2: Baran Network – Load Proportions per Node

Table B.3: Baran Test Network – Loads

Node	Load Power Active (pu)	Load Power Reactive (pu)	Power Factor ($tan\phi$)	Node	Load Power Active (pu)	Load Power Reactive (pu)	Power Factor ($tan\phi$)
1	0	0	–	18	0.151	0.067	0.444
2	0.161	0.097	0.600	19	0.151	0.067	0.444
3	0.108	0.048	0.444	20	0.152	0.067	0.444
4	0.194	0.129	0.667	21	0.152	0.068	0.444
5	0.097	0.049	0.500	22	0.153	0.068	0.444
6	0.098	0.033	0.333	23	0.108	0.060	0.556
7	0.326	0.163	0.500	24	0.676	0.322	0.476
8	0.327	0.164	0.500	25	0.683	0.325	0.476
9	0.098	0.033	0.333	26	0.098	0.041	0.417
10	0.099	0.033	0.333	27	0.072	0.030	0.417
11	0.054	0.036	0.667	28	0.099	0.033	0.333
12	0.099	0.058	0.583	29	0.199	0.116	0.583
13	0.099	0.058	0.583	30	0.335	1.005	3.000
14	0.199	0.133	0.667	31	0.252	0.118	0.467
15	0.100	0.017	0.167	32	0.252	0.120	0.476
16	0.100	0.033	0.333	33	0.101	0.068	0.667
17	0.072	0.024	0.333				

The load and net load profiles for various DRES insertion rates are illustrated in Fig. B.3. These profiles are based on the weights introduced in Section 5.1.3.1 of Chapter 5, and are used in the test cases presented in Section 5.2 of the same chapter.

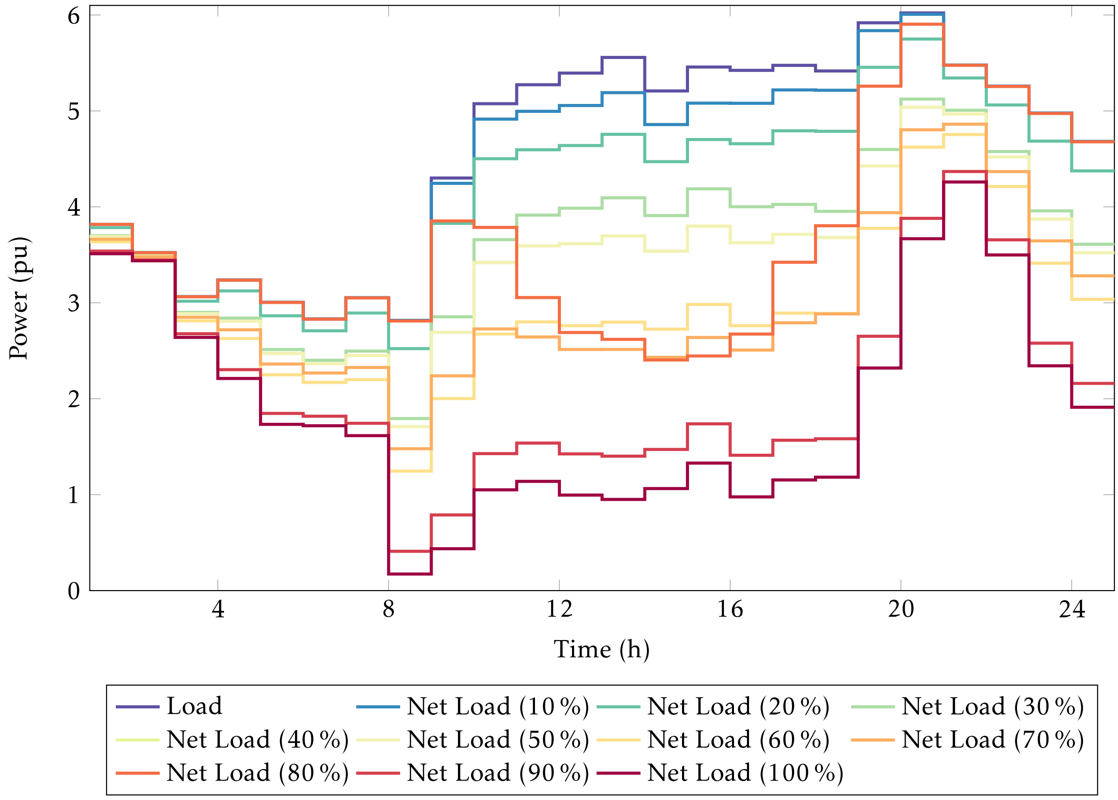


Figure B.3: Baran Network – Load and Net Load Profiles (% DRES Insertion)

B.3 ADDITIONAL DATA – PREDIS NETWORK

The per-unit resistances and reactances for the PREDIS test network are presented in Table B.4. These per-unit values are calculated on a base of 11 kV and 100 MVA.

Table B.4: PREDIS Test Network – Line Resistances and Reactances

Node From	Node To	Resistance (pu)	Reactance (pu)	Node From	Node To	Resistance (pu)	Reactance (pu)
1	2	0.001	0.800	3	13	0.395	0.160
1	3	0.001	1.600	11	10	1.680	2.625
1	10	0.001	1.600	12	11	1.680	2.625
2	5	0.560	0.875	12	13	0.560	0.875
2	4	0.250	0.216	4	7	0.613	0.350
2	8	1.330	0.585	6	9	0.153	0.088
4	6	0.766	0.438	3	8	0.067	0.029
5	9	0.056	0.088	9	10	0.040	0.016
8	7	0.613	0.350				

The spread of load types in the different nodes in the network is shown in Fig. B.4. The nodes 3 and 11 have industrial loads. However, this is only to construct the load profiles, and not for load modulation. Since this is a real-world test network where loads can be finely controlled, only type-2 load modulation is associated to the loads in this network. The connected load and load power factor at each of the nodes in the network is shown in Table B.5. The load values have been calculated on a 100 MVA base. The load and net load profiles for 50 % DRES insertion rate are illustrated in Fig. B.5. These profiles are based on the weights introduced in Section 5.1.3.1 of Chapter 5, and are used in the test cases presented in Section 5.3 of the same chapter.

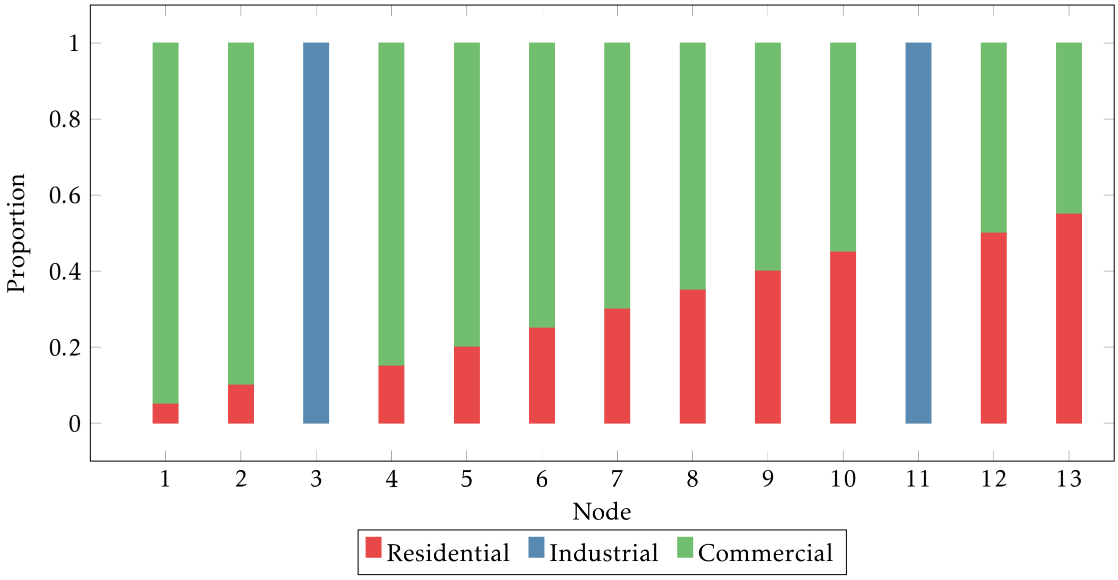


Figure B.4: PREDIS Network – Load Proportions per Node

Table B.5: PREDIS Test Network – Loads

Node	Load Power Active (pu)	Load Power Reactive (pu)	Power Factor ($tan\phi$)	Node	Load Power Active (pu)	Load Power Reactive (pu)	Power Factor ($tan\phi$)
1	0	0	0	8	0.0375	0.015	0.4
2	0.060	0	0	9	0	0	0
3	0	0	0	10	0.02	0.008	0.4
4	0.02	0.008	0.4	11	0.01	0	0
5	0.01	0	0	12	0.01	0	0
6	0.01	0	0	13	0	0	0
7	0.01	0	0				

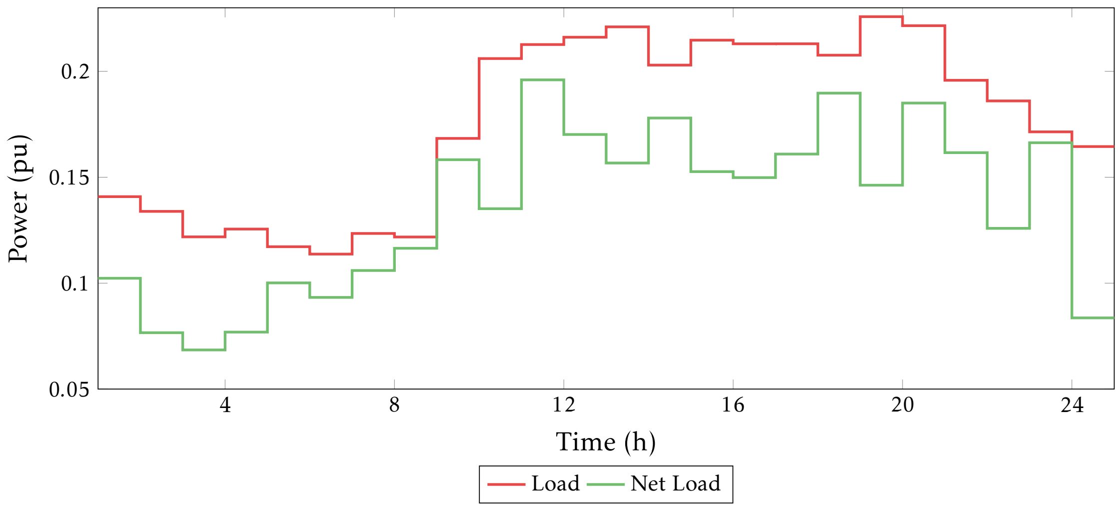
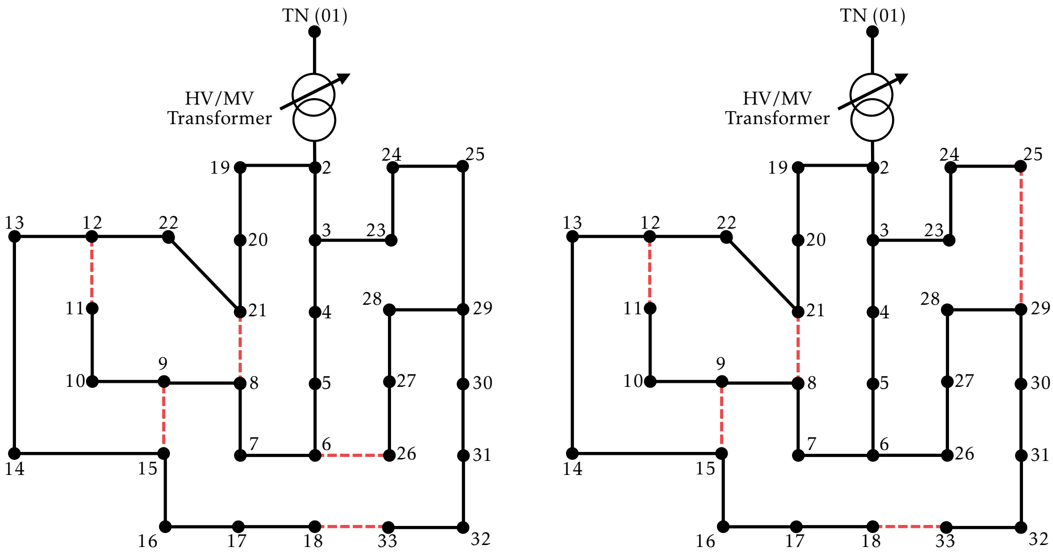


Figure B.5: PREDIS Network – Load and Net Load Profiles (50 % DRES Insertion)

B.4 NOVEL OP FORMULATION – ADDITIONAL RESULTS

B.4.1 Baran Network – Configurations

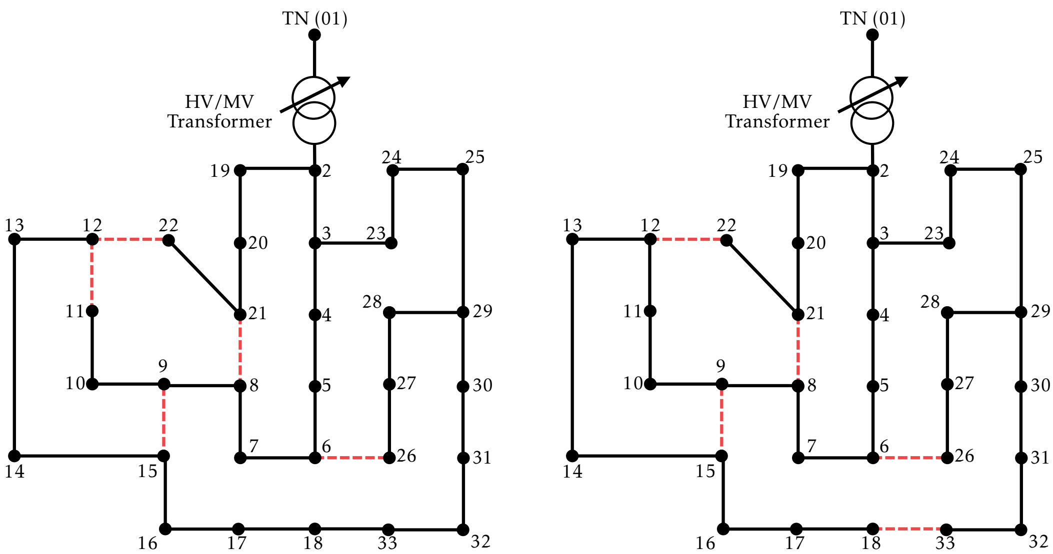
The novel OP formulation and the OP formulations under uncertainty chose 6 different configurations for the Baran network. These configurations, numbered C1 to C6, are illustrated here. The configurations C1 and C2 are first shown in Fig. B.6. The dotted red lines are the open lines in each of the configurations.



(a) C1 (b) C2

Figure B.6: Baran Network – Configurations C1 – C2 showing open lines

The open lines in configuration C1 are {6-26, 8-21, 9-15, 11-12, 18-33}. The open lines in configuration C2 are {8-21, 9-15, 11-12, 18-33, 25-29}. The configurations C3 and C4 are shown in Fig. B.7.



(a) C3 (b) C4

Figure B.7: Baran Network – Configurations C3 – C4 showing open lines

The open lines in configuration C3 are {6-26, 8-21, 9-15, 11-12, 12-22}. The open lines in configuration C4 are {6-26, 8-21, 9-15, 12-22, 18-33}. The configurations C5 and C6 are shown in Fig. B.8.

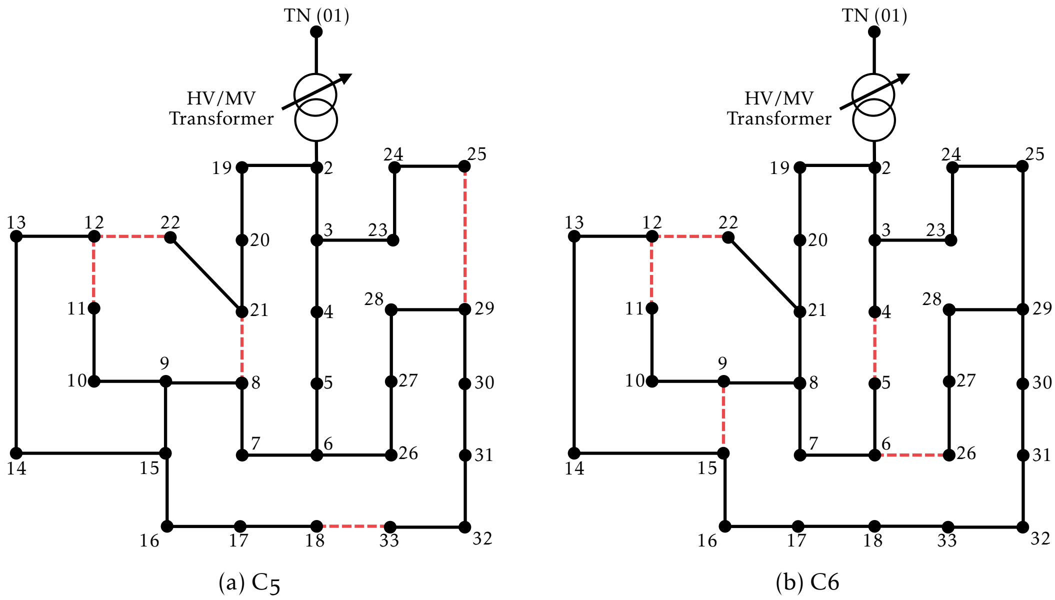


Figure B.8: Baran Network – Configurations C5 – C6 showing open lines

The open lines in configuration C5 are {8-21, 11-12, 12-22, 18-33, 25-29}. Finally, the open lines in configuration C6 are {4-5, 6-26, 9-15, 11-12, 12-22}.

B.4.2 *Additional Results – Test Case OP – eol3b*

The test case for which these results are presented is *OP – eol3b*. The results for DRES insertion rates from 10 % to 100 % are presented. The test with 90 % DRES insertion is the only test where the unoptimised network shows over-voltage problems. The unoptimised and optimised voltages for this network are therefore shown in Fig. B.9 as heat-maps. The colour profile is maintained across the figures to facilitate understanding.

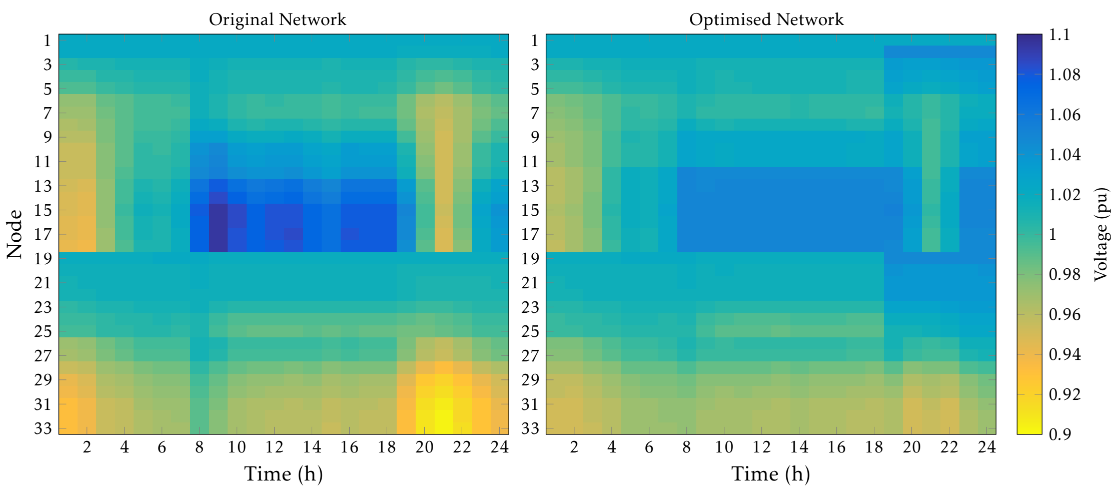


Figure B.9: Original and Optimised Voltages – Test Case *OP – eol3b* – 90 % DRES Insertion

There are a total of 66 over-voltage violations in the original network. All the over-voltage violations occur in nodes 12-18 between hours 8-18. The highest observed voltage in the network is 1.094 pu, occurring in node 15 during hour 9. They are provoked by the DRES in nodes 11, 15, and 17.

As for under-voltage violations, there are a total of 55 such violations in the network. They occur during the beginning (hours 1 & 2) and during the end (hours 19-24) of the day, in nodes 13-18 and 28-33. The lowest observed voltage is 0.904 pu occurring at node 33 during hour 21. In the optimised network, all these voltage violations are eliminated. The lowest and highest observed voltages in the optimised network are 0.95 and 1.05 pu respectively.

The load modulation chosen by the novel OP formulation in this test case for all DRES insertion rates is illustrated in Fig. B.10. The maximum load modulation used is for the case with 100 % DRES insertion, where 1318.8 kWh of load is reduced. The least amount of load modulation used is in the case with 30 % DRES insertion. Here, no load reduction occurs.

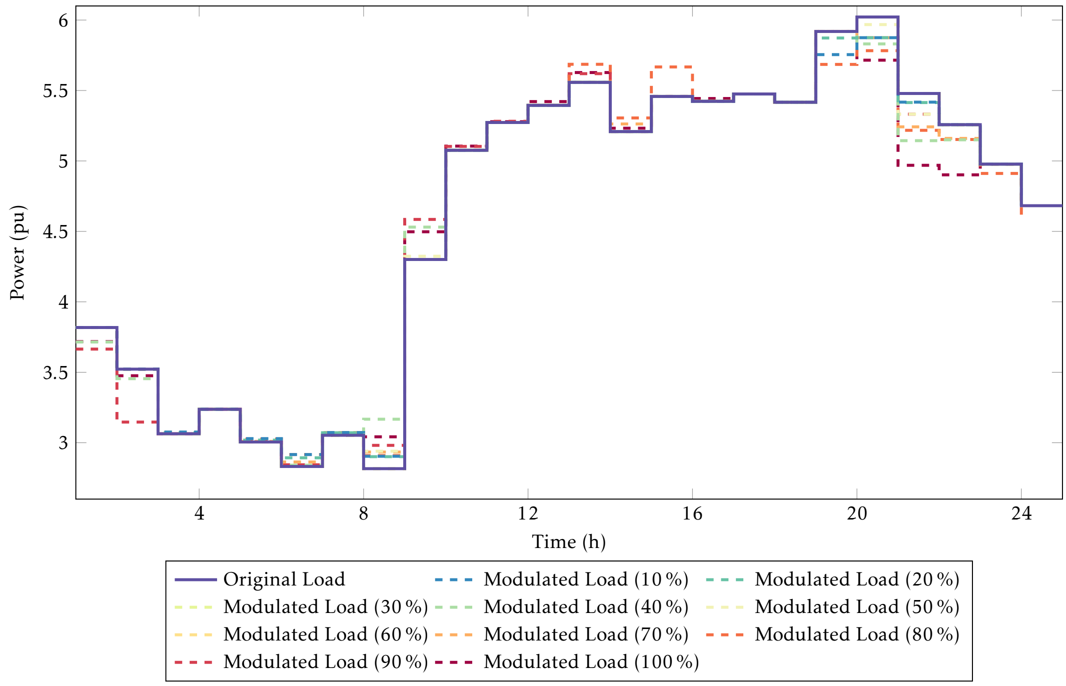


Figure B.10: Load Modulation vs Time for DRES Insertion Rates – Test Case *OP – eol3b*

The cumulative load modulated for all the insertion rates is shown in Fig. B.11. The figure also shows the proportion of each of the type of load modulation within the modulated load. Type-3 load modulation is by-far the most utilised load modulation. Its utilisation averages 0.323 MWh across the tests. Types 1 & 2 average 0.057 and 0.13 MWh respectively. This is understandable, as type-3 load modulation is economically interesting, even with the rebound constraint. Type-2 modulation is also easier to use, as it is modelled as a continuous flexibility.

For DRES insertion rates of 50, 80, 90, and 100 %, the available DRES reactive power compensation is not fully used. For example, for the case with 80 % insertion, the DRES consumes reactive power in order to regulate the voltage. This is illustrated in Fig. B.12.

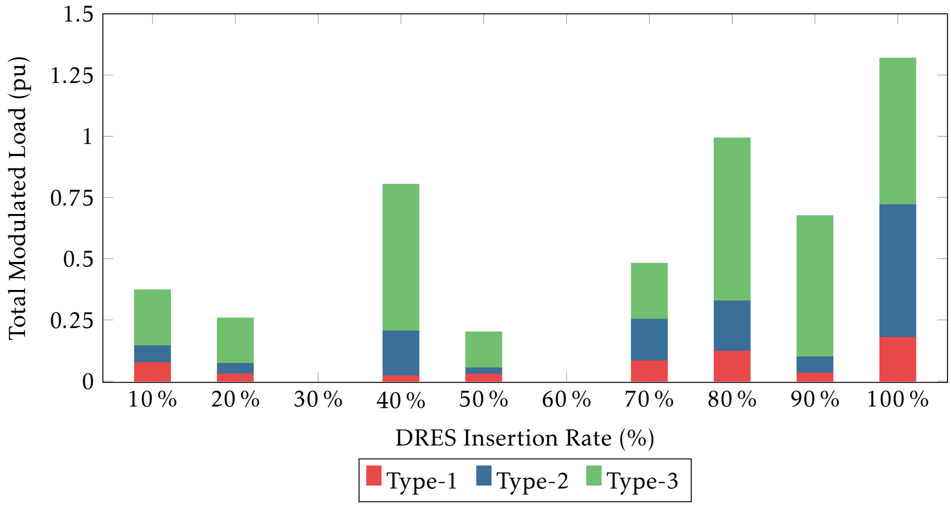


Figure B.11: Cumulative Load Modulation for DRES Insertion Rates with Type – Test Case *OP – eol3b*

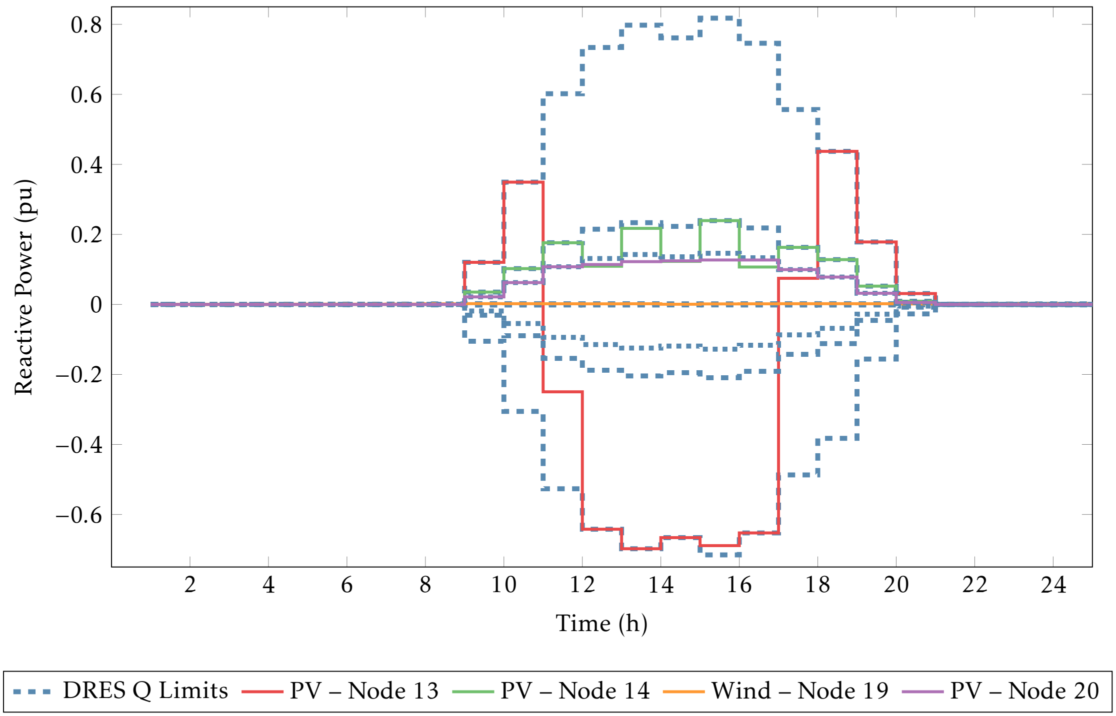


Figure B.12: Reactive Power Compensation for Test Case *OP – eol3b* with 80 % DRES Insertion

The net reactive power compensation in this case was 0.105 MVArh. The total reactive power injection was 3.703 MVArh, while the total consumption was 3.597 MVArh. Reactive power is consumed by the inverter of the PV generator in node 13 during the hours 14 – 18. This is because of the high active power injection from this PV generator during these hours, causing a voltage increase in the feeder where it is connected.

This difference can be clearly seen in the node voltages in this feeder, as illustrated in Fig. B.13. Without DRES reactive power consumption, there are a total of 30 over-voltage violations in the network. These violations occur predominantly during hours 10 to 19. The highest voltage in the network without reactive power consumption would have been 1.072 pu.

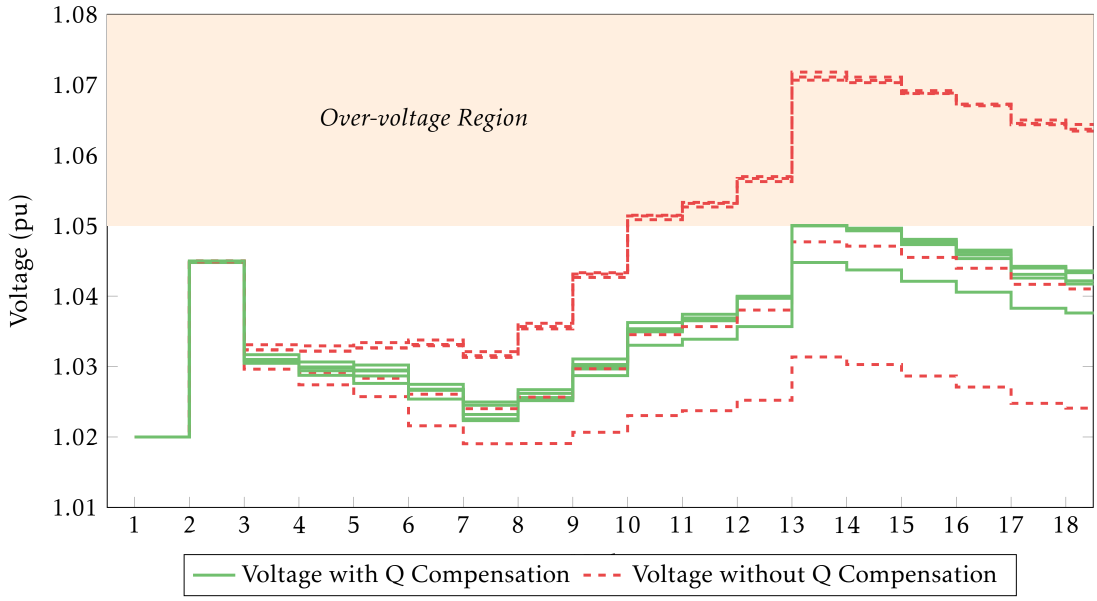


Figure B.13: Voltages with and without Q-Compensation for Test Case *OP – eol3b* with 80 % DRES Insertion

The proportion of DSO expenditures across the DRES insertion rates is shown in Fig. B.14. The main components of the expenditures are Losses (red), Load Modulation (orange), Reconfiguration (green), and OLTC (blue). There is no DRES curtailment. The use of battery systems is imperceptible and is therefore not shown.

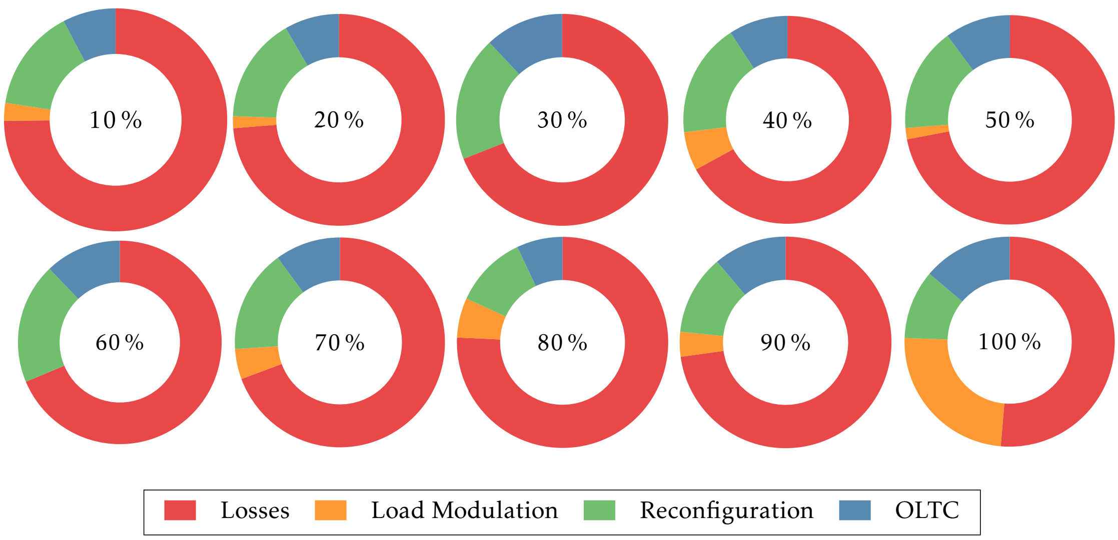


Figure B.14: Proportion of DSO Expenditures – Test Case *OP – eol3b* for 10-100 % DRES Insertion

The results show that, as is the case with all the other results, the highest expenditures arise out of copper losses (51.3 % - 75.7 %). This is not completely borne by the DSO, as they will eventually transfer these expenditures on to the customers. However, as explained earlier in this thesis, the reduction of losses is an important step for DSOs in order to eventually comply with national regulation, and to gain incentives / avoid penalties. Reconfiguration is the second biggest expenditure on an average for the DSOs across the tests (10.6 % - 19.2 %), followed by OLTCs (7 % - 13.8 %), load modulation (0 % - 24.2 %), and batteries (imperceptible use).

B.5 OP UNDER UNCERTAINTY – ADDITIONAL RESULTS

B.5.1 Two-Stage Deterministic OP – DRES Q-Compensation and Battery Use

The additional results for the hour-ahead stage of the two-stage deterministic OP formulation are presented here. We first illustrate one of the recourse actions in the hour-ahead stage, DRES reactive power compensation. This free recourse action is shown in Fig. B.15. The set-points for Q-compensation from the three DRES units in the network change in the hour-ahead stage. This change is shown in the figure. The dashed lines represent the day-ahead set-points for the DRES, while the bold lines represent the hour-ahead set-points.

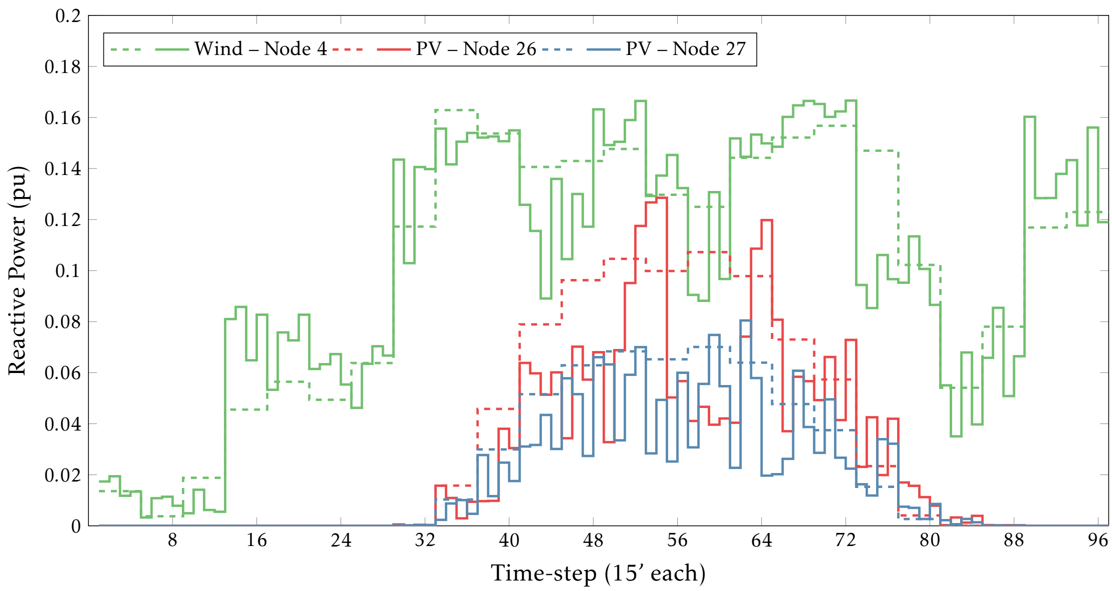


Figure B.15: Two-Stage Deterministic OP – Recourse Actions for DRES Q-Compensation

The difference in the set-points is primarily due to the change in DRES active power production. In all the cases, the ratio of the reactive power to the active power of the DRES remains close to the 40 % limit for reactive power injection. The second recourse action is the use of the battery. The power injection from the battery amounts to 35.64 kWh in the hour-ahead stage of the optimisation. This is illustrated in Fig. B.16 as a function of the nodes and the time periods.

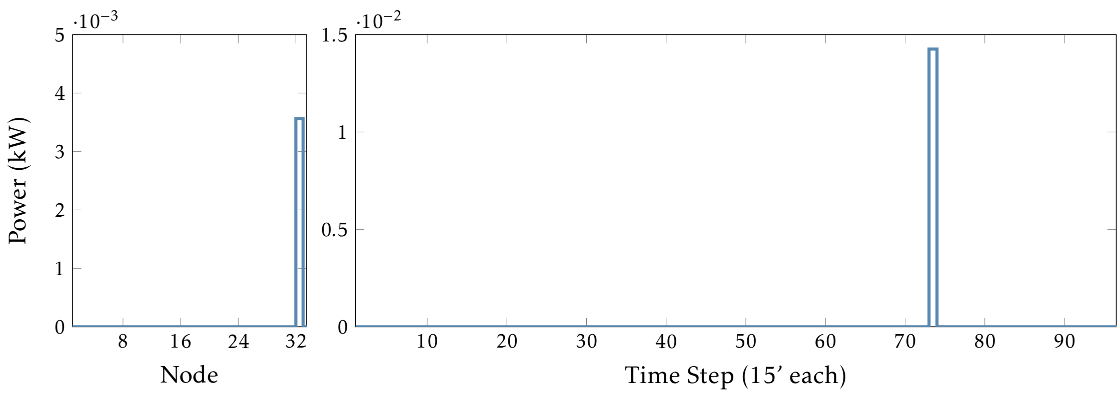


Figure B.16: Two-Stage Deterministic OP – Hour-Ahead Battery Use

As seen from the figure, the injection is provided by the battery situated in node 32, at time period 73 (second 15' period in the 19th hour of the day). This is the only time period in which the battery is used in both in the entire optimisation. We remind the reader that the day-ahead stage had no battery use.

It is to be noted that for node 32, the figure shows a battery injection (in terms of power) of 35.64 kW. For time period 73, the same injection is 142.56 kW. This is because the power injected in the node is expressed for a period of one hour, while the injection in the time periods is expressed for a period of 15 minutes. The final injected energy is the same (35.64 kWh), whether expressed with respect to the node or to the time period ($142.56 \cdot 0.25 = 35.64$ kWh).

B.5.2 Stochastic OP – DRES Q-Compensation and Battery Use

The additional results for the stochastic OP formulation are presented here. Given that the formulation has 10 scenarios, the utilisation of flexibilities whose values can change across scenarios are an interesting source of information. We first analyse the DRES Q-compensation in the different scenarios. Two illustrations to this effect are presented in Fig. B.17.

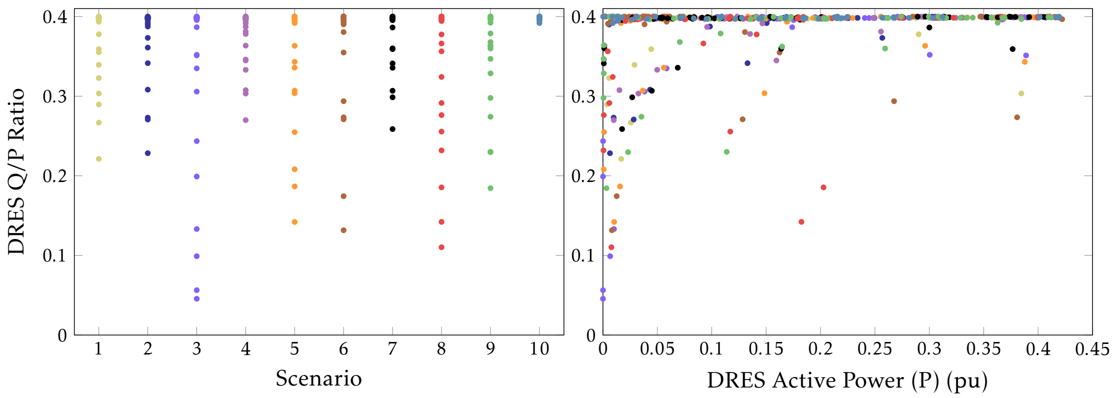


Figure B.17: Stochastic OP – DRES Q-Compensation across Scenarios

In the sub-figure on the left, the ratio of reactive to active power is represented for all the DRES in the network for each scenario. Each scenario is represented by a particular colour of the scatter marker. In the sub-figure on the right, the same ratio is represented as a function of the active power that the DRES produces. The colour of the scatter markers are maintained in this figure.

Scenario 10 shows the tightest set of DRES Q-compensation set-points, while scenario 3 has the set with the widest range of set-points. There is no correlation between the lack of DRES production and the Q-compensation (injection). Intuition would however dictate that this be the case, given that lower DRES production values are associated to lower network voltages for the Baran network.

In Chapter 7, the battery injection in Scenario 10 was illustrated. The other scenarios in which battery systems are used are scenarios 1, 4, and 5. In these scenarios however, the battery systems are used to a much lesser extent than in scenario 10 (3.46, 6.68, and 7.88 kWh, as compared to 355.7 kWh). These injections are illustrated in Fig. B.18.

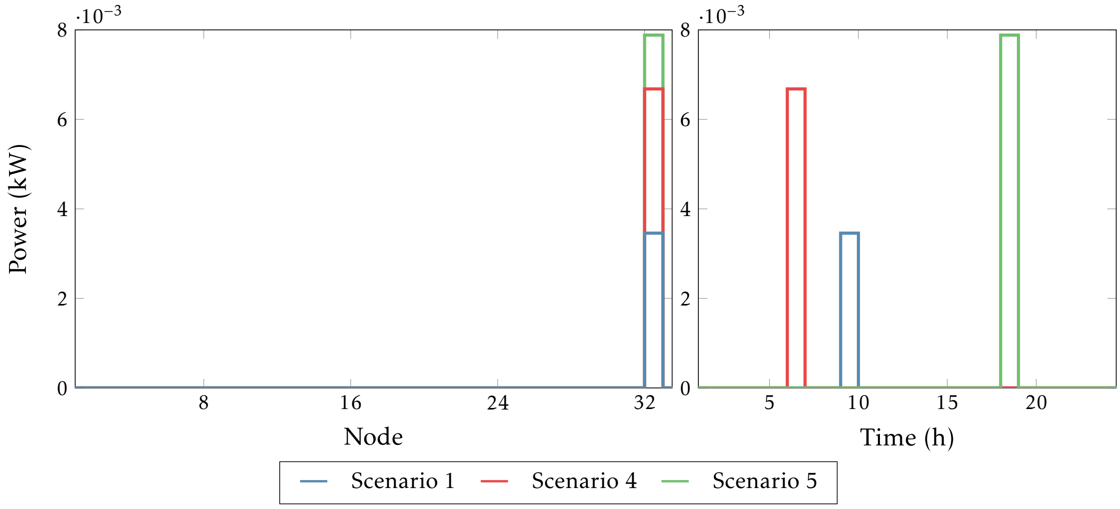


Figure B.18: Stochastic OP – Battery Use in Scenarios 1, 4 & 5

B.5.3 *Interval OP – The Use of Load Modulation*

The results presented here complement those presented for the load modulation obtained using the interval OP formulation in Section 7.4 in Chapter 7. The overall modulated load was presented in Fig. 7.17 in the same chapter. We now illustrate the modulation at individual nodes. Nine nodes where chosen for load modulation in all. Of these nodes, three nodes were chosen for type-2 load modulation: 29, 31, and 33. The load modulated in these nodes is shown in Fig. B.19.

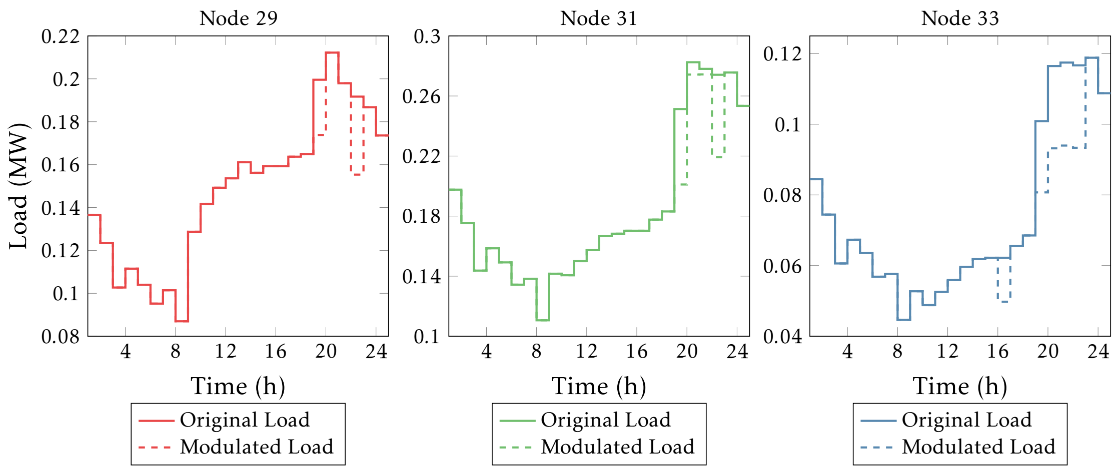


Figure B.19: Interval OP – Type-2 Load Modulation

In node 29, 62.1 kWh of load is reduced during hours 19 & 22. In node 31, 117.1 kWh is reduced during hours 19-22. And in node 33, 102.7 kWh is reduced during hours 16 & 19-22. Type-3 load modulation is employed in 6 nodes of the network: 8, 10, 26, 28, 30, and 32. Fig. B.20 shows the load modulated in nodes 8, 10, and 26.

In node 8 of the network, type-3 load modulation is solicited twice during the day, at hours 19 and 22. The load reduction achieved through this modulation amounts to 267.5 kWh. In node 10, type-3 load modulation is solicited once, during hour 20, for a reduction of 42.9 kWh. And in node 26, type-3 load modulation is solicited twice, during

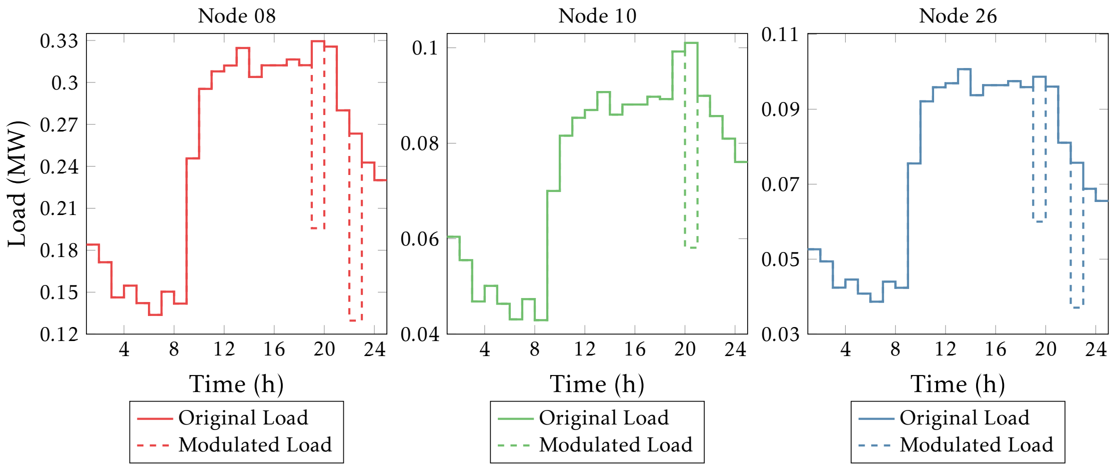


Figure B.20: The Interval OP Formulation – Type-3 Load Modulation (1)

hours 19 and 22, for a total reduction of 77.3 kWh. Fig. B.21 shows the load modulation achieved in nodes 28, 30, and 32.

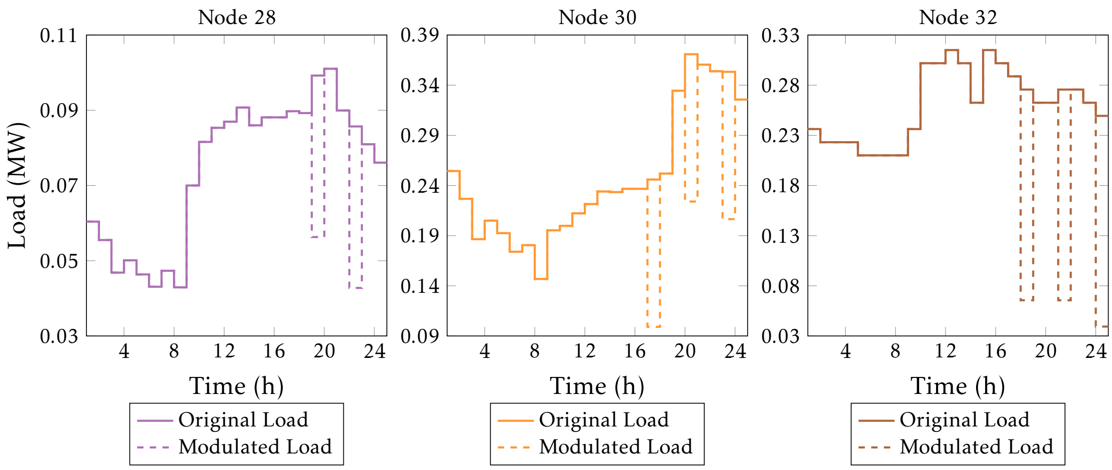


Figure B.21: The Interval OP Formulation – Type-3 Load Modulation (2)

In node 28, type-3 modulation is solicited twice, during hours 19 and 22. The load reduction achieved in the node is 85.8 kWh. In node 30, it is solicited thrice, during hours 17, 20, and 23, for a total reduction of 440.6 kWh. It is also solicited thrice in node 32, during hours 18, 21, and 24, with a total reduction of 630.1 kWh.

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Power systems are faced by the rising shares of distributed renewable energy sources (DRES) and the deregulation of the electricity system. Distribution networks and their operators (DSO) are particularly at the front-line. The passive operational practices of many DSOs today have to evolve to overcome these challenges. Active Distribution Networks (ADN), and Active Network Management (ANM) have been touted as a potential solution. In this context, DSOs will streamline investment and operational decisions, creating a cost-effective framework of operations. They will evolve and take up new roles and optimally use flexibility to perform, for example, short-term operational planning of their networks. However, the development of such methods poses particular challenges. They are related to the presence of discrete elements (OLTCs and reconfiguration), the use of exogenous (external) flexibilities in these networks, the non-linear nature of optimal power flow (OPF) calculations, and uncertainties present in forecasts. The work leading to this thesis deals with and overcomes these challenges. First, a short-term economic analysis is done to ascertain the utilisation costs of flexibilities. This provides a common reference for different flexibilities. Then, exact linear flexibility models are developed using mathematical reformulation techniques. The OPF equations in operational planning are then convexified using reformulation techniques as well. The mixed-integer convex optimisation model thus developed, called the novel OP formulation, is exact and can guarantee globally optimal solutions. Simulations on two test networks allow us to evaluate the performance of this formulation. The uncertainty in DRES forecasts is then handled via three different formulations developed in this thesis. The best performing formulations under uncertainty are determined via a comparison framework developed to test their performance.

Keywords: Active Distribution Networks, Convex Optimisation, Integration of Renewables, Flexibility, Mathematical Reformulations

Les réseaux électriques subissent deux changements majeurs : le taux croissant de générateurs d'énergie distribuée (GED) intermittents et la dérégulation du système électrique. Les réseaux de distribution et leurs gestionnaires (GRD) sont plus particulièrement touchés. La planification, construction et exploitation des réseaux de la plupart des GRD doivent évoluer face à ces changements. Les réseaux actifs de distribution et la gestion intelligente de associée est une solution potentielle. Les GRD pourront ainsi adopter de nouveaux rôles, interagir avec de nouveaux acteurs et proposer de nouveaux services. Ils pourront aussi utiliser la flexibilité de manière optimale au travers, entre autres, d'outils intelligents pour la gestion prévisionnelle de leurs réseaux de moyenne tension (HTA). Développer ces outils est un défi, car les réseaux de distribution ont des spécificités techniques. Ces spécificités sont la présence d'éléments discrets comme les régleurs en charge et la reconfiguration, les flexibilités exogènes, la non-linéarité des calculs de répartition de charge, et l'incertitude liée aux prévisions des GED intermittents. Dans cette thèse, une analyse économique des flexibilités permet d'établir une référence commune pour une utilisation rentable et sans biais dans la gestion prévisionnelle. Des modèles linéaires des flexibilités sont développés en utilisant des reformulations mathématiques exactes. Le calcul de répartition de charge est "convexifié" à travers des reformulations. L'optimalité globale des solutions obtenues, avec ce modèle d'optimisation exact et convexe de gestion prévisionnelle, sont ainsi garanties. Les tests sur deux réseaux permettent d'en valider la performance. L'incertitude des prévisions de GED peut pourtant remettre en cause les solutions obtenues. Afin de résoudre ce problème, trois formulations différentes pour traiter cette incertitude sont développées. Leurs performances sont testées et comparées à travers des simulations. Une analyse permet d'identifier les formulations les plus adaptées pour la gestion prévisionnelle sous incertitude.

Mots-clés : Réseaux actifs de distribution, Optimisation convexe, Intégration des renouvelables, Flexibilité, Reformulations mathématiques