Dynamic vehicle routing : solution methods and computational tools

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JURY

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Preface

This Ph.D. thesis has been prepared at the Department of Industrial Engineering at Universidad de Los Andes (Colombia) and the Department of Automation and Production at École des Mines de Nantes (France), between October 2009 and September 2012. It has been supervised by Professor Andrés L. Medaglia at Universidad de Los Andes and Christelle Guéret at École des Mines de Nantes.

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The present dissertation is composed by an introductory chapter, five research papers, written in collaboration with the coauthors mentioned at the beginning of each paper, and a conclusion. Each research paper is self-contained, meaning that it comprises a description of the underlying problem, its contributions, computational experiments, conclusions, and its own bibliography. In addition to the research papers, the thesis includes six appendices: Appendices A, B, and C describe the software libraries and framework developed to support the research presented in the five papers. Appendix D and E present an instance generator and the best known solutions for the instances introduced in this thesis. Finally, Appendix F summarizes the record of publications of the work developed during this thesis.

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1. Almost Colombian

Contents

Introduction

Within the wide scope of logistics management, transportation plays a central role and is a crucial activity in the delivery of goods and services. Among others, it allows for the timely distribution between suppliers, production units, warehouses, retailers, and final customers. Transportation also has an important footprint in the trade economy and on the environment. According to Hesse and Rodrigue (2004), the total logistic costs in the year 2000 in the United States (US) represented 10% of the GDP (Gross Domestic Product), while transportation on its own accounted for 5.9% of the GDP. In addition, a recent report from the Energy Information Administration (EIA, 2011) indicates that transportation was responsible for 27% of the greenhouse gas emissions in the US in 2009, while the European Environment Agency estimates this share to be 24% in the European Union (EEA, 2011).

Therefore, improving the efficiency of transportation activities is a critical step to increase competitiveness and reduce the environmental impact of organizations. In this sense, operating a fleet of vehicles is a cornerstone problem that arises both in the service industry, with, among others, the transportation of less-able people, the scheduling of school buses, or the on-site maintenance activities; and in the goods industry, with, for instance, the transport of raw materials between suppliers and factories, the relocation of trucks in carrier companies, or the pickup and delivery of goods in the retail industry.

More specifically, Vehicle Routing Problems (VRPs) deal with the design of a set of minimal-cost routes that serve the demand for goods or services of a set of geographically spread customers, satisfying a group of operational constraints. Since its first definition by Dantzig and Ramser (1959), the amount of published material on VRP has exponentially increased. As an evidence of this trend, the recent study by Eksioglu et al. (2009) reports approximately 1,500 indexed publications on vehicle routing (as of 2006). The volume of publications is closely related to the variety of routing problems, and the diversity of approaches proposed to tackle them.

The original Capacitated Vehicle Routing Problem (CVRP or simply VRP) formulation is a generalization of the Traveling Salesman Problem (TSP) presented by Flood (1956). The VRP is defined on a graph $G = (\mathcal{V}, \mathcal{E}, \mathbf{C}, \mathbf{q})$, with $\mathcal{V} = \{v_0, ..., v_n\}$ being the set of vertices, $\mathcal{E}$ the arc set, $\mathbf{C} = (c_e)_{e \in \mathcal{E}}$ a cost matrix defined on $\mathcal{E}$, and $\mathbf{q} = (q_i)_{i \in \mathcal{V}}$ a vector of demands for a certain commodity. Traditionally, vertex v_0 is called the *depot*, while the remaining vertices represent *customers* that require a commodity to be delivered. The VRP consists in finding a set of routes of minimal cost for an unlimited fleet of vehicles of identical capacity Q, starting and ending at the depot, such that each of the customers is visited exactly once, while not exceeding the capacity of the vehicles.

The above definition has been extended in a variety of forms to model a wide range of practical

applications. Among the most common extensions are those that include time-window constraints that enforce the visit of each vertex within a given time interval; the pickup and delivery constraints that require the commodity to be picked-up at certain vertices before being delivered to others; the distance constraints that limit the total distance traveled by a vehicle; and accessibility constraints that limit the set of vehicles allowed to visit a given vertex. On the other hand, common variants of the original problem statement include multiple depots, from which vehicles can start and end their routes; the possibility to split customer deliveries; and heterogeneous and/or limited fleets. Finally, related problems consider multi-period horizons; the combination of routing with inventory management; multiple levels of routing with trucks feeding hubs from which smaller vehicles start delivery routes (Nguyen et al., 2012a,b); vehicles with trailers that can be detached to visit customers with accessibility constraints; and arc-routing problems in which the demand is located on the arcs (Belenguer et al., 2010; Corberán and Prins, 2010).

Parallel to the myriad of variants, a number of optimization approaches have been proposed to tackle routing problems. We refer the interested reader to the surveys by Baldacci et al. (2007); Cordeau et al. (2007); Laporte (2009), and Toth and Vigo (2002) for a complete review of both exact and approximate approaches.

Recent exact approaches for the VRP are based on three base formulations: vehicle flow, commodity flow, and set partitioning. Vehicle flow formulations (Lysgaard et al., 2004; Naddef and Rinaldi, 2002) define an integer variable for each arc that counts the number of times a vehicle travels through it. Commodity flow formulations (Baldacci et al., 2004) are based on a continuous variable for each arc that models the flow of commodities between vertices. Finally, set partitioning formulations (Baldacci et al., 2010, 2007; Feillet, 2010; Feillet et al., 2005, 2004; Fukasawa et al., 2006; Rousseau et al., 2007) consider the set of all feasible routes and select a subset of routes of minimal cost such that all the constraints are satisfied. As it is often impossible to enumerate the whole set of feasible solutions, such approaches generally rely on a column generation scheme that iteratively generates feasible routes for the set covering model.

Despite the advances in algorithms and the constant growth of computational power, state-of-the-art exact approaches are only able to solve problems with approximately one hundred vertices, which is well below the typical size of problems faced in industry. In addition, exact approaches are closely tied to a specific VRP variant, and may take several hours to produce a solution. As a consequence, a number of (faster) approximate approaches have been developed to tackle the VRP and its variants. Approximate approaches can be divided in three categories: *classical heuristics*, *metaheuristics*, and *matheuristics*.

Classical heuristics are further divided in three categories: *constructive*, *two-phase*, and *improvement* heuristics. A well-known constructive heuristic is the Clarke and Wright (1964) savings algorithm that starts by creating one route per customer and then iteratively merges routes until the total distance can no longer be reduced. Petal heuristics (Gillett and Miller, 1974; Renaud et al., 1996; Ryan et al., 1993) are another class of constructive heuristics that start by generating a set of feasible routes, and then solve a set partitioning model to build a feasible solution. The two-phase approaches include the cluster-first, route-second (CR) and route-first, cluster-second (RC) heuristics. The CR heuristics were introduced by Fisher and Jaikumar (1981) and consists in grouping customers into clusters with-

out violating the vehicle capacity, and then solving a TSP for each cluster. The RC heuristics start by designing a giant tour visiting all customers that is then split into feasible routes. Prins (2004) demonstrated that properly-designed RC heuristics can bring significant improvements when embedded in more complex methods (Mendoza et al., 2010, 2011; Prins, 2009b; Prins et al., 2009; Villegas et al., 2010, 2011a). Finally, improvement heuristics attempt to improve a solution by considering moves that alter the sequence of customers within a route and/or exchange customers between different routes. Each type of move defines a *neighborhood* of the considered solution. Among the most widely used neighborhoods are swap, 2-opt, 3-opt (Lin, 1965), Or-opt (Or, 1976), and string exchange. The efficiency of improvement heuristics depends to a great extent on the implementation of the neighborhood exploration. For instance, Irnich et al. (2006) propose a decomposition scheme, namely sequential search, and report speedup factors of up to 10^4 for the exploration of the 3-opt neighborhood against a naive implementation.

Metaheuristics are optimization paradigms which main objective is to overcome limitations of the classical heuristics, in particular, their tendency to get trapped in local optima and their lack of robustness. Among the most popular single-solution metaheuristics are Tabu Search (TS) (Gendreau et al., 1994; Glover, 1986; Taillard, 1993; Toth and Vigo, 2003), Simulated Annealing (SA) (Kirkpatrick et al., 1983; Osman, 1993), Greedy Randomized Adaptive Search Procedure (GRASP) (Feo and Resende, 1989; Hashimoto et al., 2011; Prins, 2009a; Villegas et al., 2010), and Large Neighborhood Search (LNS) (Bent and Van Hentenryck, 2004; Pisinger and Ropke, 2007, 2010; Shaw, 1998). Population-based metaheuristics include Genetic Algorithms (GA) (Holland, 1975), Memetic Algorithms (MA) (Bontoux et al., 2010; El-Fallahi et al., 2008; Labadi et al., 2008a,b; Mendoza et al., 2010; Prins, 2009b; Vidal et al., 2011), and Ant Colony Optimization (ACO) (Bontoux and Feillet, 2008; Reimann et al., 2004). We refer the interested reader to the work by Bräysy and Gendreau (2005); Cordeau et al. (2005, 2002); Prins et al. (2010), and Gendreau et al. (2002) for an in-depth analysis of the latest advances in metaheuristics in the field of vehicle routing.

Finally, a recent trend combines heuristics with exact approaches, in what is commonly referred to as matheuristics (Maniezzo et al., 2009). In their review, Puchinger and Raidl (2005) make a distinction between collaborative and integrative matheuristics. In collaborative approaches, heuristics and exact algorithms exchange information to build a solution. This is for instance the case of the Lagrangean relaxation granular TS introduced by Prins et al. (2007), or the approach proposed by Archetti et al. (2008) for the VRP with split deliveries. More recently, researchers have used mixed integer programming as a post-optimization procedure to aggregate partial solutions explored in a metaheuristic. For instance, Villegas et al. (2011b) tackled the Truck and Trailer Routing Problem by first generating solutions using a GRASP based approach, and then solving a set-covering problem (SC) using the routes generated during the search. Pillac et al. (2012f) applied a similar approach using the solutions generated by an Adaptive Large Neighborhood Search. Finally, Mendoza and Villegas (2011, 2012) propose a simple yet effective matheuristic for the VRP with Stochastic Demands (VRPSD) that generates a large number of routes using randomized constructive heuristics and then solves a SC to build a solution, reporting state-of-the-art results. On the other hand, integrative matheuristics embed one technique into another. A sample of integrative heuristics include the Large Neighborhood Search algorithms in which an exact approach (either Integer Programming or Constraint Programming) is used to optimally ex-

plore the neighborhood of a solution (De Franceschi et al., 2006; Mouthuy et al., 2012; Prescott-Gagnon et al., 2009; Rousseau et al., 2002); the hybrid TS proposed by Ngueveu et al. (2010), which solves a b-matching problem to guide a TS procedure; or the heuristic column generation proposed by Massen et al. (2012).

Despite the development of efficient optimization algorithms that produce high quality solutions, Sörensen et al. (2008) point out that commercial routing software does not take full advantage from state-of-the-art algorithms but instead embed a large toolbox of simpler heuristics. The gap between academic research and industrial practice can be explained by the fact that the two communities face diverging incentives. Academia is driven by the publication of ground-breaking results on well-known sets of instances, or alternatively by the definition of novel optimization problems. Therefore, research is biased toward highly specialized methods able to solve a particular problem with optimal or nearly-optimal results. In contrast, industry requires that the resources invested on the development of a new decision support system (DSS) translate in significant gains once the system is operational. In this perspective, it is more efficient to develop and maintain a set of simple optimization components that fit a variety of problems and produce relatively good results, than to invest resources in the development of complex approaches tailored for a specific problem that will only bring marginal improvements.

Nonetheless, a thriving trend in the routing community attempts to develop methods able to tackle a variety of practical problems. This trend follows two main streams: *rich vehicle routing* (Doerner and Schmid, 2010; Schmid et al., 2012), which focuses on routing problems that simultaneously consider features from several VRP variants; and *unified optimization approaches*, which are designed to account for a variety of business constraints, like the Adaptive Large Neighborhood Search introduced by Pisinger and Ropke (2007) or the Unified Hybrid Genetic Search proposed by Vidal et al. (2012).

An alternative approach to foster technology transfer from academia to industry is the release of state-of-the-art algorithms as open source projects. Successful stories at the intersection of the operations research and computer science communities include the COIN-OR project [2], which puts together a variety of frameworks from metaheuristics to linear and non-linear solvers; GLPK [3], a solver for linear and mixed integer programming; Paradiseo [4], a framework for the design of metaheuristics; and Choco [5], a Constraint Programming solver implemented in Java. There exists a limited number of open-source projects that provide optimization frameworks for vehicle routing. As surveyed by Lodi and Punnen (2004), most of these initiatives are devoted to the resolution of the TSP, and to the best of our knowledge, the remaining focus on the CVRP. For instance, SYMPHONY (Ralphs et al., 2012; Ralphs, 2003; Ralphs et al., 2003) and CVRPSD (Lysgaard et al., 2004) tackle the optimal resolution of the CVRP using mathematical programming. Other projects include VRPH (Groër et al., 2010), a C/C++ framework based on local search; jCW (Mendoza et al., 2008), an object oriented implementation in Java of generalized saving heuristics; and jSplit (Villegas et al., 2008), a Java framework for the rapid development of cluster-first, route-second heuristics.

Most routing algorithms and software often rely on the assumption that all the information is known with certainty. However, in many applications, part or all the information is uncertain. An

2. `http://coin-or.org`
3. `http://www.gnu.org/s/glpk`
4. `http://paradiseo.gforge.inria.fr`
5. `http://www.emn.fr/z-info/choco-solver`

obvious example are travel times that fluctuate greatly depending on traffic or weather conditions, especially in urban areas. These problems are referred to as static and stochastic, and common examples include: stochastic customers, where a customer needs to be serviced with a given probability (Bertsimas, 1988; Waters, 1989); stochastic times, in which either service or travel times are modeled by random variables (Kenyon and Morton, 2003; Laporte et al., 1992; Verweij et al., 2003); and lastly, stochastic demands (Christiansen and Lysgaard, 2007; Dror et al., 1989; Laporte et al., 2002; Mendoza et al., 2011, 2009; Secomandi, 2000; Secomandi and Margot, 2009) where customer demands are known as probability distributions. Further details on the static stochastic vehicle routing can be found in the reviews by Bertsimas and Simchi-Levi (1996); Cordeau et al. (2007), and Gendreau et al. (1996).

In addition, recent advances in communication and geolocation technologies now allow companies to economically track their fleet in real time. These new technologies lead to the development of Intelligent Transport Systems (ITS), and more precisely Advanced Fleet Management Systems (AFMS), that combine hardware and software solutions to provide real time information on the fleet, customers, and road networks. The development of ITS and AFMS creates new challenges and opportunities for operations research. Vehicle routing is no longer limited to the design of a-priori routes that cannot be altered once the vehicles have departed the depot. Instead, it can now consider real-time reoptimization of routes, leading to what is referred to as dynamic vehicle routing problems. Nonetheless, Crainic et al. (2009) point out that while the hardware part of ITS has considerably evolved, the corresponding Decision Support Systems (DSS) and optimization models have not yet reached their maturity. Therefore, the advent of such systems require the development of a new class of efficient optimization algorithms able to manage fleets in real time.

The purpose of this dissertation is to review the state-of-the-art in the area of dynamic routing, design new algorithms for this class of problems; implement general-purpose software components that are both reusable and adaptable to a wide range of variants; apply the proposed algorithms to a real-world routing application; and finally, to release the proposed components as open-source packages to accelerate technology transfer from academia to industry.

Chapter 1 presents a comprehensive review of the literature on dynamic vehicle routing. We classify problems from the perspective of quality and evolution of information, identifying four categories depending on whether they are static or dynamic, and deterministic or stochastic. In the remaining discussion, we focuse on dynamic vehicle routing problems, for which we give a general definition and present metrics to measure their degree of dynamism. In addition, we illustrate the relevance of dynamic routing by listing applications in the service industry, transport of goods, and transport of persons. We provide an extensive review of solution methods for both dynamic and deterministic and dynamic and stochastic problems, present performance evaluation metrics, and list available benchmarks. We conclude by drawing directions for future research in this emerging field. This paper was submitted to the *European Journal of Operational Research* (Pillac et al., 2011a) and two earlier versions were published as technical reports (Pillac et al., 2011b, 2010a).

Chapter 2 focuses on dynamic and deterministic routing problems in which part or all of the input is unknown and revealed dynamically during the design or execution of routes. An important feature is that no information is available on the dynamically revealed data, therefore solution methods cannot anticipate changes in input, but may only react to them. In this chapter, we consider routing problems

in which new customers appear during the execution of routes, requiring updates in the routing plan. We propose a fast re-optimization approach, namely parallel Adaptive Large Neighborhood Search (pALNS), which produces high quality routing in limited computational time. We then illustrate its performance on a set of Dynamic Vehicle Routing Problem with Time Windows (D-VRPTW) instances derived from the Solomon (1987) benchmark. Noting that the common assumption that vehicle drivers do not know their next destination until they finish serving their current customer may not be desirable from a practical perspective, we introduce the notion of driver inconvenience and define a bi-objective optimization problem that minimizes the routing cost while maintaining its consistency throughout the day. We consider a context in which vehicles have an initial routing plan at the beginning of the day, that is then periodically updated by a decision maker. We introduce a measure of the driver inconvenience resulting from each update, and propose a bi-objective approach based on pALNS, namely pBiALNS, that is able to produce a set of non-dominated solutions in reasonable computational time. These solutions offer different tradeoffs between cost efficiency and consistency, and can be used by the decision maker to update the vehicle routing introducing a controlled number of changes. Our computational experiments study the tradeoff between cost efficiency and route consistency, and show that pBiALNS is able to produce a variety of alternative solutions in a few seconds. This chapter was published as a technical report (Pillac et al., 2012b), and an earlier version was presented at the ROADEF 2012 conference (Pillac et al., 2012g). Details on the implementation of the pALNS and pBiALNS algorithms are presented in Appendix C.

In dynamic and stochastic problems part or all the input is unknown and revealed dynamically during the execution of the routes, yet exploitable stochastic knowledge is available on the dynamically revealed information. Chapter 3 presents an event-driven framework based on a multiple scenario approach called `jMSA`. This framework is flexible, parallelized, and easily embeddable in a decision support system. It can cope with a wide variety of dynamic vehicle routing problems and may be extensible to other dynamic combinatorial optimization problems. `jMSA` generates and maintains a pool of scenarios, each containing a realization of the random variables modeling the dynamically revealed data. This pool is then used to take the routing decisions whenever required. We illustrate the flexibility of the framework by solving the VRP with Stochastic Demands and show that our approach is competitive against the state-of-the-art algorithms. This chapter was accepted for publication in *Decision Support Systems* (Pillac et al., 2012a), an earlier version of this work was published as a technical report (Pillac et al., 2011d), while preliminary results were presented at the ALIO-INFORMS 2010 and the ROADEF 2011 conferences (Pillac et al., 2010b, 2011c). Appendix C presents the implementation of the algorithm used to optimize scenarios, namely Adaptive Variable Neighborhood Search (AVNS).

In Chapter 4, we formally introduce the Technician Routing and Scheduling Problem (TRSP), which is motivated by the optimization problem faced by an industrial partner. The TRSP consists in routing a crew of technicians to serve a set of requests. Distinctive features of this problem are: the fact that technicians start and end their tour at their home; the consideration of skills, tools, and spare parts that restricts the set of technicians that can serve a specific request; the possibility for technicians to pick up additional tools and spare parts at a central depot; and finally, the objective function that considers the minimization of the total working time and the balancing of tours. The first paper in this chapter proposes a parallel adaptive large neighborhood search coupled with a set-covering

post-optimization, namely pALNS+SC, used to tackle the static TRSP. We illustrate the performance of pALNS+SC on the Solomon (1987) VRPTW instances, then we introduce a new set of instances for the TRSP, generated from the Solomon (1987) instances as described in Appendix D, and solve them using pALNS+SC. This paper was submitted to *Optimization Letters* (Pillac et al., 2012f) and preliminary results were presented at the MIC 2011 conference (Pillac et al., 2011e). The second paper tackles the dynamic TRSP and proposes two solution methods. The first is an adaptation of the fast-reoptimization approach presented in Chapter 2. The second is a multiple plan approach, which is a variant of the multiple scenario approach presented in Chapter 3. This work is available as a technical report (Pillac et al., 2012d) and preliminary results were presented at the ODYSSEUS 2012 and EURO 2012 conferences (Pillac et al., 2012c,e).

Finally, Appendices A, B, and C describe software libraries and frameworks developed to support the research presented in the five papers, Appendix D presents an instance generator for the TRSP, Appendix E details the best known solutions for the new instances, and Appendix F summarizes the record of publications developed during this thesis.

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1

Literature review

In this chapter we present a thorough review of the current state of the art in dynamic vehicle routing applications and approaches.

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– Pillac, V., Guéret, C., and Medaglia, A. L. (2010)
Dynamic Vehicle Routing: State of the Art and Prospects
Technical report, École des Mines de Nantes, France. Report 10/4/AUTO.

A Review of Dynamic Vehicle Routing Problems

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Abstract : A number of technological advances have led to a renewed interest on dynamic vehicle routing problems. This survey classifies routing problems from the perspective of information quality and evolution. After presenting a general description of dynamic routing, we introduce the notion of degree of dynamism, and present a comprehensive review of applications and solution methods for dynamic vehicle routing problems.

Keywords : Transportation ; Combinatorial optimization ; Vehicle routing ; Dynamic vehicle routing ; Stochastic and dynamic vehicle routing

1.1 Introduction

The Vehicle Routing Problem (VRP) formulation was first introduced by Dantzig and Ramser (1959), as a generalization of the Traveling Salesman Problem (TSP) presented by Flood (1956). The VRP is generally defined on a graph $G = (\mathcal{V}, \mathcal{E}, C)$, where $\mathcal{V} = \{v_0, ..., v_n\}$ is the set of vertices; $\mathcal{E} = \{(v_i, v_j) | (v_i, v_j) \in \mathcal{V}^2, i \neq j\}$ the arc set; and $C = (c_{ij})_{(v_i,v_j)\in\mathcal{E}}$ a cost matrix defined over $\mathcal{E}$, representing distances, travel times, or travel costs. Traditionally, vertex v_0 is called the *depot*, while the remaining vertices in $\mathcal{V}$ represent *customers* (or *requests*) that need to be serviced. The VRP consists in finding a set of routes for K identical vehicles based at the depot, such that each of the vertices is visited exactly once, while minimizing the overall *routing cost*.

Beyond this classical formulation, a number of variants have been studied. Among the most common are the Capacitated VRP (CVRP), where each customer has a demand for a good and vehicles have finite capacity; the VRP with Time Windows (VRPTW), where each customer must be visited during a specific time frame; the VRP with Pick-up and Delivery (PDP), where goods have to be picked-up and delivered in specific amounts at the vertices; and the Heterogeneous fleet VRP (HVRP), where vehicles have different capacities. Routing problems that involve moving people between locations are referred to as Dial-A-Ride-Problem (DARP) for land transport; or Dial-A-Flight-Problem (DAFP), for air transport.

In contrast to the classical definition of the vehicle routing problem, real-world applications often include two important dimensions: *evolution* and *quality* of information (Psaraftis, 1980). Evolution of information relates to the fact that in some problems the information available to the planner may

change during the execution of the routes, for example, with the arrival of new customer requests. Quality of information reflects possible uncertainty on the available data, for instance, when the demand of a customer is only known as a range estimate of its real demand. In addition, depending on the problem and the available technology, vehicle routes can either be designed statically (a-priori) or dynamically. For instance, the VRP with Stochastic Demands (VRPSD), can be seen from both perspectives. From a static perspective, the problem is to design a set of robust routes a-priori, that will undergo minor changes during their execution (Bertsimas and Simchi-Levi, 1996; Gendreau et al., 1996). From a dynamic perspective, the problem consists in designing the vehicle routes in an online fashion, communicating to the vehicle which customer to serve next as soon as it becomes idle (Novoa and Storer, 2009; Secomandi, 2001; Secomandi and Margot, 2009). Based on these dimensions, Table 1.1 identifies four categories of routing problems.

		Information quality	
		Deterministic input	Stochastic input
Information evolution	Input known beforehand	Static and deterministic	Static and stochastic
	Input changes over time	Dynamic and deterministic	Dynamic and stochastic

Table 1.1: Taxonomy of vehicle routing problems by information evolution and quality.

In *static and deterministic* problems, all input is known beforehand and vehicle routes do not change once they are in execution. This classical problem has been extensively studied in the literature, and we refer the interested reader to the recent reviews of exact and approximate methods by Baldacci et al. (2007); Cordeau et al. (2007b); Laporte (2007, 2009), and Toth and Vigo (2002).

Static and stochastic problems are characterized by input partially known as random variables, which realizations are only revealed during the execution of the routes. Additionally, it is assumed that routes are designed a-priori and only minor changes are allowed afterwards. For instance, allowable changes include planning a trip back to the depot or skipping a customer. Applications in this category do not require any technological support. Uncertainty may affect any of the input data, yet the three most studied cases are (Cordeau et al., 2007b): stochastic customers, where a customer needs to be serviced with a given probability (Bertsimas, 1988; Waters, 1989); stochastic times, in which either service or travel times are modeled by random variables (Kenyon and Morton, 2003; Laporte et al., 1992; Verweij et al., 2003); and lastly, stochastic demands (Christiansen and Lysgaard, 2007; Dror et al., 1989; Laporte et al., 2002; Mendoza et al., 2011, 2009; Secomandi, 2000; Secomandi and Margot, 2009). Further details on the static stochastic vehicle routing can be found in the reviews by Bertsimas and Simchi-Levi (1996); Cordeau et al. (2007b), and Gendreau et al. (1996).

In *dynamic and deterministic* problems, part or all of the input is unknown and revealed dynamically during the design or execution of the routes. For these problems, vehicle routes are redefined in an ongoing fashion, requiring technological support for real-time communication between the vehicles and the decision maker (e.g., mobile phones and global positioning systems). This class of problems are also referred to as *online* or *real time* by some authors (Jaillet and Wagner, 2008a).

Similarly, *dynamic and stochastic* problems have part or all of their input unknown and revealed dynamically during the execution of the routes, but in contrast with the latter category, exploitable stochastic knowledge is available on the dynamically revealed information. As before, the vehicle routes can be redefined in an ongoing fashion with the help of technological support.

Besides dynamic routing problems, where customer visits must be explicitly sequenced along the routes, there are other related vehicle dispatching problems, such as managing a fleet of emergency vehicles(Brotcorne et al., 2003; Gendreau et al., 2001; Haghani and Yang, 2007), or the so-called *dynamic allocation problems* in the area of long haul truckload trucking (Godfrey and Powell, 2002; Powell et al., 2002; Spivey and Powell, 2004). In this paper, we focus solely on dynamic problems with an explicit routing dimension.

The remainder of this document is organized as follows. Section 1.2 presents a general description of dynamic routing problems and introduce the notion of *degree of dynamism*. Section 1.3 reviews different applications in which dynamic routing problems arise, while Section 1.4 provides a comprehensive survey of solution approaches. Finally, Section 1.5 concludes this paper and gives directions for further research.

1.2 Dynamic vehicle routing problems

1.2.1 A general definition

The first reference to a dynamic vehicle routing problem is due to Wilson and Colvin (1977). They studied a single vehicle DARP, in which customer requests are trips from an origin to a destination that appear dynamically. Their approach uses insertion heuristics able to perform well with low computational effort. Later, Psaraftis (1980) introduced the concept of *immediate request*: a customer requesting service always wants to be serviced as early as possible, requiring immediate replanning of the current vehicle route.

A number of technological advances have led to the multiplication of real-time routing applications. With the introduction of the Global Positioning System (GPS) in 1996, the development and widespread use of mobile and smart phones, combined with accurate Geographic Information Systems (GIS), companies are now able to track and manage their fleet in real time and cost effectively. While traditionally a two-step process (i.e., plan-execute), vehicle routing can now be done dynamically, introducing greater opportunities to reduce operational costs, improve customer service, and reduce environmental impact.

The most common source of dynamism in vehicle routing is the online arrival of customer *requests* during the operation. More specifically, requests can be a demand for goods (Attanasio et al., 2004; Goel and Gruhn, 2008; Hvattum et al., 2006, 2007; Ichoua et al., 2006; Mes et al., 2007; Mitrović-Minić and Laporte, 2004; Van Hemert and Poutré, 2004) or services (Beaudry et al., 2010; Bent and Van Hentenryck, 2005; Bertsimas and Van Ryzin, 1991; Gendreau et al., 1999; Larsen et al., 2004; Thomas, 2007). Travel time, a dynamic component of most real-world applications, has been recently taken into account (Attanasio et al., 2007; Barcelo et al., 2007; Chen et al., 2006; Fleischmann et al., 2004; Güner et al., 2012; Haghani and Jung, 2005; Lorini et al., 2011; Potvin et al., 2006; Tagmouti et al., 2011; Taniguchi and

Shimamoto, 2004; Zeimpekis et al., 2007a); while service time has not been explicitly studied (but can be added to travel time). Finally, some recent work considers dynamically revealed demands for a set of known customers (Novoa and Storer, 2009; Novoa, 2005; Secomandi, 2000; Secomandi and Margot, 2009) and vehicle availability (Li et al., 2009a,b; Mu et al., 2011), in which case the source of dynamism is the possible breakdown of vehicles. In the following we use the prefix "D-" to label problems in which new requests appear dynamically.

To better understand what we mean by *dynamic*, Figure 1.1 illustrates the route execution of a single vehicle D-VRP. Before the vehicle leaves the depot (time t_0), an initial route plans to visit the currently known requests (A, B, C, D, E). While the vehicle executes its route, two new requests (X and Y) appear at time t_1 and the initial route is adjusted to fulfill them. Finally, at time t_f the executed route is (A, B, C, D, Y, E, X).

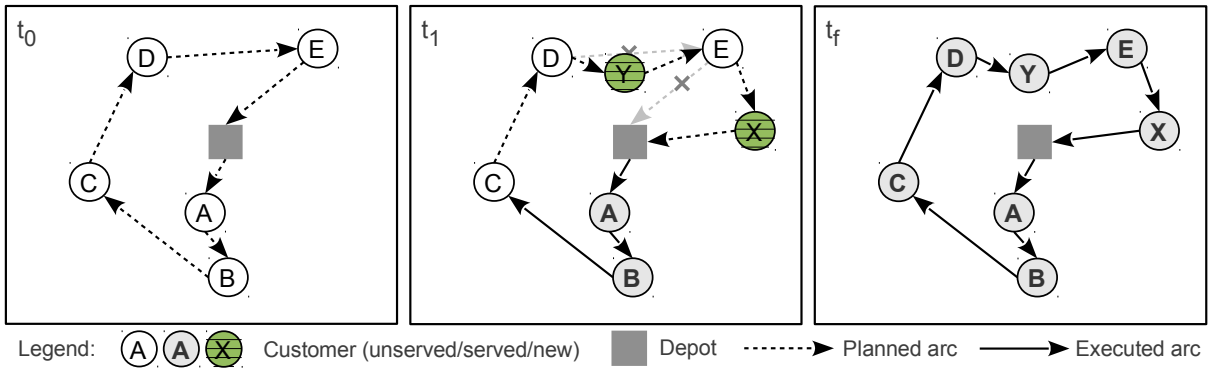


Figure 1.1: Example of dynamic vehicle routing

This example reveals how dynamic routing inherently adjusts routes in an ongoing fashion, which requires real-time communication between vehicles and the dispatching center. Figure 1.2 illustrates this real-time communication scheme, where the *environment* refers to the *real-world* while the *dispatcher* is the agent that gives instructions to the vehicle. Once the vehicle is ready (first dotted arrow), the dispatcher makes a *decision* and instructs the vehicle to fulfill request A (first double-headed arrow). When the vehicle starts (second dotted arrow) and ends (third dotted arrow) service at request A, it notifies the dispatcher, which in turns updates the available information and communicates the vehicle its next request (second double-headed arrow).

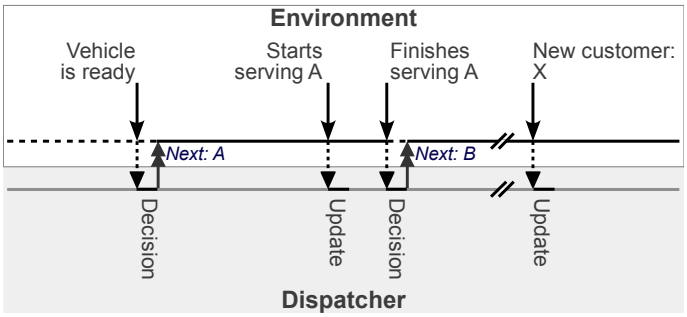


Figure 1.2: Timeline of events for the dynamic routing of a single vehicle

1.2.2 Differences with static routing

In contrast to their static counterparts, dynamic routing problems involve new elements that increase the complexity of their decisions (more degrees of freedom) and introduce new challenges while judging the merit of a given route plan.

In some contexts, such as the pick-up of express courier (Gendreau et al., 1999), the transport company may deny a customer request. As a consequence, it can reject a request either because it is simply impossible to service it, or because the cost of serving it is too high. This process of acceptance/denial has been used in many approaches (Attanasio et al., 2004; Fagerholt et al., 2009; Gendreau et al., 1999; Ichoua et al., 2000, 2003, 2006; Li et al., 2009a) and is referred to as *service guarantee* (Van Hentenryck and Bent, 2006).

In dynamic routing, the ability to redirect a moving vehicle to a new request nearby allows for additional savings. Nevertheless, it requires real-time knowledge of the vehicle position and being able to communicate quickly with drivers to assign them new destinations. Thus, this strategy has received limited interest, with the main contributions being the early work by Regan et al. (1995, 1998, 1996), the study of diversion issues by Ichoua et al. (2000), and the work by Branchini et al. (2009).

Dynamic routing also frequently differs in the objective function (Psaraftis, 1995). In particular, while a common objective in the static context is the minimization of the routing cost, dynamic routing may introduce other notions such as service level, throughput (number of serviced requests), or revenue maximization. Having to answer to dynamic customer requests also introduces the notion of response time: a customer might request to be serviced as soon as possible, in which case the main objective may become to minimize the delay between the arrival of a request and its service.

Dynamic routing problems require making decisions in an online manner, which often compromises reactiveness with decision quality. In other words, the time invested searching for better decisions, comes at the price of a lower reactiveness to input changes. This aspect is of particular importance in contexts where customers call for a service and a good decision must be made as fast as possible.

1.2.3 Measuring dynamism

Different problems (or instances of a same problem) can have different levels of dynamism, which can be characterized according to two dimensions (Ichoua et al., 2007): the frequency of changes and the urgency of requests. The former is the rate at which new information becomes available, while the latter is the time gap between the disclosure of a new request and its expected service time. From this observation three metrics have been proposed to measure the dynamism of a problem (or instance).

Lund et al. (1996) defined the *degree of dynamism* δ as the ratio between the number of dynamic requests n_d and the total number of requests n_{tot} as follows:

$$\delta = \frac{n_d}{n_{tot}} \tag{1.1}$$

Based on the fact that the disclosure time of requests is also important (Psaraftis, 1988, 1995), Larsen (2001) proposed the *effective degree of dynamism* δ^e. This metric can be interpreted as the normalized

average of the disclosure times. Let T be the length of the planning horizon, $\mathcal{R}$ the set of requests, and t_i the disclosure time of request $i \in \mathcal{R}$. Assuming that requests known beforehand have a disclosure time equal to 0, δ^e can be expressed as:

$$\delta^e = \frac{1}{n_{tot}} \sum_{i \in \mathcal{R}} \frac{t_i}{T} \tag{1.2}$$

Larsen (2001) also extended the effective degree of dynamism to problems with time windows to reflect the *level of urgency* of requests. He defines the *reaction time* as the difference between the disclosure time t_i and the end of the corresponding time window l_i, highlighting that longer reaction times mean more flexibility to insert the request into the current routes. Thus, the effective degree of dynamism measure is extended as follows:

$$\delta^e_{TW} = \frac{1}{n_{tot}} \sum_{i \in \mathcal{R}} \left(1 - \frac{l_i - t_i}{T}\right) \tag{1.3}$$

It is worth noting that these three metrics only take values in the interval $[0, 1]$ and all increase with the level of dynamism of a problem. Larsen et al. (2002, 2007) use the effective degree of dynamism to define a framework classifying D-VRPs among weakly, moderately, and strongly dynamic problems, with values of δ^e being respectively lower than 0.3, comprised between 0.3 and 0.8, and higher than 0.8.

Although the effective degree of dynamism and its variations have proven to capture well the time-related aspects of dynamism, it could be argued that they do not take into account other possible sources of dynamism. In particular, the geographical distribution of requests, or the traveling times between requests, are also of great importance in applications aiming at the minimization of response time. Although not considered, the frequency of updates in problem information has a dramatical impact on the time available for optimization.

1.3 A review of applications

Recent advances in technology have allowed the emergence of a wide new range of applications for vehicle routing. In particular, the last decade has seen the development of Intelligent Transport Systems (ITS), which are based on a combination of geolocation technologies, with precise geographic information systems, and increasingly efficient hardware and software for data processing and operations planning. We refer the interested reader to the study by Crainic et al. (2009) for more details on ITS and the contributions of operations research to this relatively new domain.

Among the ITS, the Advanced Fleet Management Systems (AFMS) are specifically designed for managing a corporate vehicle fleet. The core problem is generally to deliver (pick-up) goods or persons to (from) locations distributed in a given area. While customer requests can either be known in advance or appear dynamically during the day, vehicles are dispatched and routed in real time, potentially, by taking into account changing traffic conditions, uncertain demands, or varying service times. A key technological feature of AFMS is the optimization component. Traditionally, vehicle routing relies on

teams of human dispatchers, meaning a critical operational process is bound to the competence and experience of dispatchers, as well as the management costs that are directly linked to the size of the fleet (Attanasio et al., 2007). Advances in computer science have allowed a technological transfer from operational research to AFMS, as presented in the studies by Attanasio et al. (2007); Du et al. (2007); Godfrey and Powell (2002); Powell and Topaloglu (2005); Roy (2001); Simao et al. (2009), and Slater (2002).

The remainder of this section presents applications where dynamic routing has been or can be implemented. The interested reader is also referred to the work by Gendreau and Potvin (1998) and Ichoua et al. (2007) for complementary reviews.

1.3.1 Services

In this category of applications, a service request is defined by a customer location and a possible time window; while vehicle routes just fulfill service requests without considering side constraints such as capacity. Perhaps the simplest, yet most illustrative case in this category is the dynamic traveling salesman problem (Larsen et al., 2004).

A common application of dynamic routing can be found in the area of maintenance operations. Maintenance companies are often committed by contract to their customers, which specify periodical or planned visits to perform preventive maintenance, and may also request corrective maintenance on short notice. Therefore, each technician is first given a route with known requests at the beginning of the day, while new urgent requests are inserted dynamically throughout the day. An interesting feature of this problem is the possible mix of skills, tools, and spare part requirements, which have to be matched in order to service the request. This problem has been studied by Borenstein et al. (2010) with an application to British Telecom.

Another application of dynamic routing arises in the context of the French non-profit organization *SOS Médecins*. This organization operates with a crew of physicians, who are called on duty via a call center coordinated with other emergency services. When a patient calls, the severity of the case is evaluated, and a visit by a practitioner is planned accordingly. As in other emergency services, having an efficient dispatching system reduces the response time, thus improving service level for the society. On the other hand, it is important to decide in real-time whether or not to send a physician, so that it is possible to ensure a proper service level in areas where emergencies are likely to appear.

Dynamic aspects can also appear on arc routing problems. This is for instance the case in the study by Tagmouti et al. (2011) on the operation of a fleet of vehicles for winter gritting applications. Their work consider a network of streets or road segments that need to be gritted when affected by a moving storm. Depending on the movements of the storm, new segments may have to be gritted, and the routing of vehicles has to be updated accordingly.

1.3.2 Transport of goods

Due to the fact that urban areas are often characterized by highly variable traveling times, transport of goods in such areas have led to the definition of a specific category of applications known as *city logistics*. City logistics can be defined as an integrated vision of transport activities in urban

areas, taking into account factors such as traffic and competition or cooperation between transport companies (Taniguchi and Thompson, 2002). Barcelo et al. (2007) developed a general framework for city logistics applications. They describe the different modules ranging from modeling the city road network and acquiring real-time traffic data to the dynamic routing of a fleet of vehicles. Zeimpekis et al. (2007a) proposed a Decision Support System (DSS) for city logistics which takes into account dynamic travel and service times.

A typical application in city logistics is the courier service present in most urban areas. Couriers are dispatched to customer locations to collect packages, and either deliver them to their destination (short haul) or to a unique depot (long haul). Depending on the level of service paid by the customer, couriers may consolidate pick-ups from various customers, or provide an expedited service. Companies offering courier services often have an heterogeneous fleet composed of bicycles, motorbikes, cars, and small vans. The problem is then to dynamically route couriers, taking into account not only the known requests, their type, pick-up and delivery locations, and time windows, but also considering traffic conditions and varying travel times. A case study by Attanasio et al. (2007) outlines the benefits of using an optimization-enabled AFMS at eCourier Ltd, a London based company offering courier services. The authors illustrate that aside from the improvements in service quality, response time, and courier efficiency, the use of an automated system allows decoupling the fleet size from the need for more dispatchers. Further results motivated by a similar application can be found in Gendreau et al. (2006) and Ghiani et al. (2009).

The delivery of newspapers and magazines is a domain in which customer satisfaction is of first importance. When a magazine or newspaper is not delivered, a subscriber contacts a call center and is offered to choose between a voucher or a future delivery. In the latter case, the request is then forwarded to the delivery company, which assigns it to a driver that will do a priority delivery. Traditionally, this process relies on an exchange of phone calls, faxes, and printed documents, that ultimately communicate the driver about the pending delivery, once he/she comes back to the depot. As an alternative, Bieding et al. (2009) propose a centralized application that makes use of mobile phones to communicate with drivers and intelligently perform the routing in real time, reducing costs and improving customer satisfaction. More recently, Ferrucci et al. (2011) developed an approach that makes use historical data to anticipate future requests.

Another application in which customer requests need to be answered with short delays can be found in companies with a direct service model, such as grocery delivery services. In general, the customer selects products on a website, and then chooses a time frame for the delivery at his home. Traditionally, the vendor defines an arbitrary number of customers that can be serviced within a time window, and the time window is made unavailable to customers as soon as the capacity is reached. Campbell and Savelsbergh (2005) defined the Home Delivery Problem, in which the goal is to maximize the total expected revenue by dynamically deciding whether or not to accept a customer request within a specific time window. In comparison with the traditional approach, this means that the time windows available for a customer are dynamically defined taking into consideration the possible future requests. The authors propose a Greedy Randomized Adaptive Search Procedure (GRASP) and compare different cost functions to capture the problem uncertainty. Later, Azi et al. (2011) proposed an Adaptive Large Neighborhood Search (ALNS) that take into account uncertainty by generating scenarios containing

possible demand realizations.

Apart from classical routing problems, related operational problems also arise in many organizations. The review by Stahlbock and Voss (2008) on operations research applications in container terminals describes the dynamic stacker crane problem (Balev et al., 2009; Berbeglia et al., 2010), which considers the routing of container carriers loading and unloading ships in a terminal. Other applications include transport of goods inside warehouses (Smolic-Rocak et al., 2010), factories, and hospitals, where documents or expensive medical instruments must be transferred efficiently between services (Fiegl and Pontow, 2009).

1.3.3 Transport of persons

The transport of persons is in general–and by many aspects–similar to the transport of goods, yet it is characterized by additional constraints such as regulation on waiting, travel, and service times.

Taxis are arguably the most common on-demand individual transport systems. Requests are composed of a pick-up location and time, possibly coupled with a destination. They can be either known in advance, for instance when a customer books a cab for the next day, or they can arrive dynamically, in which case a taxi must be dispatched in the shortest time. When customers cannot share a vehicle, the closest free taxi is generally the one which takes the ride, leaving limited space for optimization. The study by Caramia et al. (2002), generalized by Fabri and Recht (2006), focuses on a multi-cab metropolitan transportation system, where a taxi can transport more than one passenger at the same time. In this case the online algorithms minimize the total traveled distance, while assigning requests to vehicles and computing the taxi routes. This multi-cab transportation system can be generalized as an on-demand or door-to-door transport service.

Many applications involve the transport of children, the elderly, disabled people, or patients, from their home to schools, place of work, or medical centers. Xiang et al. (2008) studied a DARP with changing travel speeds, vehicle breakdowns, and traffic congestion; while Dial (1995), followed by Horn (2002a,b, 2004), studied demand-responsive transport systems. An extensive review of this class of problems can be found in the studies by Cordeau et al. (2007a) and Berbeglia et al. (2010).

A singular application of on-demand transportation systems can be found in major hospitals, with services possibly spread across various buildings on several branches. Depending on the medical procedure or facility capacity, a patient may need to be transferred on short notice from one service to another, possibly requiring trained staff or specific equipment for his/her care. This application has been studied by Beaudry et al. (2010); Kergosien et al. (2011), and Melachrinoudis et al. (2007).

Air taxis developed as a flexible response to the limitations of traditional airlines. Air taxis offer passengers the opportunity to travel through smaller airports, avoiding waiting lines at check-in and security checks. Air taxi companies offer an on-demand service: customers book a flight a few days in advance, specifying whether they are willing to share the aircraft, stop at an intermediate airport, or have flexible traveling hours. Then, the company accommodates these requests, trying to consolidate flights whenever possible. The underlying optimization problems have not been subject to much attention, except in the studies by Cordeau et al. (2007a); Espinoza et al. (2008a,b); Fagerholt et al. (2009), and Yao et al. (2007). Similar problems arises in helicopter transportation systems, typically used by oil

and gas companies to transport personnel between offshore petroleum platforms (Gribkovskaia et al., 2008; Romero et al., 2007).

1.4 Solution Methods

Few research was conducted on dynamic routing between the work of Psaraftis (1980) in 1980 and the late 1990s. However, the last decade has seen a renewed interest for this class of problems (Eksioglu et al., 2009), with solution techniques ranging from linear programming to metaheuristics. This section presents the major contributions in this field, and the reader is referred to the reviews, books, and special issues by Gendreau and Potvin (1998, 2004); Ghiani et al. (2003); Goel (2008); Ichoua (2001); Ichoua et al. (2006, 2007); Jaillet and Wagner (2008b); Larsen et al. (2008), and Zeimpekis et al. (2007b), to complement our review.

1.4.1 Dynamic and deterministic routing problems

This section presents approaches that have been successfully applied to dynamic routing, in the absence of stochastic information. In this context, critical information is revealed over time, meaning that the complete instance is only known at the end of the planning horizon. As a consequence, exact methods only provide an optimal solution for the current state, but do not guarantee that the solution will remain optimal once new data becomes available. Therefore, most dynamic approaches rely on heuristics that quickly compute a solution to the current state of the problem. Approaches for dynamic and deterministic vehicle routing problems can be divided into two categories: those based on *periodic reoptimization*, and those based on *continuous reoptimization*.

1.4.1.1 Periodic reoptimization

To the best of our knowledge, the first periodic reoptimization approach is due to Psaraftis (1980), with the development of a dynamic programming approach. His research focuses on the DARP and consists in finding the optimal route each time a new request is known. The main drawback of dynamic programming is the well-known *curse of dimensionality* (Powell, 2007, Chap. 1), which prevents its application to large instances.

More generally, periodic reoptimization approaches start at the beginning of the day with a first optimization that produces an initial set of routes. Then, an optimization procedure periodically solves a static problem corresponding to the current state, either whenever the available data changes, or at fixed intervals of time –referred to as decision epochs (Chen and Xu, 2006) or time slices (Kilby et al., 1998). The advantage of periodic reoptimization is that it can be based on algorithms developed for static routing, for which extensive research has been carried out. The main drawback is that all the optimization needs to be performed before updating the routing plan, thus increasing delays for the dispatcher.

Yang et al. (2004) addressed the real-time truckload PDP, in which a fleet of trucks has to service point-to-point transport requests arriving dynamically. Important assumptions are that all trucks can only handle one request at a time, with no possible preemption, and they travel at the same constant

speed. The authors propose MYOPT, a rolling horizon approach based on a linear program (LP) that is solved whenever a new request arrives. Along the same line of linear programming, Chen and Xu (2006) designed a dynamic column generation algorithm (DYCOL) for the D-VRPTW. The authors propose the concept of *decision epochs* over the planning horizon, which are the dates when the optimization process runs. The novelty of their approach relies on dynamically generating columns for a set-partitioning model, using columns from the previous decision epoch. The authors compared DYCOL to a traditional column generation with no time limit (COL). Computational results based on the Solomon benchmark (Solomon, 1987) demonstrate that DYCOL yields comparable results in terms of objective function, but with running times limited to 10 seconds, opposed to the various hours consumed by COL.

Montemanni et al. (2005) developed an Ant Colony System (ACS) to solve the D-VRP. Similar to Kilby et al. (1998), their approach uses time slices, that is, they divide the day in periods of equal duration. A request arriving during a time slice is not handled until the end of the time bucket, thus the problem solved during a time slice only considers the requests known at its beginning. Hence, the optimization is run statically and independently during each time slice. The main advantage of this time partition is that similar computational effort is allowed for each time slice. This discretization is also possible by the nature of the requests, which are never urgent, and can be postponed. An interesting feature of their approach is the use of the pheromone trace to transfer characteristics of a good solution to the next time slice. A similar approach was also used by Gambardella et al. (2003) and Rizzoli et al. (2007).

1.4.1.2 Continuous reoptimization

Continuous reoptimization approaches perform the optimization throughout the day and maintain information on good solutions in an adaptive memory (Taillard et al., 2001). Whenever the available data changes, a decision procedure aggregates the information from the memory to update the current routing. The advantage is that the computational capacity is maximized, possibly at the expense of a more complex implementation. It is worth noting that because the current routing is subject to change at any time, vehicles do not know their next destination until they finish the service of a request.

To the best of our knowledge, the first continuous reoptimization approach is due Gendreau et al. (1999) with the adaptation of the parallel Tabu Search (TS) framework introduced by Taillard et al. (1997) to a D-VRPTW problem arising in the local operation of long distance express courier services. Their approach maintains a pool of good routes–the adaptive memory–which is used to generate initial solutions for a parallel TS. The parallelized search is done by partitioning the routes of the current solution, and optimizing them in independent threads. Whenever a new customer request arrives, it is checked against all the solutions from the adaptive memory to decide whether it should be accepted or rejected. This framework was also implemented for the D-VRP (Ichoua et al., 2000, 2003), while other variations of TS have been applied to the D-PDP (Barcelo et al., 2007; Chang et al., 2003) and the DARP (Attanasio et al., 2004; Beaudry et al., 2010).

Bent and Van Hentenryck (2004b) introduced the Multiple Plan Approach (MPA) as a generalization of the TS with adaptive memory (Gendreau et al., 1999). The general idea is to populate and maintain

a solution pool (the routing *plans*) that are used to generate a *distinguished solution*. Whenever a new request arrives, a procedure is called to check whether it can be serviced or not; if it can be serviced, then the request is inserted in the solution pool and incompatible solutions are discarded. Pool updates are performed periodically or whenever a vehicle finishes servicing a customer. This pool-update phase is crucial and ensures that all solutions are coherent with the current state of vehicles and customers. The pool can be seen as an adaptive memory that maintains a set of alternative solutions.

In an early work, Benyahia and Potvin (1998) studied the D-PDP and proposed a Genetic Algorithm (GA) that models the decision process of a human dispatcher. More recently, GAs were also used for the same problem (Cheung et al., 2008; Haghani and Jung, 2005) and for the D-VRP (Van Hemert and Poutré, 2004). Genetic algorithms in dynamic contexts are very similar to those designed for static problems, although they generally run throughout the planning horizon and solutions are constantly adapting to the changes made to the input.

1.4.2 Dynamic and stochastic routing problems

Dynamic and stochastic routing problems can be seen as an extension of their deterministic counterparts, where additional (stochastic) knowledge is available in the dynamically revealed input. Approaches for this class of problems can be divided in two categories: those based on *sampling* and those based on *stochastic modeling*. As their name suggests, sampling strategies incorporate stochastic knowledge by generating *scenarios* based on realizations drawn from random variable distributions. Each scenario is then optimized by solving the static and deterministic problem they define. On the other hand, approaches based on stochastic modeling integrate stochastic knowledge analytically. The advantage of sampling is its relative simplicity and flexibility on distributional assumptions, while its drawback is the massive generation of scenarios to accurately reflect reality. Alternatively, stochastic modeling strategies formally capture the stochastic nature of the problem, but they are highly technical in their formulation and require to efficiently compute possibly complex expected values. Examples of these two strategies follow.

1.4.2.1 Stochastic modeling

Powell et al. (1988) formulated a truckload PDP as a Markov Decision Process (MDP). Later, MDPs were used by Thomas and White (2004) and Thomas (2007) to solve a VRP in which known customers may ask for service with a known probability. Kim et al. (2005) also used MDPs to tackle the VRP with dynamic travel times. Unfortunately, the curse of dimensionality and the simplifying assumptions make this approach unsuitable in most real-world applications. Nonetheless, it allowed new insights in the field of dynamic programming.

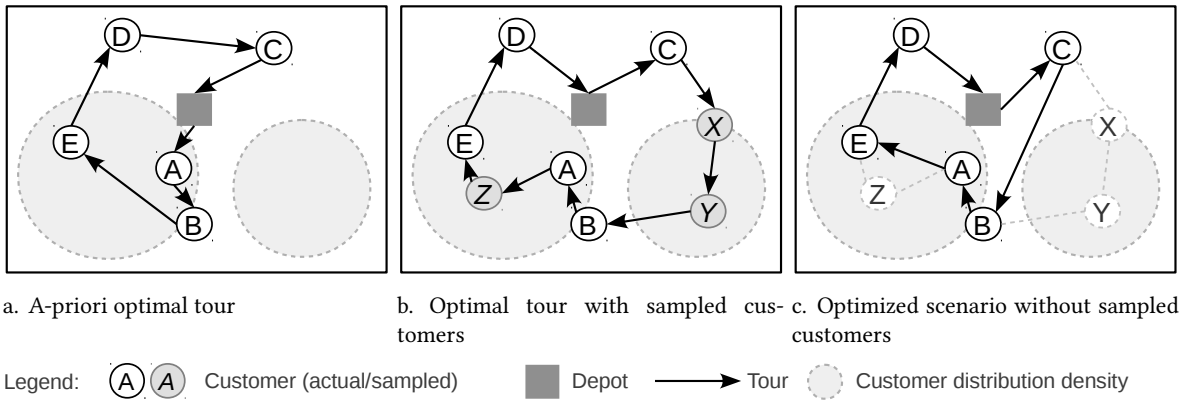
To cope with the scalability problems of traditional dynamic programming, Approximate Dynamic Programming (ADP) steps forward in time, approximates the value function, and ultimately avoids the evaluation of all possible states. We refer the interested reader to Powell (2007, 2009) for a more detailed description of the ADP framework. ADP has been successfully applied to freight transport (Powell et al., 2007; Powell and Topaloglu, 2003) and fleet management problems (Godfrey and Powell, 2002; Powell and Topaloglu, 2005; Simao et al., 2009). In particular, Novoa and Storer (2009) propose

an ADP algorithm to dynamically solve the VRPSD.

Linear programming has also been adapted to the dynamic and stochastic context. The OPTUN approach, proposed by Yang et al. (2004) as an extension of MYOPT (see § 1.4.1.1), considers *opportunity costs* on each arc to reflect the expected cost of traveling to isolated areas. Consequently, the optimization tends to reject isolated requests, and avoids traversing arcs that are far away from potential requests. Later, Yang et al. (2005) studied the emergency vehicle dispatching and routing and proposed a mathematical formulation that was later used by Haghani and Yang (2007) on a similar problem.

1.4.2.2 Sampling

Sampling approaches rely on the generation of scenarios containing possible realizations of the random variables. Figure 1.3 illustrates how scenarios are generated for the D-VRP. Solely based on the current customers, the optimal tour would be (A, B, E, D, C) (1.3a.), which ignores two zones (gray areas) where customers are likely to appear. By sampling the customer spatial distributions, customers X, Y, and Z are generated, and the new optimal tour is (C, X, Y, B, A, Z, E, D) (1.3b.). Removing the sampled (potential) customers leads to the tour (C, B, A, E, D) (1.3c.) which is suboptimal regarding a myopic cost evaluation, but leaves room to accommodate new customers at a lower cost.



a. A-priori optimal tour

b. Optimal tour with sampled customers

c. Optimized scenario without sampled customers

Figure 1.3: Scenario generation in sampling approaches.

The Multiple Scenario Approach (MSA) is a predictive adaptation of the MPA framework discussed in § 1.4.1.2. The idea behind MSA is to take advantage of the time between decisions to continuously improve the current scenario pool. During the initialization, the algorithm, generates a first set of scenarios based on the requests known beforehand. Throughout the day, scenarios are then reoptimized and new ones are generated and added to the pool. When a decision is required, the scenario optimization procedure is suspended, and MSA uses the scenario pool to select the request to service next. MSA then discards the scenarios that are incompatible with the current routing, and resumes the optimization. Computational experiments on instances adapted from the Solomon benchmark (Solomon, 1987) showed that MSA outperforms MPA both in terms of serviced customers and traveled distances, especially for instances with high degrees of dynamism (Bent and Van Hentenryck, 2004b). Flatberg et al. (2007) adapted the SPIDER commercial solver to use multiple scenarios and a consensus algorithm to

tackle the D-VRP, while Pillac et al. (2012) implemented an event-driven optimization framework based on MSA and showed significant improvements over state-of-the-art algorithms for the D-VRPSD.

An important component of scenario based-approaches such as MSA is the *decision process*, which defines how the information from the scenario pool is used to reach upon a decision regarding the next customer to visit. The most common algorithms used to reach a decision in MSA are: *consensus*, *expectation*, and *regret*. The consensus algorithm (Bent and Van Hentenryck, 2004b,c) selects the customer appearing first with the highest frequency among scenarios. Expectation (Bent and Van Hentenryck, 2004a,c; Chang et al., 2000) consists in evaluating the cost of visiting each customer first by forcing its visit in all scenarios and performing a complete optimization. Finally, regret (Bent and Van Hentenryck, 2004a) approximates the expectation algorithm and avoids the reoptimization of all scenarios. Even though these algorithms were initially designed for the routing of a single vehicle, they can be extended to the multi-vehicle case (Van Hentenryck and Bent, 2006).

Hvattum et al. (2006) developed the Dynamic Sample Scenario Hedge Heuristic (DSHH), an approach similar to the consensus algorithm for D-VRP. This method divides the planning horizon into time intervals. At the beginning of each interval, DSHH revises the routing by assigning a subset of promising requests to the vehicles, depending on the frequency of their assignment over all scenarios. DSHH later led to the development of the Branch and Regret Heuristic (BRH), where scenarios are merged to build a unique solution.

Various local search approaches have been developed for the stochastic and dynamic problems. Ghiani et al. (2009) developed an algorithm for the D-PDP that only samples the near future to reduce the computational effort. The main difference with MSA is that no scenario pool is used and the selection of the distinguished solution is based on the expected penalty of accommodating requests in the near future. Azi et al. (2011) developed an Adaptive Large Neighborhood Search (ALNS) for a dynamic routing problem with multiple delivery routes, in which the dynamic decision is the acceptance of a new request. The approach maintains a pool of scenarios, optimized by an ALNS, that are used to evaluate the opportunity value of an incoming request.

Tabu search has also been adapted to dynamic and stochastic problems. Ichoua et al. (2006) and Attanasio et al. (2007) tackled with tabu search the D-VRPTW and the D-PDP, respectively.

1.4.2.3 Other strategies

In addition to the general frameworks described previously, the use of stochastic knowledge allows for the design and implementation of other strategies that try to adequately respond to upcoming events.

The waiting strategy consists in deciding whether a vehicle should wait after servicing a request, before heading toward the next customer; or planning a waiting period on a strategic location. This strategy is particularly important in problems with time windows, where time lags appear between requests. Mitrović-Minić et al. (2004) proved that in all cases it is better to wait after servicing a customer, but a more refined strategy can lead to further improvements. The problem is in general to evaluate the likelihood of a new request in the neighborhood of a serviced request and to plan a waiting period accordingly. The waiting strategy has been implemented in various frameworks for

the D-VRP (Branke et al., 2005; Thomas, 2007), D-VRPTW (Bent and Van Hentenryck, 2007; Branchini et al., 2009; Ichoua et al., 2006; Van Hentenryck and Bent, 2006), D-PDP (Ghiani et al., 2009; Mitrović-Minić et al., 2004), and Dynamic and Stochastic TSP (Ghiani et al., 2008). The strategy has shown good results, especially in the case of a limited fleet facing a high request rate (Van Hentenryck and Bent, 2006).

Aside from the waiting after or before servicing a customer, a vehicle can be relocated to a strategic position, where new requests are likely to arrive. This strategy is the keystone of emergency fleet deployment, also known as Emergency Vehicle Dispatching–or Redeployment–Problem (Gendreau et al., 2001; Haghani and Yang, 2007). The relocation strategy has also been applied to other vehicle routing problems, such as the D-VRP (Larsen, 2001),D-VRPTW (Bent and Van Hentenryck, 2007; Branchini et al., 2009; Ichoua et al., 2006; Van Hentenryck and Bent, 2006), D-TSPTW (Larsen et al., 2004), D-PDP (Ghiani et al., 2009; Pureza and Laporte, 2008), and the Resource Allocation Problem (RAP) (Godfrey and Powell, 2002).

Request buffering, introduced by Pureza and Laporte (2008), consists in delaying the assignment of some requests to vehicles in a priority buffer, so that more urgent requests can be handled first.

1.4.3 Performance evaluation

In contrast to static problems, where measuring the performance of an algorithm is straightforward (i.e., running time and solution quality), dynamic problems require the introduction of new metrics to assess the performance of a particular method.

Sleator and Tarjan (1985) introduced the *competitive analysis* (Jaillet and Wagner, 2008a; Larsen et al., 2007). Let P be a minimization problem and $\mathcal{I}$ the set of all instances of P. Let $z^*(I_{\text{off}})$ be the optimal cost for the *offline instance* I_{off} corresponding to $I \in \mathcal{I}$. For offline instance I_{off}, all input data from instance I, either static or dynamic, is available when building the solution. In contrast, the data of the online version I is revealed in real time, thus an algorithm $\mathcal{A}$ has to take into account new information as it is revealed and produce a solution relevant to the current state of knowledge. Let $z_{\mathcal{A}}(I) = z(x_{\mathcal{A}}(I))$ be the cost of the final solution $x_{\mathcal{A}}(I)$ found by the online algorithm $\mathcal{A}$ on instance I. Algorithm $\mathcal{A}$ is said to be *c-competitive*, or equivalently to have a *competitive ratio* of c, if there exists a constant α such that

$$z_{\mathcal{A}}(I) \leq c \cdot z^*\left(I_{\text{off}}\right) + \alpha \quad , \quad \forall\, I \in \mathcal{I} \tag{1.4}$$

In the case where $\alpha = 0$, the algorithm is said to be *strictly c-competitive*, meaning that in all cases the objective value of the solution found by $\mathcal{A}$ will be at most of c times the optimal value. The competitive ratio metric allows a worst-case absolute measure of an algorithm performance in terms of the objective value. We refer the reader to Borodin and El-Yaniv (2005) for an in-depth analysis of this measure, and to Jaillet and Wagner (2008a) and Fink et al. (2009) for results on various routing problems.

The main drawback of the competitive analysis is that it requires to prove the previously stated inequality analytically, which may be complex for real-world applications. The *value of information* proposed by Mitrović-Minić et al. (2004) constitutes a more flexible and practical metric. We denote by

$z_{\mathcal{A}}(I_{\text{off}})$ the value of the objective function returned by algorithm $\mathcal{A}$ for the offline instance I_{off}. The value of information $V_{\mathcal{A}}(I)$ for algorithm $\mathcal{A}$ on instance I is then defined as

$$V_{\mathcal{A}}(I) = \frac{z_{\mathcal{A}}(I) - z_{\mathcal{A}}(I_{\text{off}})}{z_{\mathcal{A}}(I_{\text{off}})} \tag{1.5}$$

The value of information can be interpreted as the gap between the solution returned by an algorithm $\mathcal{A}$ on a instance I and the solution returned by the same algorithm when all information from I is known beforehand. In contrast with the competitive ratio, the value of information gives information on the performance of an algorithm based on empirical results, without requiring optimal solutions for the offline instances. It captures the impact of the dynamism on the solution yield by the algorithm under analysis. For instance, Gendreau et al. (1999) report a value of information between 2.5% and 4.1% for their tabu search algorithm for the D-VRPTW, while Tagmouti et al. (2011) reports values between 10% and 26.7% for a variable neighborhood search descent applied to a dynamic arc routing problem.

1.4.4 Benchmarks

To date, there is no reference benchmark for dynamic routing problems. Although, it is worth noting that various authors based their computational experiments on adaptations of the Solomon (1987) instances for static routing (Bent and Van Hentenryck, 2004a,b; Chen et al., 2006; Chen and Xu, 2006; Gendreau et al., 1999). Van Hentenryck and Bent (2006, Chap. 10) describe how the original benchmark by Solomon (1987) can be adapted to dynamic problems.

The interested reader is referred to the website of Pankratz and Krypczyk (2009) for an updated list of publicly available instances sets for dynamic vehicle routing problems.

1.5 Conclusions

Recent technological advances provide companies with the right tools to manage their fleet in real time. Nonetheless, these new technologies also introduce more complexity in fleet management tasks, unveiling the need for decision support systems adapted to dynamic contexts. Consequently, during the last decade, the research community have shown a growing interest for the underlying optimization problems, leading to a new family of approaches specifically designed to efficiently address dynamism and uncertainty. By analyzing the current state of the art, some directions can be drawn for future research in this relatively new field.

First, further work should aim at creating a taxonomy of dynamic vehicle routing problem, possibly by extending existing research on static routing (Eksioglu et al., 2009). This would allow a more precise classification of approaches, evaluate similarities between problems, and foster the development of generic frameworks.

Second, there is currently no reference benchmark for dynamic vehicle routing problems. Therefore, there is a strong need for the development of publicly available benchmarks for the most common dynamic vehicle routing problems.

Third, with the advent of multi-core processors on desktop computers, and low-cost graphical processing units (GPU), parallel computing is now readily available for time-consuming methods such as those based on sampling. Although early studies considered distributed optimization (Gendreau et al., 1999), most approaches reviewed in this document do not take advantage of parallel architectures. The development of parallel algorithms is a challenge that could reduce the time needed for optimization and provide decision makers with highly reactive tools.

Fourth, our review of the existing literature revealed that a large fraction of work done in the area of dynamic routing does not consider stochastic aspects. We are convinced that developing algorithms that make use of stochastic information will improve the fleet performance and reduce operating costs. Thus this line of research should become a priority in the near future.

Finally, researchers have mainly focused on the routing aspect of the dynamic fleet management. However, in some applications there is more that can be done to improve performance and service level. For instance, in equipment maintenance services, the call center has a certain degree of freedom in fixing service appointments. In other words, it means that the customer time windows can be defined, or influenced, by the call center operator. As a consequence, a system in which aside from giving a yes/no answer to a customer request, suggests convenient times for the company would be highly desirable in such contexts.

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2

Dynamic and deterministic routing

In *dynamic and deterministic* problems, part or all of the input is unknown and revealed dynamically during the design or execution of the routes. This class of problems are also referred to as *online* or *real time* by some authors (Jaillet and Wagner, 2008).

In this chapter we present a fast re-optimization approach able to produce high quality routing in limited computational time, then we introduce a bi-objective dynamic routing problem and study the trade-off between route consistency and cost efficiency in dynamic routing.

The full reference of the paper presented in this chapter is:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012)
  A fast re-optimization approach for dynamic vehicle routing
  Technical report, École des Mines de Nantes, France. Report 12/6/AUTO.

Previous versions of this work were presented in the ROADEF 2012 conference:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012)
  Route stability in dynamic vehicle routing: a bi-objective approach
  In *ROADEF 2012*, Angers, France.

Fast re-optimization approaches for dynamic vehicle routing

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Journal : *Technical Report 12/6/AUTO*

State : Working paper

Abstract : The present work deals with dynamic vehicle routing problems in which new customers appear during the design or execution of the routing. We propose a parallel Adaptive Large Neighborhood Search (pALNS) that produces high quality routes in a limited computational time. Then, we introduce the notion of driver inconvenience and define a bi-objective optimization problem that minimizes the cost of routing while maintaining its consistency throughout the day. We consider a problem setting in which vehicles have an initial routing plan at the beginning of the day, that is periodically updated by a decision maker. We introduce a measure of the driver inconvenience resulting from each update and propose a bi-objective approach based on pALNS that is able to produce a set of non-dominated solutions in reasonable computational time. These solutions offer different tradeoffs between cost efficiency and consistency, and can be used by the decision maker to update the routing of the vehicles introducing a controlled number of changes.

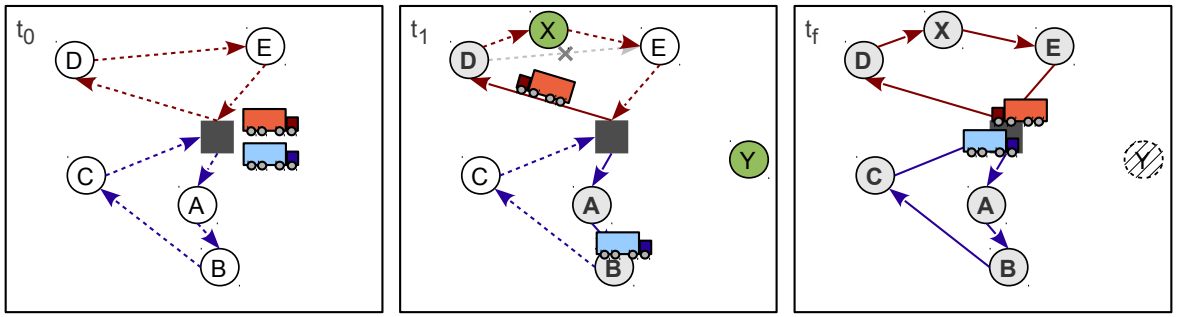
Keywords : Dynamic vehicle routing ; route consistency ; bi-objective optimization

2.1 Introduction

The problem of operating a fleet of vehicles arises in many contexts, from pickup and delivery of goods to the transportation of patients in hospitals. More specifically, Vehicle Routing Problems (VRP) deal with the design of a set of minimal-cost vehicle routes that serve the demand for goods or services of a group of geographically spread customers, satisfying operational constraints. From an information perspective, such problems generally include two dimensions: *evolution* and *quality* of information (Psaraftis, 1980). Information evolution relates to the fact that the data available to the planner may change during the execution of the routes, for example with the arrival of new customer requests. Information quality reflects possible uncertainty on the available data, for instance, when the demand of a customer is only known as a range estimate of its real demand, or when the geographical distribution of customers can be forecasted. Based on these dimensions, Pillac et al. (2011) classify vehicle routing problems in four categories depending on whether the problem is static/dynamic and deterministic/stochastic. Dynamism in routing can emerge from different aspects of the problem. The most common source of dynamism is the arrival of new customers with a demand for goods or services. Other sources of dynamic include dynamically revealed demands for a set of known customers,

dynamic travel times, and vehicle availability.

The present work focuses on *dynamic and deterministic* routing, also referred to as *online* routing, in which part or all of the input is unknown and revealed dynamically and unpredictably during the execution of the routes. Vehicle routes are redefined in an ongoing fashion, requiring technological support for real time communication between the vehicles and the decision maker (e.g., mobile phones and global positioning systems). More specifically, we study the Dynamic Vehicle Routing Problem with Time Windows (D-VRPTW), in which a limited fleet of identical capacitated vehicles must deliver a product to a set of customers over a single day horizon. Each customer has a geographic position, requires a known quantity of product, and must be served within a given time frame. While a set of (*static*) customers is known beforehand, new (*dynamic*) customers may appear during the day.



a. Initial routing b. New customers c. Final routing

Figure 2.1: Illustration of a typical dynamic vehicle routing problem.

Figure 2.1 illustrates the routing of two vehicles in a dynamic context. Before the vehicles leave the depot (2.1a.), two routes are designed to visit the currently known customers: (A, B, C) and (D, E). While the vehicles execute their route, two new customers (X and Y) appear at time t_1 (2.1b.). At this stage, the dispatcher must decide whether or not it should *accept* or *reject* the new requests. In this case, Y is far from the current routes and vehicles, therefore its service may not be feasible or may be too costly. Customer Y is thus rejected and a penalty is paid. On the other hand, X is accepted and inserted in the second route. Finally, at time t_f the executed route are (A, B, C) and (D, X, E) (2.1c.). This example reveals how dynamic routing inherently adjusts routes in an ongoing fashion, which requires real-time communication between vehicles and the dispatching center. In this context, the problem is first to design an initial set of routes, visiting all the static customers. Then, each time a new customer appears, the problem is to decide whether it can be served or not, and eventually, to reoptimize the vehicle routes. We assume that by rejecting customers we incur a penalty that can be interpreted as an outsourcing cost. Dynamic routing problems introduce new challenges as they require to react quickly to changes in the available data. According to Ichoua et al. (2007), the level of dynamism of a problem can be characterized according to two dimensions: the *frequency* of changes and the *urgency* of customer requests. The former is the rate at which new information becomes available, while the latter is the period of time between the disclosure of a new customer and its expected service time. From this observation different metrics have been proposed to measure the dynamism of a problem (or instance). Lund et al. (1996) defined the *degree of dynamism* δ as the ratio between the number of

dynamic customers n_d and the total number of customers n_{tot}: $\delta = \frac{n_d}{n_{tot}}$. Larsen (2001) extended the degree of dynamism to take into account the disclosure date and the time windows of the dynamic customers.

To the best of our knowledge, the first application of an optimization technique to dynamic routing is due to Psaraftis (1980) with the development of a dynamic programming approach. His research focuses on the Dial A Ride Problem (DARP) and consists in finding the optimal route each time a new customer is known. The main drawback of dynamic programming is the well-known *curse of dimensionality* (Powell, 2007, Chap. 1), which often prevents its application to large instances. Few research was conducted on dynamic routing between Psaraftis (1980) and the late 1990s. However, the last decade has seen a renewed interest in dynamic routing, with numerous approaches tackling a variety of problems. This section classifies the major contributions in this field in two categories: 1) *periodic reoptimization* and 2) *continuous reoptimization.* The reader is referred to the reviews, books, and special issues by Gendreau and Potvin (2004); Ghiani et al. (2003); Ichoua et al. (2007); Larsen et al. (2008); Pillac et al. (2011), and Zeimpekis et al. (2007), to complement our review.

Figure 2.1 presents an overview of periodic reoptimization approaches: the algorithm starts at the beginning of the day and a first optimization produces an initial solution S_0. Then, the procedure waits for an update in the available data, or for a fixed period of time, followed by a new optimization trigger that leads to an updated solution S_{t+1}. The advantage of periodic reoptimization approaches is that they can be based on algorithms developed for static routing, for which extensive research has been conducted. Their main drawback is that all the optimization has to be performed before updating the solution, which can increase the delays for the dispatcher, while the computational power is unused during waiting times.

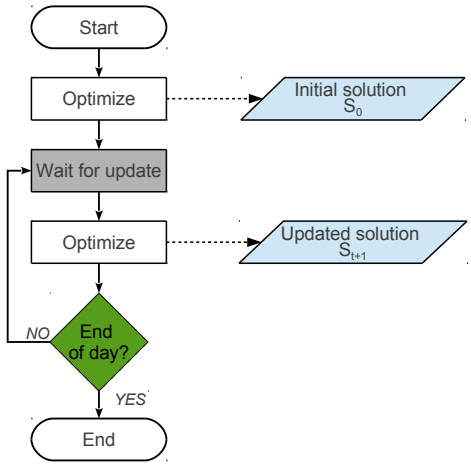


Figure 2.2: Overview of periodic reoptimization approaches

Periodic reoptimization approaches were used in different contexts to tackle dynamic routing problems. Chen and Xu (2006) designed a dynamic column generation algorithm (DYCOL) for the D-VRPTW. The authors use the concept of *decision epochs* over the planning horizon, which are the dates when the optimization process runs. It is worth noting that a new customer is not handled until the next decision epoch, hence, the optimization is run statically and independently at each de-

cision epoch. The main advantage of this time partition is that similar computational effort is allowed for each time slice. The novelty of their approach relies on dynamically generating columns for a set-partitioning model, using columns from the previous decision epoch. The authors compared DYCOL to a traditional column generation with no time limit (COL). Computational results based on the Solomon benchmark (Solomon, 1987) demonstrate that DYCOL yields comparable results in terms of objective function, but with running times limited to 10 seconds, opposed to the various hours consumed by COL. Using a notion similar to decision epochs, Montemanni et al. (2005) developed an Ant Colony System (ACS) to solve the D-VRP. An interesting feature of their approach is the use of the pheromone trace to transfer characteristics of a good solution to the next time slice. ACS was also used by Gambardella et al. (2003) and Rizzoli et al. (2007). Other heuristic approaches, such as Tabu Search (TS), were also used to tackle the Dynamic Pickup and Delivery Problem (D-PDP) (Barcelo et al., 2007; Chang et al., 2003) and the Dynamic Dial-a-Ride Problem (D-DARP) (Attanasio et al., 2004; Beaudry et al., 2010).

In contrast, continuous reoptimization approaches perform the optimization throughout the day in an *optimization loop* and store information on good solutions in an *adaptive memory* (see Figure 2.1). In parallel, a *decision loop* aggregates the information from the memory whenever needed. The advantage of such approaches is that the computational power utilization is maximized, at the price of possibly cumbersome implementation.

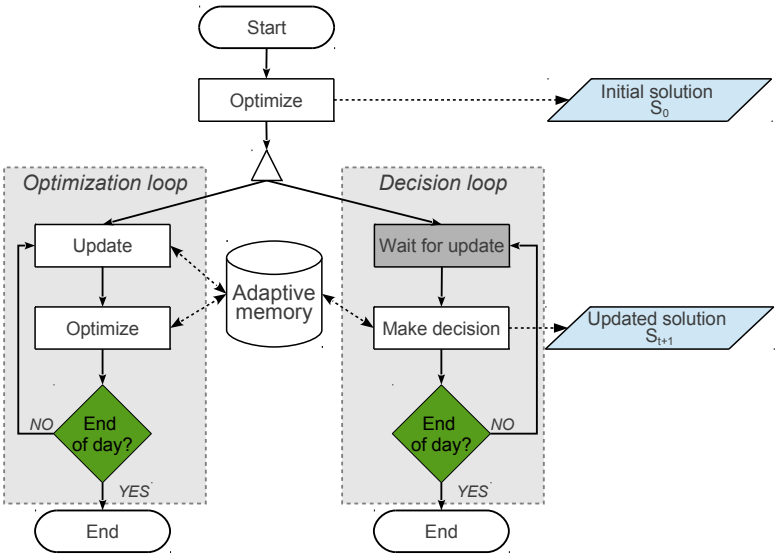


Figure 2.3: Overview of continuous reoptimization approaches

To the best of our knowledge, the first application of continuous reoptimization is due to Gendreau et al. (1999). Their approach consists in the adaptation of the Tabu Search (TS) framework introduced by Taillard et al. (1997) to a dynamic context motivated by the local operation of long distance express courier services, which can be seen as a D-VRPTW. The general idea is to maintain a pool of good routes–the *adaptive memory* (Taillard et al., 2001)–which is used to generate initial solutions for a parallel tabu search. The parallelized search is done by partitioning the routes of the current solution and optimizing them in independent threads. Whenever a new customer request arrives, it is

checked against all the solutions from the adaptive memory to decide whether it should be accepted or rejected. This framework was also implemented for the D-VRP (Ichoua et al., 2000, 2003). Bent and Van Hentenryck (2004) generalized this framework and introduced the Multiple Plan Approach (MPA) to tackle the D-VRPTW. The general idea is to populate and maintain a solution pool (the routing *plans*) that are used to generate a *distinguished solution*. Whenever a new customer arrives, a procedure is called to check whether it can be served or not; if it can be served, then the customer is inserted in the solution pool and incompatible solutions are discarded. Pool updates are performed periodically or whenever a vehicle finishes servicing a customer. This pool-update phase is crucial and ensures that all solutions are coherent with the current state of vehicles and customers. The pool can be seen as an adaptive memory that maintains a set of alternative solutions. Following a different approach, Benyahia and Potvin (1998) studied the D-PDP and proposed a Genetic Algorithm (GA) that models the decision process of a human dispatcher. More recently, other GAs were also used for the same problem (Cheung et al., 2008; Haghani and Jung, 2005) and for the D-VRP (Van Hemert and Poutré, 2004). Genetic algorithms in dynamic contexts are very similar to those designed for static problems, except that they run throughout the planning horizon and solutions are constantly adapting to the changes made to the input.

In this work we propose two parallelized periodic reoptimization approaches. Section 2.2 presents a parallel adaptive large neighborhood search to tackle the D-VRPTW; Section 2.3 introduces a bi-objective extension of the D-VRPTW and proposes a reoptimization approach; finally, Section 2.4 concludes this work and gives directions for further research.

2.2 Fast reoptimization for dynamic routing

The proposed approach is based on a parallel Adaptive Large Neighborhood Search (pALNS) algorithm which is used to compute an initial solution, and then, to reoptimize the solution whenever a new customer request arrives. In the remainder of this section we present the original Adaptive Large Neighborhood Search (ALNS) algorithm, discuss the proposed parallelization scheme and the reoptimization approach, and present computational results on the D-VRPTW.

2.2.1 The Adaptive Large Neighborhood Search

The ALNS algorithm, originally proposed by Pisinger and Ropke (2007), is an extension of the Large Neighborhood Search (LNS) algorithm (Shaw, 1998). LNS works by successively destroying (removing customers) and repairing (inserting customers back) a current solution, using *destroy* and *repair operators*. ALNS adds an adaptive layer that randomly selects operators depending on their past performance, automatically fitting the algorithm to the instance at hand. We refer the interested reader to Pisinger and Ropke (2010) for a detailed description of LNS, ALNS, and related methods.

Algorithm 2.1 presents the outline of the ALNS approach. ALNS starts with an initial solution $\mathbf{\Pi}_0$. Then for I iterations, the algorithm selects destroy and repair operators (line 4) with a roulette wheel that reflects their past performance. Destroy operators remove a subset of customers from the current solution, while repair operators reinsert them using heuristics that are known to perform well on the

Algorithm 2.1 Adaptive Large Neighborhood Search (ALNS) algorithm

Input: $\mathbf{\Pi}_0$ initial solution, z evaluation function, Θ^-/Θ^+ set of destroy/repair operators, I number of iterations
Output: $\mathbf{\Pi}^*$ the best solution found

1: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}_0$ ▷ Initialize best solution
2: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}_0$ ▷ Initialize current solution
3: **for** I iterations **do**
4: $d \leftarrow \texttt{select}(\Theta^-); r \leftarrow \texttt{select}(\Theta^+)$ ▷ Select destroy/repair
5: $\mathbf{\Pi}' \leftarrow \texttt{r}(\texttt{d}(\mathbf{\Pi}))$ ▷ Generate a neighbor
6: **if** $\texttt{accept}(\mathbf{\Pi}', \mathbf{\Pi})$ **then** ▷ $\mathbf{\Pi}'$ is accepted as current solution
7: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}'$ ▷ Update current solution
8: **end if**
9: **if** $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then** ▷ An improvement has been found
10: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ Update best solution
11: **end if**
12: $\texttt{updateScore}(d, r, \mathbf{\Pi}')$ ▷ Update scores
13: **end for**
14: **return** $\mathbf{\Pi}^*$

problem at hand (line 5). The resulting new solution is conditionally accepted as current solution according to a simulated annealing criterion (line 6). At the end of each iteration, the scores of the destroy and repair operators are updated depending on the solution they generated (line 12).

2.2.2 Parallel Adaptive Large Neighborhood Search

We propose pALNS, an extension of the Adaptive Large Neighborhood Search (ALNS) algorithm that includes a novel parallelization scheme that efficiently spreads the computational effort among independent processors.

Algorithm 2.2 presents the outline of pALNS. The algorithm maintains a pool $\mathcal{P}$ of N promising solutions that are optimized in K subprocesses (note that $N \geq K$). For each *master* iteration, a subset of K promising solutions is selected randomly (line 2) and distributed among independent subprocesses. Each subprocess performs I^p ALNS iterations (lines 3-14) by destroying and repairing the current solution $\mathbf{\Pi}^p$ as in the original ALNS algorithm. The final current solution of each subprocess is added to the pool of promising solutions (line 13) and a filtering procedure ensures that the pool contains at most N solutions, including the best solution found so far (line 15). The algorithm stops after I^m master iterations, which corresponds to $I = I^m \times I^p$ ALNS iterations. Note that the implementation of pALNS ensures that no synchronization is required between subprocesses to avoid deadlocks. The following paragraphs present in more detail the different components of the algorithm.

2.2.2.1 Destroy

Destroy operators remove a random fraction $\xi \in [\xi_{min}, \xi_{max}]$ of the customers from the current solution. We denote $\mathcal{R}$ the set of customers served in the solution, and $\mathcal{U}$ the set of customers that are not served. We used three destroy operators originally proposed by Pisinger and Ropke (2007): *random*, *related*, and *critical*.

Algorithm 2.2 Parallel Adaptive Large Neighborhood Search (pALNS) algorithm

Input: $\mathcal{P}$ initial solutions, z evaluation function, Θ^-/Θ^+ set of destroy/repair operators, N maximum size of the solution pool, K number of subprocesses, I^m number of master iterations, I^p number of iterations performed in parallel.
Output: $\mathbf{\Pi}^*$, the best solution found

for I^m iterations **do**
  $\mathcal{P}' \leftarrow \texttt{selectSubset}\,(\mathcal{P}, K)$ ▷ Select a subset of K solutions
  parallel forall $\mathbf{\Pi}$ **in** $\mathcal{P}'$ **do**
    $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}$ ▷ Current solution for this subprocess
    for I^p iterations **do**
      $d \leftarrow \texttt{select}\,(\Theta^-)\,; r \leftarrow \texttt{select}\,(\Theta^+)$ ▷ Select destroy/repair
      $\mathbf{\Pi}' \leftarrow \texttt{r}\,(\texttt{d}\,(\mathbf{\Pi}^p))$ ▷ Destroy and repair current solution
      if $\texttt{accept}\,(\mathbf{\Pi}', \mathbf{\Pi}^p)$ **then**
        $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is accepted as current solution
      end if
      $\texttt{updateScore}\,(d, r, \mathbf{\Pi}')$ ▷ Update d and r scores
    end for
    $\mathcal{P} \leftarrow \mathcal{P} \cup \{\mathbf{\Pi}^p\}$ ▷ Add $\mathbf{\Pi}^p$ to the pool $\mathcal{P}$
  end forall
  $\mathcal{P} \leftarrow \texttt{retain}\,(\mathcal{P}, N)$ ▷ Retain at most N solutions in the pool $\mathcal{P}$
end for
return $\mathbf{\Pi}^* = \arg\min_{\mathbf{\Pi} \in \mathcal{P}} \{z(\mathbf{\Pi})\}$

The random destroy operator selects customers randomly and removes them from their actual tours.

The related destroy attempts to remove customers that share some characteristics. Let the *relatedness* r_{ij} of customers i and j be a measure of how related two customers are (the lower the r_{ij}, the more related i and j). The procedure starts by randomly removing a *seed* customer i ($\mathcal{U} = \{i\}$), then it iteratively selects a customer $i \in \mathcal{U}$, and removes the most related customer j^*:

$$j^* = \arg\min_{j \in \mathcal{R}} \{r_{ij}\} \tag{2.1}$$

There are different ways to measure the relatedness. We propose a new metric that can be precalculated, namely a-priori relatedness, that does not depend on the actual position of customers in tours:

$$r^s_{ij} = \left(1 + \frac{c_{ij}}{M_c}\right)^{\theta_c} \left(1 + \frac{|b_i - b_j|}{M_t}\right)^{\theta_t} \tag{2.2}$$

Where c_{ij} is the distance between i and j, b_i and b_j are the end of the time windows of customers i and j, M_c and M_t are scaling constants, θ_c and θ_t define the weight given to the geographic distance between the two customers, and the difference between due dates respectively.
On the other hand, time-oriented relatedness (Pisinger and Ropke, 2007) measures the difference be-

tween the current times of service A_i and A_j of customers i and j:

$$r_{ij}^t = |A_i - A_j| \tag{2.3}$$

Finally, critical destroy consists in removing the customer i^* such that the cost of the resulting solution is minimal:

$$i^* = \arg\max_{i \in \mathcal{R}} \{c_{i-1,i+1} - c_{i-1,i} - c_{i,i+1}\} \tag{2.4}$$

Where $i-1$ and $i+1$ are the predecessor and successor of i.

In practice related and critical operators are randomized and the $\lfloor y^p |\mathcal{R}| \rfloor$-th best customer is selected, where y is a random number in $[0, 1)$ and $p \geq 1$ is a parameter that controls the level of randomness (the lower the p, the more randomness is introduced).

2.2.2.2 Repair

Repair operators attempt to insert customers that are currently unserved. Our implementation is based on *regret-q heuristics* (Potvin and Rousseau, 1993): at each iteration the algorithm inserts (at the best position) the customer with the lowest *regret* value. The regret-q value r_i^q of customer i is a measure of how desirable it is to insert i in the current iteration assuming that the best insertion will no longer be feasible in the next iteration. It is defined as:

$$r_i^q = \sum_{h=2}^{q} \left(\Delta z_i^h - \Delta z_i^1 \right) \tag{2.5}$$

Where Δz_i^q is the cost of the q-th best insertion of customer $i \in \mathcal{U}$. Note that ties are resolved by selecting the customer with the lowest Δz_i^1 value, and therefore regret-1 corresponds to the classical best insertion heuristic. We used three regret levels: regret-1, regret-2, and regret-3.

2.2.2.3 Adaptive layer

At each iteration, the pALNS algorithm selects a destroy and a repair operator using a selection roulette, such that operator $\theta \in \Theta^\cdot$ is selected with probability w_θ, where $\Theta^\cdot$ is either the set of destroy (Θ^-) or repair (Θ^+) operators. Probabilities are initialized with value $\frac{1}{|\Theta^\cdot|}$, and then updated every l iterations (a *segment*) as follows:

$$w_\theta \leftarrow (1-\rho) w_\theta + \rho \frac{s_\theta}{\sum_{\theta \in \Theta^\cdot} s_\theta} \tag{2.6}$$

Where $\rho \in [0, 1]$ is the *reaction factor* which defines how quickly probabilities are adjusted, and s_θ is the *score* of operator θ in the last l iterations. The scores s_θ are reset to 0 every l iterations and updated at the end of each iteration depending on the new solution: a score of σ_1 is granted for a new best solution, σ_2 for an improving solution, σ_3 for a non-improving but accepted solution, and σ_4 for a rejected solution. It is worth noting that in contrast with the adaptive scheme originally proposed by

Pisinger and Ropke (2007), this formula ensures that $\sum_{\theta \in \Theta}. w_\theta = 1$ at all time, which makes it easier to interpret the relative weight of each component.

2.2.2.4 Objective function

The initial solution or the solution resulting from the destroy operator can leave some customers unserved ($\mathcal{U} \neq \emptyset$). Therefore we need to be able to evaluate a partial solution $\mathbf{\Pi}'$ to account for the unserved customers. Given an evaluation function z and an initial solution $\mathbf{\Pi}_0$, Pisinger and Ropke (2007) define the cost of partial solution $\mathbf{\Pi}'$ as follows:

$$z_\phi(\mathbf{\Pi}') = z(\mathbf{\Pi}') + \phi|\mathcal{U}|z(\mathbf{\Pi}_0) \tag{2.7}$$

Where ϕ is a parameter that controls the unserved customer penalty.

2.2.2.5 Acceptance criterion

As in the original ALNS, the pALNS algorithm relies on a simulated annealing acceptance criterion which accepts a new solution $\mathbf{\Pi}'$ with probability $e^{\frac{z(\mathbf{\Pi})-z(\mathbf{\Pi}')}{T}}$, where T is the *temperature* parameter. The temperature is initialized with the value T_0 and it is reduced at each iteration by a *cooling factor* c. The two parameters T_0 and c are set depending on the initial solution and the target number of iterations (Ropke and Pisinger, 2006). Given an initial solution $\mathbf{\Pi}_0$, T_0 is defined such that a solution with value $(1 + w)z(\mathbf{\Pi}_0)$ is accepted with probability p, and c is set such that the temperature after n iterations is equal to αT_0.

2.2.2.6 Computation of an initial solution

The pALNS algorithm requires an initial solution which is computed with a regret-3 constructive heuristic: starting with empty routes for each vehicle, the algorithm iteratively inserts the customer with the lowest regret value as described in §2.2.2.2.

2.2.2.7 Solution pool

The solution pool acts as a shared memory and allows subprocesses to collaborate efficiently. In the original algorithm, the simulated annealing acceptance criterion results in a search scheme that starts from a diversification phase, in which poor solutions may be accepted as current solutions, and progressively switch to an intensification phase, in which only improving solutions are accepted. The use of a solution pool that would contains the N best solutions found so far tend to break this scheme, as poor solutions may never be kept in the pool and will therefore not be exploited properly. To overcome this limitation we propose to maintain a pool of *diverse* solutions that are promising in terms of cost.

This is achieved by the `retain` method (line 15) which ensures that $\mathcal{P}$ contains at most N solutions: if $|\mathcal{P}| > N$ then the method retains the N best solutions according to the fitness function f:

$$f(\mathbf{\Pi}) = (1 - \lambda)\text{rank}_z(\mathbf{\Pi}) + \lambda\text{rank}_d(\mathbf{\Pi}) \tag{2.8}$$

Where λ is a weight between 0 and 1, $\mathrm{rank}_z(\mathbf{\Pi})$ is the rank of solution $\mathbf{\Pi}$ according to its objective value, and $\mathrm{rank}_d(\mathbf{\Pi})$ is the rank of $\mathbf{\Pi}$ according to its average *broken-pairs distance* (Prins, 2009) relative to the other solutions from $\mathcal{P}$. The broken pairs distance counts the number of arcs that differ between two solutions. This fitness function is inspired by the *biased fitness* introduced by Vidal et al. (Vidal et al., 2011) in a genetic algorithm with diversity management. The weight λ can either be fixed a-priori, or adjusted throughout the search to switch from diversification ($\lambda = 1$) to intensification ($\lambda = 0$). Note that we ensure that $\mathcal{P}$ always contains the best solution found so far.

2.2.3 Parallel reoptimization approach for the D-VRPTW

Figure 2.4 illustrates the proposed reoptimization approach: the algorithm starts by producing an initial solution S_0 by using a constructive heuristic coupled with the pALNS described in the previous section. Then each time a new customer appears, it fixes the currently executed portion of the routes, and re-runs the pALNS for a limited number of iterations to produce an updated solution S'_t. If pALNS is able to insert the new customer request, then the customer is *accepted* and S'_t becomes the new current solution, otherwise the customer is *rejected* and S_t remains as the current solution.

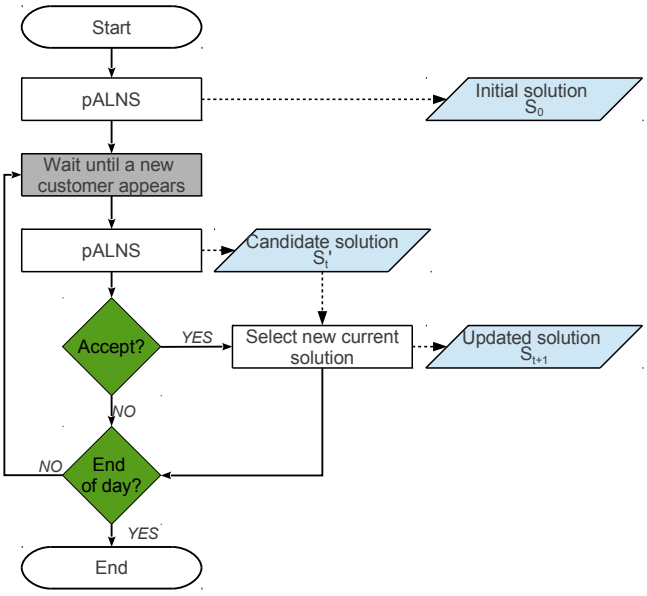


Figure 2.4: Overview of the proposed approach

It is important to note that the immediate commitment of idle vehicles to customers may lead to difficulties when new customers appear. Figure 2.5 illustrates this with a single vehicle. Suppose that at time t a vehicle is assigned to a customer i, if the vehicle is dispatched immediately to i (upper left time line), it will travel to i then wait at its destination until the start of the time window (black brackets). On the other hand, if a waiting strategy is used (lower left time line), the vehicle will remain idle until the latest moment such that it will not wait at i. If at time $t+1$ a new customer j appears, in the first case j cannot be served as the vehicle is already waiting at i, while in the second case a visit to j can be inserted right before i. As a consequence, vehicles are considered to remain idle at their current location until the latest departure time such that it will not wait at the next customer, leaving

time for further insertions.

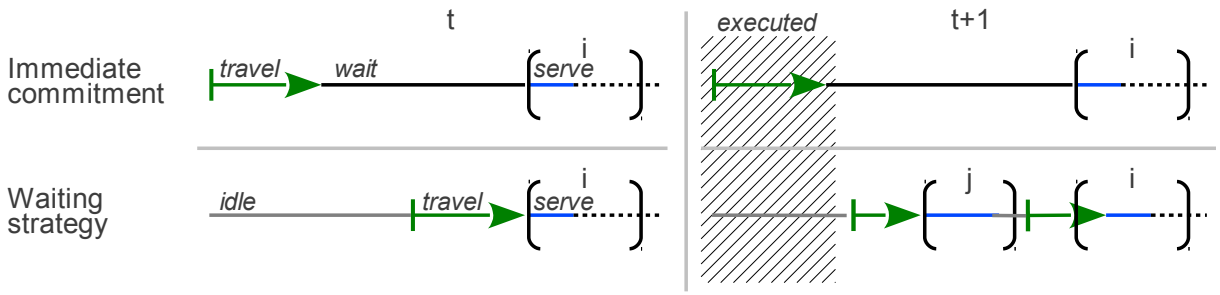


Figure 2.5: Illustration of the waiting strategy.

2.2.4 Computational results

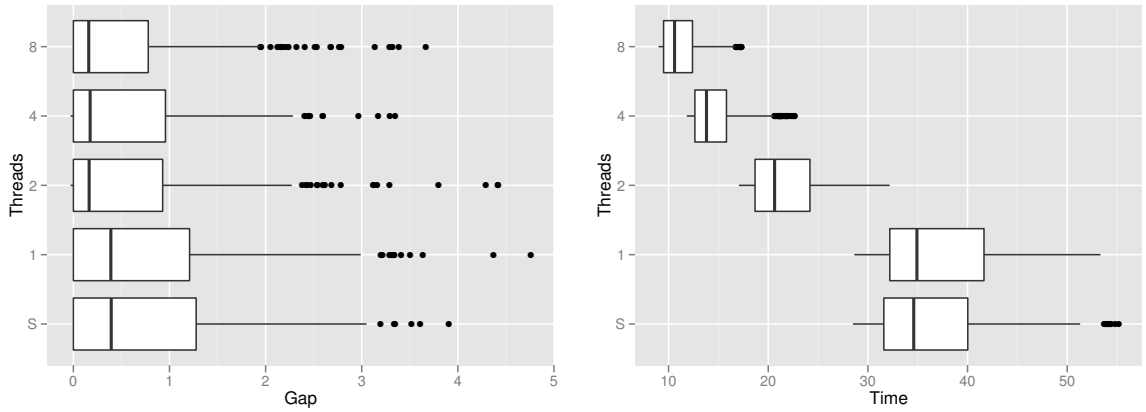
To assess the effect of parallelization we tested our algorithm on the static instances for the VRPTW proposed by Solomon (1987) on a quad-core desktop computer [1]. For the detailed parameter setting of the algorithm please refer to Appendix 2.A.

		Parallel - Num. of Threads							
	Seq.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Gap	0.74%	0.72%	0.55%	0.69%	0.54%	0.70%	0.52%	0.66%	0.48%
Gap (st. dev.)	0.87%	0.88%	0.76%	0.89%	0.70%	0.86%	0.74%	0.82%	0.66%
Time (s)	36.58	37.32	22.07	17.60	14.70	14.69	13.39	12.37	11.32
Time (s, st. dev.)	6.27	6.33	4.06	3.17	2.72	2.57	2.50	2.27	2.15

Table 2.1: Comparison of gap to the best known solutions and running times for different levels of parallelization.

Table 2.1 presents aggregated values over the 53 instances, with ten run per instance and 25,000 ALNS iterations [2]. The first column corresponds to the original sequential (Seq.) implementation of the ALNS, and the following to the parallel implementation with 1 to 8 threads. The first and second rows contain the mean and standard deviation of the gap value relative to either the optimal or the best known solution. Finally, the third and fourth rows show the mean and standard deviation of the CPU times. Note that increasing the number of threads has a limited impact on the gap to the best known solutions, which is consistently around 0.6%, but it allows a reduction of running times by a factor 3.3. Figure 2.6 presents the box plot of the distribution of the gap and CPU times for the sequential (S) and parallel implementations with 1, 2, 4, and 8 threads. A graphical analysis shows that the median gap and variance slightly decrease with the number of threads. In contrast, the median running time and variance decreases sharply with the number of threads. Therefore, we selected the configuration with 8 threads as it offers the best compromise between speed and quality. Note that the processor used is a quad-core with Intel hyper-threading technology which allows two threads per core. This partially explains the relatively small reduction of CPU times when switching from 4 to 8 threads.

1. CPU: Intel i7 860 (4x2.8GHz), RAM: 6GB DDR3, OS: Ubuntu 11.10 x64, Java 7
2. To ensure that $I = I^m \times I^p \times K \simeq 25000$, we used $I^m = \left\lceil \frac{25000}{40 \times K} \right\rceil$



a. Gap (%) vs. number of threads

b. CPU time (s) vs. number of threads

Figure 2.6: Impact of the number of threads on the gap and CPU time.

We tested the pALNS algorithm on the instances proposed by Lackner (2004) and based on the Solomon (1987) benchmark, in which a fraction of the customers is revealed dynamically. The instances contain 100 customers located randomly (R), in clusters (C), or combining both (RC); while the planning horizon is either short (type 1) or long (type 2); and the number of dynamic customers (or degree of dynamism, δ) is either 10, 30, 50, 70, or 90. These instances are organized combining location, horizon length, and degree of dynamism. We consider the minimization of the traveled distance. For each instance, we performed 10 simulations in which pALNS is initially run for 25,000 iterations to produce an initial solution. Then, each time a new customer appears, pALNS is run for 5,000 iterations to produce a solution that will be used until the next customer is revealed. Finally, pALNS is run for 50,000 iterations to solve the a-posteriori problem, in which all the accepted customers are assumed to be known beforehand.

Table 2.2 presents the *Value of Information* (VI) (Lund et al., 1996) for each instance group and degree of dynamism (δ). The value of information for instance I is defined as the ratio $\frac{z(I)-z(I_{\text{off}})}{z(I_{\text{off}})}$ where $z(I)$ is the value of the solution found by the algorithm for the dynamic instance, and $z(I_{\text{off}})$ is the value of the solution for a-posteriori instance I_{off}. As expected, results indicate that the VI increases with the degree of dynamism, which can be explained by the fact that suboptimal routing decisions add up over time, and more decisions are made in highly dynamic instances. However, even when 90 out of 100 customers appear dynamically, the VI is of just 11% on average, which means that the algorithm is still able to produce a final routing that is very close to what would have been done if all the customers were known from the beginning of the day.

Table 2.3 presents a comparison of approaches for the Lackner (2004) instances. The first and second columns present the traveled distance and number of rejected customers for pALNS, averaged over 10 runs and for each group and degree of dynamism. The third and fourth columns report the average distance, relative average additional distance (in parenthesis), and number of rejected customers for the Large Neighborhood Search (LNS) approach proposed by Hong (2012), while the fifth and sixth columns report the same values for the Genetic Algorithm (GA) developed by Lackner (2004). Note that the experimental setting of the two cited studies is not explicitly presented, which limits the rele-

δ	R1	C1	RC1	R2	C2	RC2	Avg.
10	2.05%	2.89%	3.06%	1.70%	1.66%	1.61%	**2.14%**
30	4.67%	5.83%	5.83%	4.34%	1.74%	4.70%	**4.54%**
50	6.41%	9.28%	9.03%	8.15%	2.82%	5.38%	**6.93%**
70	8.29%	11.18%	10.24%	10.17%	5.41%	8.60%	**9.03%**
90	9.33%	12.49%	11.84%	11.83%	6.51%	12.33%	**10.71%**

Table 2.2: Average value of information for the Lackner (2004) instances

vance of direct comparisons. Nonetheless, figures show that our approach is competitive both in terms of traveled distance and number of rejected customers. In addition, average running times are of just 5.3s for the initial optimization, and 2.0s for subsequent reoptimizations, which is significantly less than the 33s and 47s reported by Hong (2012) and Lackner (2004) respectively.

2.3 Route consistency in dynamic routing: a bi-objective approach

Most studies on dynamic routing consider that routes are designed online, which means that vehicle drivers do not know their next destination until they finish serving their current customer. Although this assumption is theoretically appealing and allows a better optimization of the cost function, it may not be desirable if drivers are used to know their routes from the beginning of the day. In practice, having a set of routes known a-priori that are then changed may be desirable over purely dynamic routing. Hence there is a need for approaches able to maintain consistency in the vehicles routes throughout the day while ensuring cost efficiency.

To the best of our knowledge, all studies on dynamic routing focus on the optimization of a single criterion, such as the minimization of the total traveled distance or the maximization of the number of served customers. On the other hand, and as surveyed by Jozefowiez et al. (2008), a growing number of studies on static routing consider multiple objectives in an attempt to better fit operational contexts. In this section we present a preliminary study that takes into account driver inconvenience. The proposed approach is an adaptation of the pALNS algorithm that simultaneously minimizes a cost function and maximizes the route consistency throughout the day.

2.3.1 Measuring consistency

Assuming that an initial set of routes are handed to the drivers at the beginning of the day, it seems natural to consider them as the *reference* routes for each driver. To prevent multiple and unnecessary changes in routes, we assume that drivers will only be informed of changes in their routes at the last possible moment. As a consequence, a change will take effect only when necessary. From the driver's perspective, four types of changes can be made to the route: one or more customers may be a) inserted between existing customers; b) removed; c) swapped within the same route; d) substituted by a customer previously unvisited. In this context, minimizing inconvenience is therefore equivalent to minimizing the number of changes communicated to the driver.

		pALNS		Hong (2012)		Lackner (2004)	
Group	δ	**Dist.**	**Rej.**	**Dist.**	**Rej.**	**Dist.**	**Rej.**
R1	**10**	1197.4	0.25	1257.1 (4.99%)	0.17	1278.1 (6.74%)	0.47
	30	1212.9	0.80	1286.6 (6.08%)	0.58	1337.9 (10.30%)	0.72
	50	1225.0	1.25	1295.8 (5.78%)	0.67	1330.0 (8.57%)	0.78
	70	1237.3	1.71	1331.3 (7.60%)	1.75	1336.1 (7.98%)	0.94
	90	1230.1	2.55	1335.9 (8.60%)	2.33	1278.3 (3.92%)	0.75
C1	**10**	850.6	0.11	895.8 (5.31%)	0.22	996.4 (17.14%)	0.00
	30	874.9	0.11	962.1 (9.97%)	0.33	1066.9 (21.95%)	0.00
	50	903.4	0.11	1001.2 (10.82%)	0.22	1236.1 (36.82%)	0.00
	70	919.1	0.11	1031.7 (12.25%)	0.22	1261.3 (37.24%)	0.00
	90	929.9	0.11	1039.8 (11.81%)	0.22	1479.6 (59.11%)	0.00
RC1	**10**	1389.4	0.04	1436.2 (3.37%)	1.13	1426.9 (2.70%)	0.46
	30	1421.5	0.28	1492.2 (4.98%)	1.13	1439.7 (1.28%)	0.42
	50	1463.4	0.23	1514.7 (3.50%)	1.38	1448.1 (-1.05%)	0.46
	70	1470.1	0.58	1511.3 (2.80%)	1.88	1488.4 (1.25%)	0.58
	90	1495.5	0.51	1513.9 (1.23%)	2.00	1475.2 (-1.36%)	0.42
R2	**10**	893.0	0.00	950.0 (6.39%)	0.09	1052.9 (17.90%)	0.03
	30	915.6	0.00	985.5 (7.63%)	0.00	1085.4 (18.54%)	0.15
	50	948.6	0.00	1016.5 (7.17%)	0.00	1138.8 (20.05%)	0.21
	70	967.7	0.00	1032.0 (6.65%)	0.09	1116.9 (15.42%)	0.30
	90	981.7	0.00	1047.8 (6.73%)	0.09	1193.3 (21.55%)	0.52
C2	**10**	597.2	0.00	594.7 (-0.42%)	0.00	629.1 (5.35%)	0.00
	30	597.6	0.00	651.4 (9.01%)	0.00	632.3 (5.81%)	0.04
	50	604.0	0.00	605.0 (0.17%)	0.00	689.3 (14.12%)	0.13
	70	619.2	0.00	636.5 (2.79%)	0.00	743.8 (20.12%)	0.21
	90	625.7	0.00	636.8 (1.78%)	0.00	792.5 (26.66%)	0.29
RC2	**10**	1024.4	0.00	1103.3 (7.70%)	0.00	1220.9 (19.18%)	0.00
	30	1053.1	0.00	1166.0 (10.73%)	0.25	1244.9 (18.21%)	0.04
	50	1060.5	0.00	1190.5 (12.26%)	0.13	1244.9 (17.38%)	0.00
	70	1091.4	0.00	1239.5 (13.57%)	0.00	1269.3 (16.30%)	0.00
	90	1130.3	0.00	1257.2 (11.23%)	0.13	1346.8 (19.16%)	0.13
Average			**0.29**	**(+6.75%)**	**0.50**	**(+15.61%)**	**0.27**

Table 2.3: Comparison of approaches for the Lackner (2004) instances.

We use the *edit distance* (or Levenshtein distance) as a proxy for the driver's inconvenience. The edit distance between two routes is defined as the minimum number of insertions, removals, or substitutions of customers that have to be applied to transform one route into the other. Therefore the inconvenience of a new solution relative to a reference solution is equal to the sum of edit distances between each vehicle's reference and new routes. The advantage of this metric is that it is efficiently computed and models accurately the changes described above, and it can be adapted to give weights to each type of change. The main limitation of this proxy is that it does not necessarily reflect the effective number of changes communicated to the driver as sections of the route may be changed later.

Figure 2.7 illustrates the evaluation of the edit distance between a reference and a new route. The gray nodes correspond to the portion of the route that has already been executed. The distance between the reference and new route is 3, with 1 substitution (SUB), 1 insertion (INS), and 1 removal (REM).

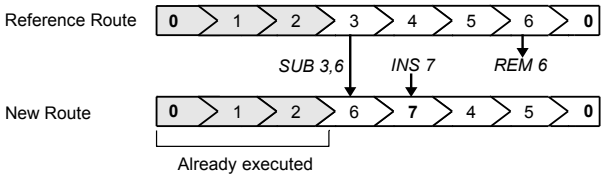


Figure 2.7: Example of the edit distance between two routes.

2.3.2 The proposed approach

The proposed approach, namely parallel Bi-objective Adaptive Large Neighborhood Search (pBiALNS), is an extension of the pALNS algorithm described in Section 2.2, and it is inspired by the bi-objective LNS proposed by Schmid and Hartl (2011). In a nutshell, the central idea is to maintain and optimize a set of non-dominated and possibly infeasible solutions. In addition, our approach introduces a parallelization scheme that improves performance and allows its use in a dynamic context.

The adaptation of the pALNS algorithm to deal with the bi-objective case is straightforward: the algorithm maintains the set $\bar{\mathcal{P}}$ of non-dominated solutions that are optimized in K subprocesses. For I^m master iterations, a subset of K non-dominated solutions is selected randomly and distributed among independent subprocesses. Each subprocess performs I^p ALNS iterations by destroying and repairing the current solution, considering only the main objective (cost). In contrast to the original pALNS algorithm, each temporary solution is considered for inclusion in the set of non-dominated solutions, and the number of solutions stored in $\bar{\mathcal{P}}$ is not limited. Finally, the algorithm returns the whole set of non-dominated solutions $\bar{\mathcal{P}}$, from which the decision maker selects a single solution.

It is important to note that the optimization itself, which takes place in the ALNS iterations, only considers the minimization of the cost. Therefore, there is an implicit lexicographic ordering of the objectives, the maximization of the consistency being handled implicitly with the set of non-dominated solutions. This choice is motivated by the fact that at each ALNS iteration the algorithm needs to introduce changes in the current solution by removing and inserting customers, and introducing the consistency at this level would steer the approach away from cost-effective solutions.

Note that pBiALNS may visit infeasible solutions that do not visit all customers. Therefore, we define a dominance relation that ensures that no feasible solution will be dominated by an infeasible solution:

Definition 1 (Dominance). *A solution* Π *dominates (denoted* $\prec$*) a solution* Π' *if and only if* Π *is as good as* Π' *in both objectives, and strictly better in one objective, and either* Π *is feasible or both* Π *and* Π' *are infeasible.*

2.3.3 Computational results

We tested the pBiALNS approach on the Lackner (2004) instances described in §2.2.4 with a similar experimental setting. pALNS is first run for 25,000 iterations to produce the *reference* (initial) solution; then, each time a new customer appears pBiALNS is run for 5,000 iterations to produce a set of candidate *new* solutions to choose from; finally, pALNS is run for 50,000 iterations to produce the a-posteriori solution to the problem.

Figure 2.8 represents the objective space explored by pBiALNS after 5,0000 iterations for one instance, at a given step of the simulation (ie., after a new customer appeared). The graph illustrates the diversity of solutions offered to the decision maker, ranging from the least-cost solution (upper left) to the most similar to the reference solution (lower right). For the purpose of benchmarking and to assess the tradeoff between the two objectives, we define a *threshold selection policy* and select the non-dominated solution that is closest to the reference, allowing a deviation in cost of at most γ percent from the least-cost solution (green diamond). This policy models the behavior of an expert dispatcher who would select one solution among the non-dominated set.

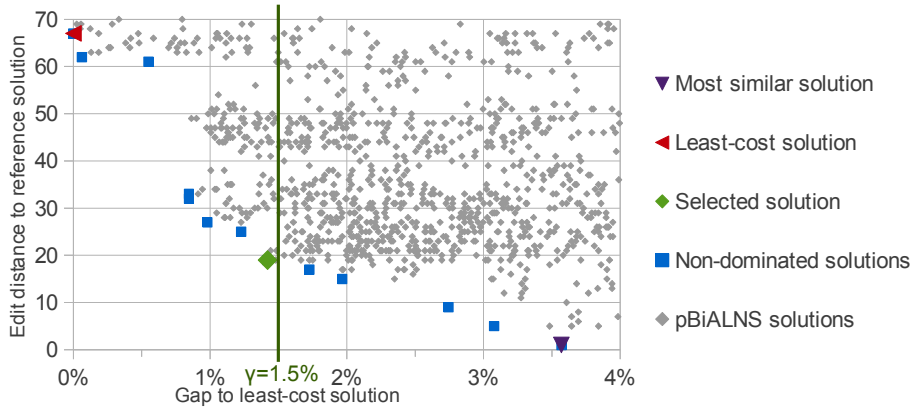


Figure 2.8: Objective space for instance R101 and illustration of the threshold policy.

Table 2.4 presents (a) the average edit distance between the final solution and the reference solution, and (b) the average gap between the cost of the final solution and the cost of a solution evaluated a-posteriori and the average number of rejected requests, for different values of γ and degree of dynamism (δ). Running times are of 2.5 seconds on average at each decision. As expected, the edit distance relative to the reference solution is negatively correlated to γ, and is minimal for $\gamma = \infty$. In this case we always choose the solution which is the closest to the reference solution, in other words

we simply insert new customers in the current solution, which leads to a distance equal to the number of accepted dynamic customers. It is important to note that the quality of the routing, measured by the gap to the static solution, is positively correlated to γ. This confirms the intuition that poor routing decisions tend to add up over time and can lead to larger deviations at the end of the day. Our results also indicate that, for problems with low degree of dynamism, it can be worth sacrificing quality of solution to gain route stability. For instance, with $\delta = 10$, the value $\gamma = 5\%$ leads to a gap of 6% versus 2% with $\gamma = 0\%$, but it reduces the number of required changes by a factor 3. However, this statement no longer holds for instances with higher degrees of dynamism where numerous changes are necessary to insert all customers. In this case it is better to focus on optimizing the routing, as it does not lead to excessive instability in routes.

(a) Average edit distance to reference solution

	γ					
δ	**0%**	**1%**	**2%**	**5%**	**10%**	∞
10	32.8	19.3	17.0	12.9	12.6	9.8
30	59.4	48.1	44.2	39.2	36.4	29.6
50	78.2	70.3	65.9	61.4	58.2	49.4
70	87.6	84.0	81.7	78.5	75.7	69.2
90	95.7	94.5	93.9	92.7	91.3	88.9

(b) Average gap to a-posteriori solution (%) and number of rejected requests (in parenthesis)

	γ					
δ	**0%**	**1%**	**2%**	**5%**	**10%**	∞
10	2.0 (0.1)	2.8 (0.1)	4.2 (0.1)	6.1 (0.1)	8.1 (0.1)	11.2 (0.2)
30	4.3 (0.3)	5.6 (0.3)	6.5 (0.3)	10.9 (0.2)	16.3 (0.2)	29.3 (0.4)
50	6.4 (0.3)	7.6 (0.3)	9.1 (0.4)	13.1 (0.3)	18.7 (0.3)	50.1 (0.6)
70	9.0 (0.4)	10.3 (0.4)	11.8 (0.5)	15.3 (0.5)	20.5 (0.4)	71.0 (0.8)
90	9.8 (0.7)	10.8 (0.7)	11.6 (0.6)	14.4 (0.6)	19.4 (0.7)	95.5 (1.1)

Table 2.4: Evolution of the distance to reference solution and gap to a-posteriori solution for different degrees of dynamism and values of γ

2.4 Conclusions

In this work we proposed an efficient parallelization scheme for an Adaptive Large Neighborhood Search, namely pALNS. This algorithm distributes the optimization of promising solutions across multiple processors, resulting in factor 3.3 speedups on a quad-core desktop machine. The efficiency of pALNS relies on the presence of a promising solution pool with diversity management, which prevents deadlocks between optimization threads, and improves the exploration of the search space. We illustrated the efficiency of pALNS on the Solomon (1987) CVRPTW instances, for which it produces solutions in average 0.7% away from the optimal/best known solution in just 12s.

We also introduced a fast-reoptimization approach based on pALNS to tackle the dynamic VRPTW. This approach consists in running pALNS to produce an initial solution at the beginning of the day,

and then running it for a limited number of iterations whenever a new customer appears. We tested our approach on the instance set proposed by Lackner (2004). Computational results show that pALNS is capable of achieving state of the art results in competitive time, bringing improvements of up to 12% over previous approaches.

Finally, we presented a preliminary bi-objective extension of the classical D-VRPTW that attempts to captures the drivers inconvenience resulting from dynamic routing. It is based on the notion of having a reference routing plan handled to the drivers at the beginning of the period, that will then undergo changes as new customers arrive. We introduced an inconvenience metric that measures the consistency between an updated routing plan and the reference plan. We proposed a fast bi-objective optimization approach based on pALNS, namely pBiALNS, which maintains and optimizes in parallel the set of non-dominated solutions.

This optimization algorithm was used coupled with a threshold policy modeling an expert dispatcher to tackle the D-VRPTW instances proposed by Lackner (2004). Our results indicate that there is a clear tradeoff between minimizing the traveled distance and maintaining consistency in routes. Furthermore, it appears that for problems with a low degree of dynamism it can be worth sacrificing cost efficiency to maintain consistency. In contrast, in highly dynamic problems the priority should be given to the minimization of the cost, as it does not lead to excessive inconsistency in routing.

Future research should focus on the development of a continuous reoptimization approach based on pALNS that runs throughout the day and maintains a pool of alternative promising solutions as adaptive memory. In addition, pALNS could be improved by having completely independent subprocesses that pull their starting solution from the pool, and push their final solution, without waiting for other subprocesses to finish. pBiALNS could be refined to better approximate the Pareto front, first in the selection of the non-dominated solutions to optimize, then by applying a local search or a path relinking between non-dominated solutions.

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2.A Parameter setting

Table 2.5 presents the detail parameter setting used in the pALNS algorithm. The number of parallel iterations and the maximum size of the pool where selected after running experiments with values $I^p \in \{10, 50, 100, 500, 1000\}$ and $N \in \{1, 5, 10, 20, 30, 40, 50\}$. We also tested two schemes for the solution pool, the first with a fixed value of 0.5 for λ, the second using an adaptive scheme starting with $\lambda = 0.5$ and decreasing its value using the same process as the one used to decrease the simulated annealing temperature. Over all our experiments the combination of an adaptive diversity management with $I^p = 50$ and $N = 40$ showed the best results for 25,000 pALNS iterations, and $I^p = 100$ and $N = 10$ for 5,000 pALNS iterations. The remaining parameters were directly derived from the work by Pisinger and Ropke (2007).

Parameter	Value	Description
K	8	Number of threads
I^p	50 (100)	Number of parallel iterations
N	40 (10)	Maximum promising solution pool size
ϕ	0.10	Penalization for unserved customers
ξ_{min}	0.10	Minimum proportion of customers to be removed
ξ_{max}	0.40	Maximum proportion of customers to be removed
w	0.05	Reference objective degradation
p	0.5	Initial probability of accepting a degrading solution
α	0.002	Fraction of the initial temperature to be reached at the end
ρ	0.40	Reaction factor
σ_1	1.00	Score for new best solution
σ_2	0.25	Score for improving solution
σ_3	0.40	Score for non-improving accepted solution
σ_4	0.00	Score for rejected solution
l	100	Operator probability (w_θ) update frequency

Table 2.5: Detailed parameter setting for the pALNS algorithm for 25,000 iterations, values in parenthesis indicate adjusted values for 5,000 iterations.

3

Dynamic and stochastic routing

In dynamic and stochastic problems, part or all the input is unknown and revealed dynamically during the execution of the routes, and exploitable stochastic knowledge is available on the dynamically revealed information. Vehicle routes can be redefined in an ongoing fashion with the help of technological support.

Our focus being on developing software components that can be used for a wide range of applications, we chose to develop an event-driven framework based on the Multiple Scenario Approach proposed by Van Hentenryck and Bent (2006). In this chapter we present the general framework and its implementation, and then illustrate the validity of this approach by tackling the Dynamic Vehicle Routing Problem with Stochastic Demands (D-VRPSD).

The full reference of the paper presented in this chapter is:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012)
An event-driven optimization framework for dynamic vehicle routing
Decision Support Systems, Accepted manuscript
doi:10.1016/j.dss.2012.06.007.

A previous version of the paper was published as a technical report:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011)
An event-driven optimization framework for dynamic vehicle routing
Technical report, École des Mines de Nantes, France. Report 11/2/AUTO.

Preliminary results of this work were presented two conferences:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011)
A dynamic approach for the vehicle routing problem with stochastic demands
In *ROADEF 2011*, St Etienne, France.

– Pillac, V., Guéret, C., and Medaglia, A. L. (2010)
Solving the vehicle routing problem with stochastic demands with a multiple scenario approach
In *ALIO-INFORMS 2010*, Buenos Aires (Argentina).

An event-driven optimization framework for dynamic vehicle routing

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Abstract : The real-time operation of a fleet of vehicles introduces challenging optimization problems. In this work, we propose an event-driven framework which anticipates unknown changes arising in the context of dynamic vehicle routing. The framework is intrinsically parallelized to take advantage of modern multi-core and multi-threaded computing architectures. It is also designed to be easily embeddable in decision support systems that cope with a wide range of contexts and side constraints. We illustrate the flexibility of the framework by showing how it can be adapted to tackle the dynamic vehicle routing problem with stochastic demands.

Keywords : Dynamic vehicle routing ; event-driven framework ; multiple scenario approach ; online stochastic optimization ; D-VRPSD ; D-VRP

3.1 Introduction

The problem of operating a fleet of vehicles arises in many contexts, from pickup and delivery of goods to relocation of trucks in carrier companies. More specifically, Vehicle Routing Problems (VRP) deal with the design of a set of minimal-cost vehicle routes that serve the demand for goods or services of a group of geographically spread customers, satisfying operational constraints. From an information perspective, such problems generally include two dimensions: *evolution* and *quality* of information (Psaraftis, 1980). Information evolution relates to the fact that in some problems the information available to the planner may change during the execution of the routes, for example with the arrival of new customer requests. Information quality reflects possible uncertainty on the available data, for instance, when the demand of a customer is only known as a range estimate of its real demand. In addition, depending on the problem and the available technology, vehicle routes can either be designed a-priori or online. Based on these dimensions, Table 3.1 identifies four categories of routing problems.

The *static and deterministic* category includes the classical Vehicle Routing Problem (VRP) as defined by Dantzig and Ramser (1959) in which all information is known beforehand and with certainty. In contrast, problems from the *static and stochastic* class are characterized by input partially known as random variables, which realizations are only revealed during the execution of the routes. Additionally, it is assumed that routes are designed a-priori and only minor changes are allowed afterward.

		Information quality	
		Deterministic input	Stochastic input
Information evolution	Input known beforehand	Static and deterministic	Static and stochastic
	Input changes over time	Dynamic and deterministic	Dynamic and stochastic

Table 3.1: Taxonomy of vehicle routing problems by information evolution and quality.

A common example is the VRP with Stochastic Demands (VRPSD), in which customer demands are uncertain. We refer the interested reader to the surveys by Cordeau et al. (2007), Baldacci et al. (2007), and Laporte (2009) for a recent review of these two classes of problems.

In *dynamic and deterministic* problems, also referred to as *online* problems, part or all of the input is unknown and revealed dynamically and unpredictably during the design or execution of the routes. On the other hand, *dynamic and stochastic* problems include partial stochastic knowledge on the dynamically revealed information. For these problems, vehicle routes are redefined in an ongoing fashion, requiring technological support for real time communication between the vehicles and the decision maker (e.g., mobile phones and global positioning systems). Techniques for both classes are reviewed in the studies by Ichoua et al. (2007) and Pillac et al. (2011).

Dynamism in routing can emerge from different aspects of the problem. The most common source of dynamism is the arrival of new customers with a demand for goods or services. Other researchers consider dynamically revealed demands for a set of known customers, dynamic travel times, and vehicle availability.

Fig. 3.1 illustrates the Dynamic Vehicle Routing Problem (D-VRP), in which new customers appear while the vehicle is executing its route. Before the vehicle leaves the depot (at time t_0), an initial route plans to visit the currently known customers (A, B, C, D, E). While the vehicle executes its route, two new customers (X and Y) appear (at time t_1) and the initial route is adjusted to accommodate them. Finally (at time t_f), the executed route is (A, B, C, D, Y, E, X). This example reveals that dynamic routing requires to adjust the routes in an ongoing fashion, which implies real-time communication between vehicles and the dispatching center.

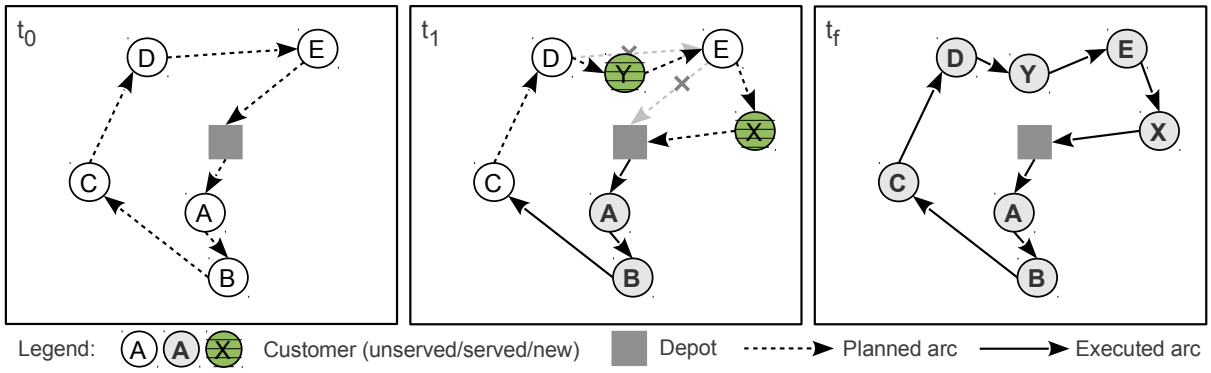

Figure 3.1: Example of dynamic vehicle routing

Until recently, the lack or high cost of real-time communication technologies steered vehicle routing research away from dynamic problems (Eksioglu et al., 2009). Nevertheless, recent advances in communication and geolocation technologies now allow companies to economically track their fleet in real time. These new technologies lead to the development of Intelligent Transport Systems (ITS), and more precisely Advanced Fleet Management Systems (AFMS), that combine hardware and software solutions to provide real time information on the fleet, customers, and road networks.

The development of ITS and AFMS creates new challenges and opportunities for operations research. The advent of these systems demands a new class of efficient optimization algorithms to handle various difficult aspects of fleet management. Nevertheless, Crainic et al. (2009) suggest that while the hardware part of ITS has considerably evolved, the corresponding Decision Support Systems (DSS) and optimization models have not yet reached their maturity.

From a practical perspective, we can identify the following desirable characteristics of a dynamic routing DSS:

- *Event-driven.* Organizations are expected to react quickly to changes in their environment. Having a DSS which is periodically updated implies longer reaction delays. Thus, a DSS should be driven by the same transactional events that keep the business operating (e.g., customer requests).
- *Parallelized.* As dynamic routing requires fast decisions, the underlying optimization algorithms should be parallelized, taking advantage of the now ubiquitous parallel (and distributed) computing architectures able to perform several tasks concurrently.
- *Flexible.* The landscape of vehicle routing problem variants is vast. Thus, a DSS should be easily extensible to account for operational constraints in a continuously evolving environment.

In this paper, we propose an application-oriented optimization framework for dynamic and stochastic vehicle routing that is event-driven, parallelized and flexible. The rest of this document is organized as follows. Section 3.2 reviews the literature on dynamic routing optimization techniques and related decision support systems. Section 3.3 describes the proposed framework, Section 3.4 illustrates its application to the dynamic VRPSD, and Section 3.5 presents experimental results. Finally, Section 3.6 concludes this paper and discusses how the framework can be generalized and extended to other dynamic optimization settings.

3.2 Literature review

A growing body of research has been carried out on dynamic routing, leading to new optimization techniques and innovative DSS. In this section we will review some of the most significant contributions in the dynamic routing field.

3.2.1 Dynamic routing

A wide range of techniques have been developed to address the dynamic nature of routing problems. Dynamic methods can be divided in two categories: *non-anticipative*, which only react to updates in the problem data; and *anticipative*, which take into account knowledge on the dynamically

revealed information to anticipate the future. Non-anticipative methods are designed for dynamic and deterministic problems. They generally are a direct adaptation of static methods such as integer programming (Yang et al., 2004), large neighborhood search (Goel and Gruhn, 2008), tabu search (Beaudry et al., 2010; Gendreau et al., 1999; Ichoua et al., 2003), genetic algorithms (Benyahia and Potvin, 1998; Haghani and Jung, 2005), or ant colony optimization (Montemanni et al., 2005). Conversely, anticipative methods often make better decisions by using stochastic information available in the form of probability distributions. Anticipative methods are further classified into one of two families: *stochastic modeling* or *sampling*.

Anticipative methods based on stochastic modeling accurately describe the problem's stochasticity. In an early work, Powell (1988) formulated the D-VRP as a Markov Decision Process (MDP). Nevertheless, the exponential growth of the state and action spaces causes traditional MDP to stall. This problem has led to the development of Approximate Dynamic Programming (ADP). The main idea behind ADP is to decompose the time in decision epochs. At each decision epoch the goal is to minimize the current deterministic cost plus an approximation of the expected future cost. This technique has been successfully applied to different dynamic fleet management problems (Godfrey and Powell, 2002; Powell and Topaloglu, 2005; Simao et al., 2009) and vehicle routing with stochastic demands (Novoa and Storer, 2009). The strength of ADP is that it accurately encapsulates stochastic information in the model, but at the expense of a higher complexity and stronger assumptions on the probability distributions.

On the other hand, anticipative methods based on sampling are to some extent simpler, but require more effort to capture the problem's stochasticity. These methods sample the probability distributions to generate *scenarios* that are used to make decisions. Such approaches include the dynamic sample scenario hedge heuristic proposed by Hvattum et al. (2006), the tabu search heuristics proposed by Ichoua et al. (2006) and Attanasio et al. (2007), and the Multiple Scenario Approach (MSA) proposed by Van Hentenryck and Bent (2006).

Among the anticipative methods based on sampling, MSA is unique in the sense that it provides a more general framework for dynamic problems. More specifically, MSA maintains a *pool of scenarios* with realizations of the problem random variables and a solution to the corresponding deterministic problem. A distinctive feature of MSA is that the next customer to visit is selected based on the whole *scenario pool* by means of a *decision* process. The algorithm starts by initializing the scenario pool based on the currently known information. Periodically, MSA updates the scenario pool to reflect the current environment state, selects the next customer, and optimizes the scenarios. As new information is disclosed, some scenarios might become obsolete and are removed from the pool, leaving space for new ones.

The strength of MSA is that optimization is performed on scenarios and only requires to solve a static and deterministic problem. Therefore this approach is very flexible as it can virtually be adapted to any problem, provided an optimization algorithm for its static and deterministic version. Nonetheless, its integration in a real-world context is far from trivial, especially considering communication between the method and its environment. Additionally, the fact that it relies on time steps induces delays between the arrival of new information and its processing.

3.2.2 Decision support systems for dynamic routing

There exists a wide range of DSS for the operation of a fleet of vehicles, as surveyed by Zak (2010). In the following paragraphs we will focus on dynamic routing DSS and review the body of research in this area.

The operation of a fleet of vehicles in an urban area is a key component of city logistics (Taniguchi et al., 2001), and the core subject of various DSS developments. For instance, Fleischmann et al. (2004) presented an event-based DSS that takes into account changing travel times and the arrival of new customers in the context of a local area courier service. The framework continuously optimizes a single routing plan in which new customers are inserted either with an assignment model or insertion algorithms. A similar problem was addressed by Attanasio et al. (2007) who showed that the proposed DSS allows for an efficient operation (low administrative cost) as the fleet size (number of couriers) increases, a key competitive advantage in this sector. Comparable conclusions were drawn by Petrakis et al. (2012) for the dynamic routing and scheduling of field technicians. Likewise, Barcelo et al. (2007) presented a flexible DSS for vehicle routing and scheduling in city logistics and its application to the delivery of goods in two Italian cities. Their DSS includes a real time traffic simulator, connection to common GIS systems, and various routing models and optimization modules. Dahl and Derigs (2011) studied the effectiveness of a DSS that allows for cooperation between carriers, increasing the utilization of vehicles. In a different context, Zeimpekis et al. (2007) developed a DSS that takes into account unexpected events such as traffic conditions or vehicle breakdowns to re-optimize an existing distribution schedule. Li et al. (2007) also studied vehicle breakdowns in an application to waste collection in Brazil.

Dynamic DSS generally rely on specific technology to ensure the communication between vehicles and the dispatching center (Zeimpekis et al., 2007). In contrast Bieding et al. (2009) propose a DSS based on a WAP (Wireless Application Protocol) server and mobile phones to manage the delivery of newspapers. The use of web technologies for DSS is promising, as highlighted by the study by Bhargava et al. (2007), especially for dynamic routing, as it allows users to access the DSS with mobile devices such as cell phones or tablet computers.

As pointed out by Crainic et al. (2009), there is a gap between state-of-the-art optimization techniques and the optimizers embedded in real-life DSS. This may be explained by the complexity and level of specialization of certain approaches, that render difficult their extension and integration in an application-oriented context. To address this issue, we propose a flexible optimization framework, based on MSA, easily embeddable in any DSS for dynamic routing.

3.3 Proposed framework

The framework, called jMSA, is a flexible, parallel, and event-driven Java implementation of the multiple scenario approach. The proposed framework has been designed to facilitate and accelerate the development and deployment of MSA-based algorithms embeddable in DSS. This section presents the proposed framework in detail.

3.3.1 Scenarios and decisions

Scenarios capture uncertainty in MSA. Each scenario contains a realization of the random variables, and a solution to the static and deterministic problem defined by this realization. For instance, in the Dynamic VRPSD (D-VRPSD), in which vehicles can be dynamically rerouted, each scenario contains a realization of the customer demands; while in the D-VRP, it contains a set of sampled (potential) customers, aside from the known customers. An optimization algorithm is used to solve the static and deterministic routing problem defined by both actual and sampled data. Virtually, any optimization algorithm can be used to optimize scenarios. Nonetheless, it should be fast enough to be able to optimize the whole scenario pool between two events. Additionally, as the same scenario may be optimized more than once, it should be capable of escaping from local optima to further improve the solution.

Fig. 3.2 illustrates how scenarios are generated for the D-VRP. Solely based on the actual customers, the optimal tour would be (A, B, E, D, C), which ignores two zones (gray areas) where customers are likely to appear. By sampling the customer spatial distributions, customers X, Y and Z are generated, and the new optimal tour is (C, X, Y, B, A, Z, E, D). Removing the sampled customers leads to the tour (C, B, A, E, D) which is sub-optimal based on a myopic cost evaluation, but leaves room to accommodate new customers at a lower cost.

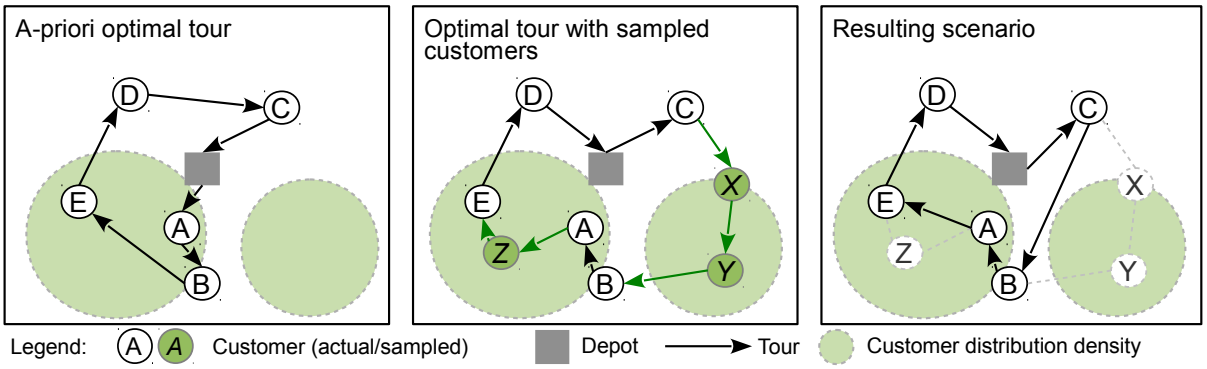

Figure 3.2: Scenario generation in MSA

Another key element in MSA is the *decision process*, which defines how to select the next customer to serve based on the information of the scenario pool. MSA's accuracy relies to a great extent on the decision process, being the most common algorithms *expectation*, *consensus*, and *regret*. The *expectation* algorithm (Chang et al., 2000) evaluates the cost of visiting each customer first, by forcing its visit and reoptimizing each scenario. The *consensus* algorithm (Bent and Van Hentenryck, 2004b) selects the customer appearing first with the highest frequency. Finally, the *regret* algorithm (Bent and Van Hentenryck, 2004a) approximates the cost of visiting each customer first.

The jMSA framework unifies these decision processes in the generic Algorithm 3.1, in which a subset of candidate customers (line. 1) is evaluated against the scenario pool (line. 6) to select the *best* one (line. 9). The evaluation of each customer reflects how desirable it is to serve it first depending on the objective. In most routing problems, the customer with the highest evaluation should be the one

that ensures the lowest expected routing distance when visited first.

Algorithm 3.1 A general algorithm for the decision process in jMSA

Input: scenario pool $\mathcal{P}$, set of pending customers $\mathcal{R}$
Output: r^* the next customer to serve

```
C ← selectCandidates(R, P)          ▷ Select a subset of candidate customers
f* ← −∞, r* ← ∅
for all r ∈ C do
    f ← 0
    for all s ∈ P do
        f ← f + evaluateRequestProfit(r, s)
    end for
    if f > f* then
        f* ← f, r* ← r
    end if
end for
return r*
```

3.3.2 Event-driven interaction

The original description of MSA is implicitly based on the discretization of time in intervals. This implies a time lag between an update in the problem data, such as the arrival of a new customer, and the response of the system, corresponding to the time before the next time interval. Consequently, in jMSA we propose a description of MSA from an event-driven perspective, suitable for its integration as a component of a real-world decision support system.

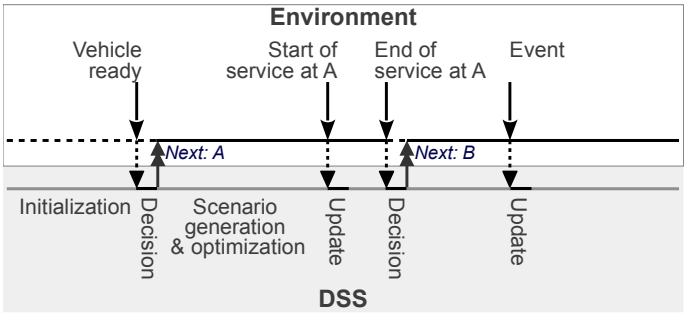

Figure 3.3: Time line of events for the dynamic routing of a single vehicle

Fig. 3.3 illustrates a typical sequence of events while routing a single vehicle in a dynamic context. The *environment* refers to the *real-world*, the *DSS* is assumed to be based on the MSA algorithm, and *active* (*idle*) times are represented with a continuous (dotted) segment. While the vehicle is parked at the depot, the MSA procedure initializes a scenario pool based on the currently known customers. Once the vehicle is ready (first dotted arrow), MSA analyzes the scenario pool and instructs the vehicle to service customer A (first double-headed arrow). While the vehicle is traveling towards customer A, MSA generates and reoptimizes the scenario pool. When the vehicle reaches its destination, an event is sent to the system (second dotted arrow) and triggers an update of the scenario pool. The remaining

service time is used by MSA to reoptimize the pool until the vehicle is ready to depart. This event (third dotted arrow) triggers the decision procedure, which recommends visiting customer B (second double-headed arrow). At some point in time while the vehicle is traveling to B, an event (last dotted arrow) triggers an update of the scenario pool. Such event could be the arrival of a new customer in the D-VRP, or an update in the traffic information in the case of routing with dynamic travel times.

The main advantage of this event-driven interaction between the environment and the system is that it increases the responsiveness of the DSS by feeding real-time information to the system and communicating decisions without delay.

3.3.3 Framework design

As illustrated in Fig. 3.4, the proposed framework is divided in two layers: a *kernel*, common to all dynamic combinatorial optimization problems; and a *problem layer*, with problem-specific components.

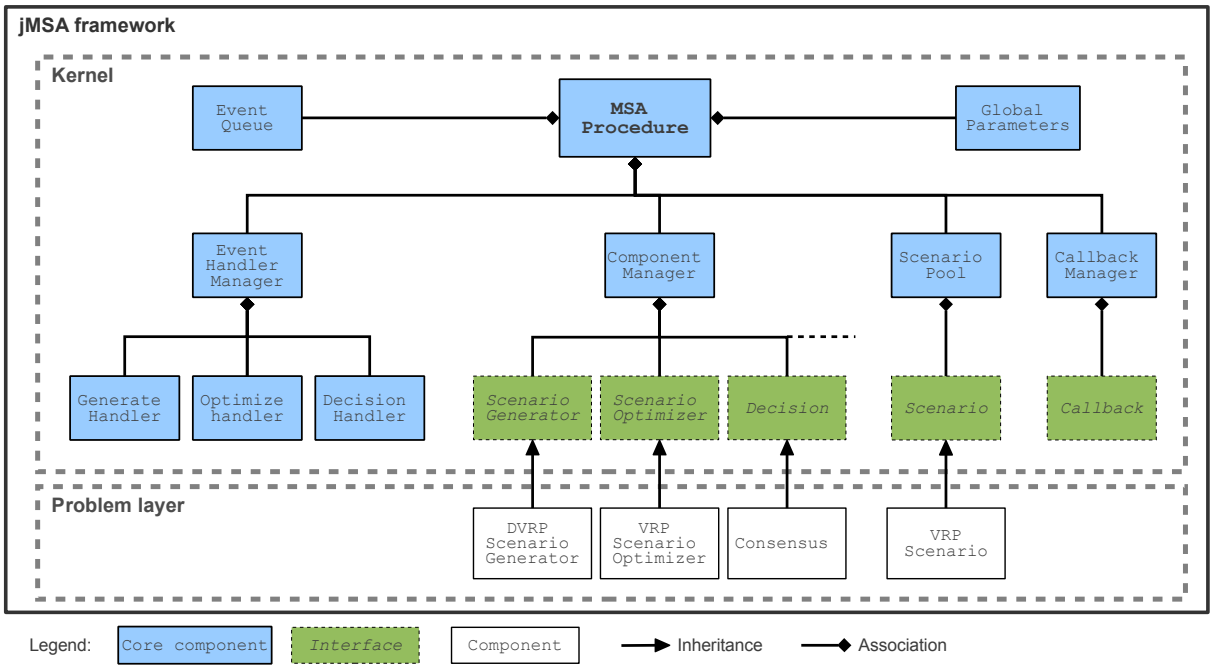

Figure 3.4: Design overview of the jMSA framework

The central component of the *kernel* is the `MSAProcedure`, which contains the logic of the algorithm and instantiates all other components. The `MSAProcedure` is configured via the `GlobalParameters` that can be set programmatically or via a configuration file.

The event-driven behavior is modeled using two elements: *events* and *event handlers*. Fig. 3.5 shows how events drive the framework. The MSA procedure continuously dequeues events from the *event queue*, and then processes them by using the corresponding *event handler* in the *event handler manager*.

Events are designed to increase the framework responsiveness. To ensure that *important* events are handled first, events are prioritized and the event queue is sorted accordingly. Additionally, some events are *preemptive*, meaning that the handling of a non-preemptive event is always aborted in favor of a preemptive event.

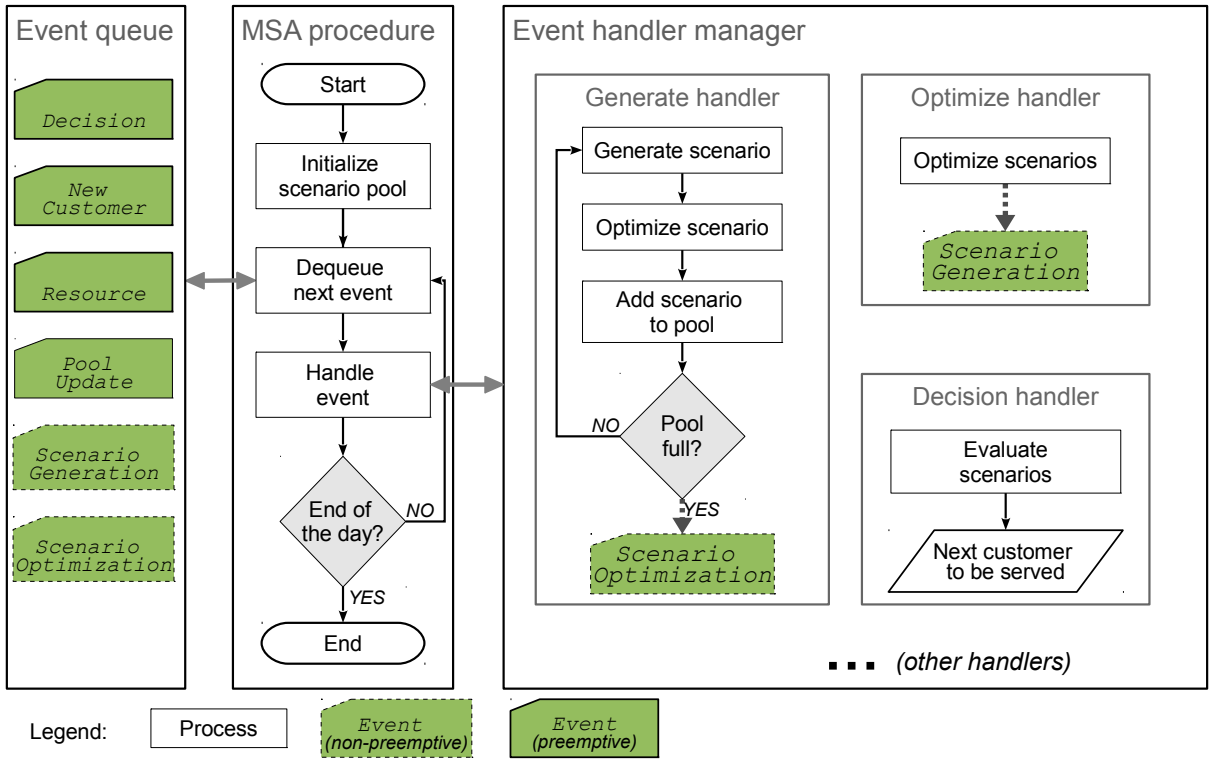

Figure 3.5: Event-driven MSA framework

Event handlers define at a very high level what actions are triggered by a given event. By design, these handlers do not contain any problem-specific logic which is instead delegated to *components*. The *component manager* contains references to all components and acts as an interface between event handlers and problem-specific implementations.

Fig. 3.6 illustrates how event handlers and components interact for the `ScenarioGeneration` event. First, `GenerateHandler` calls the `generateScenario` method of the `ComponentManager` that internally uses the registered `ScenarioGenerator`. Then it calls the `optimizeScenario` method, delegated to the instance of `ScenarioOptimizer` in use, and adds the scenario to the pool. The process repeats until the pool is full, moment when the event handling terminates by raising a `Scenario-Optimization` event that is further pushed to the event queue.

The framework includes a *callback* system that provides users with further control over the MSA procedure. Users may implement a callback simply by extending the `Callback` interface provided in the framework, and registering it in the MSA procedure. User-defined callbacks are automatically invoked at specific points of the procedure and allow customized uses such as logging to a file or dynamic parameter tunning.

Tied, yet decoupled to the kernel, the jMSA framework offers a problem-specific layer containing components that provide ready-to-use functionalities for common dynamic combinatorial optimization problems. Fig. 3.4 illustrates some components that could be combined for the D-VRP. `Consensus` is an implementation of the consensus algorithm that is common to many dynamic problems solved under MSA; `VRPScenario` is an implementation of `Scenario` for routing problems containing a set of routes;

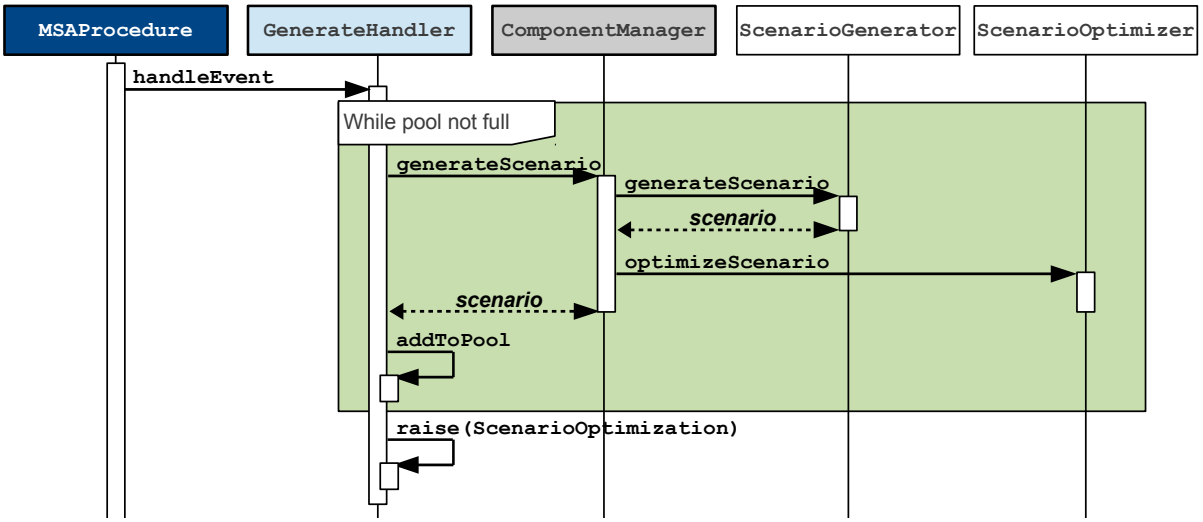

Figure 3.6: Interaction between the `GenerateHandler` and the different components.

`VRPScenarioOptimizer` is a generic solver for the VRP; and finally `DVRPScenarioGenerator` is the only component specific to the D-VRP that is responsible for the generation of new scenarios.

This two-layer architecture ensures flexibility and extensibility. While kernel elements are defined at a high level and are designed to be problem independent, the problem layer provides implementations for specific problems. Thus, users only have to define or extend components, in particular for scenario generation and optimization, without worrying how they will be integrated in the MSA procedure.

3.3.4 Parallelization via multi-threading

The ubiquitous presence of multi-core processors can be exploited in parallelizable algorithms such as MSA. Nevertheless, parallelization often comes at the price of a higher implementation complexity. The jMSA framework offers multi-threaded parallelization of the most time-consuming tasks, hiding it from the user. That is, under jMSA, users do not have to explicitly write a parallel algorithm, but simply rely on the `ComponentManager` which internally distributes tasks among different threads.

Fig. 3.7 illustrates how threads interact within the jMSA framework. At time t_0 the *MSA thread* dequeues an `OptimizePool` event, and processes it with the corresponding `OptimizeHandler`. In parallel to the MSA thread, two other threads are started by the `ComponentManager` to optimize the scenarios of the pool. At t_1, a preemptive `NewCustomer` and a `Decision` event are pushed by the environment, causing the MSA thread to prematurely abort the optimization. To avoid inconsistencies, the main thread waits for the pool executor to terminate, sends a signal to the callback thread to notify that the `OptimizePool` event was handled, and raises a `GenerateScenarios` event. Finally, the procedure dequeues the `NewCustomer` event, which has a higher priority than the `Decision` event, and processes it.

It is worth noting that aside from time-consuming tasks such as scenario generation and optimization, parallelization is also used to execute callbacks. Callbacks can be particularly useful when

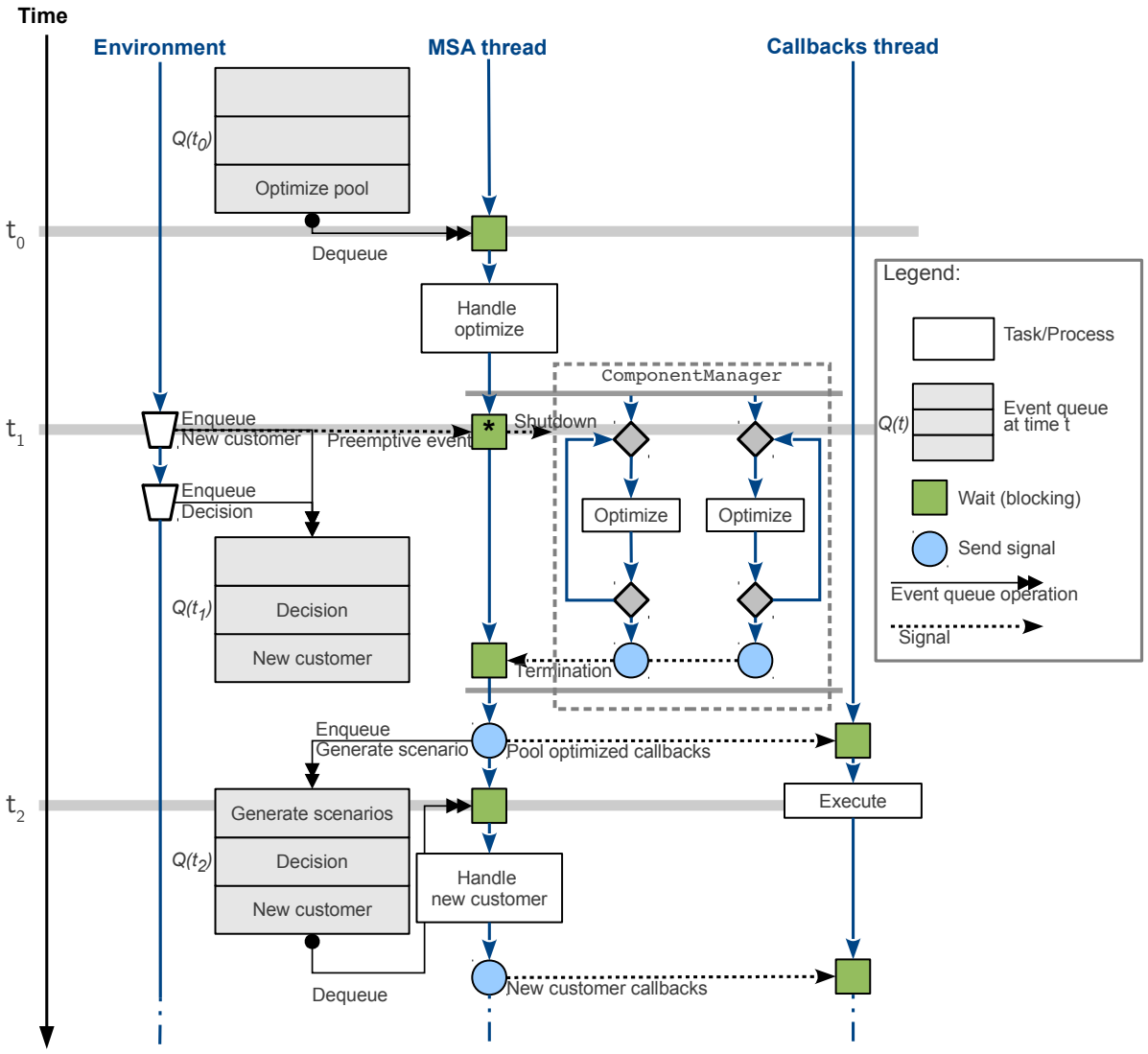

Figure 3.7: Multiple threads interacting in jMSA

writing files or updating the state of a user interface as it does not affect the performance of the main algorithm. This behavior can be overridden using synchronous callbacks.

3.4 Application to the dynamic VRP with stochastic demands

This section illustrates the flexibility of the jMSA framework on the Dynamic VRP with Stochastic Demands, and we illustrate how under the proposed approach we can easily relax the assumptions on the demand distributions required by state-of-the-art approaches, thus leading us to the solution of a more general problem with jMSA.

3.4.1 Problem description

The fundamental difference between the classic VRP and the VRP with Stochastic Demands (VRPSD) is that in the latter customer demands are known as random variables. The randomness in the VRPSD implies that a customer demand realization might exceed the vehicle remaining capacity, leading to a route *failure* that requires a *recourse action.* An intuitive recourse action is for the vehicle to go back to the depot to restore its initial capacity and then resume its route (Mendoza et al., 2009), or to allow the service of additional customers before returning to the depot (Novoa, 2005). It is important to stress that in this context all customers are known beforehand and the only dynamically revealed information is the realization of the customer demands.

Uncertainty in the VRPSD has been addressed by various solution approaches, of which the two most studied are the *Chance Constrained Programming (CCP)* and the *Stochastic Programming with Recourse (SPR).* Both methods are based on a two-stage approach: the first phase builds a *robust* routing plan; while the second phase takes recourse (corrective) actions as the realizations of the customer demands are unveiled. The conceptual difference between the two approaches lies in the objective of the first-stage optimization: in CCP, the goal is to ensure an upper bound on the probability of a failure, regardless of the expected cost of the second phase; while SPR seeks the minimization of the total expected cost, including recourse actions.

The Dynamic VRPSD (D-VRPSD) is an extension of the VRPSD in which it is possible to freely reroute vehicles upon new demand realizations, allowing more complex recourse actions. Literature on the D-VRPSD is scarce, with the main contributions being the work by Novoa (2005), Novoa and Storer (2009), Secomandi (2001), and Secomandi and Margot (2009). The only publicly available instances for the D-VRPSD are those from Novoa (2005), therefore we will use the same problem definition defined therein to allow a fair comparison between algorithms. In our work, as in all studies on the D-VRPSD, we consider the single-vehicle case with discrete and uniformly distributed demand distributions. If at some point the realization $\hat{\xi}$ of the demand of a customer exceeds the vehicle remaining capacity $\bar{Q}$, the vehicle serves the quantity $\bar{Q}$, and returns to the depot to restore its capacity. Afterwards, a subsequent visit to the customer is planned to serve the remaining demand $\hat{\xi} - \bar{Q}$.

3.4.2 Scenarios and decisions

In the context of the D-VRPSD, scenarios contain different realizations of the customer demands, along with a feasible routing for these values. Given that the vehicle can go back to the depot during its service, a scenario can contain different routes that will be executed in a sequential order by the same vehicle.

The fact that customer locations are identical across scenarios suggests that different scenarios might have similar routes. Therefore, we use the consensus algorithm to select the next customer to visit. Let us consider the scenario pool of Fig. 3.8. The customers who have already been served (4 and 1) appear first in all scenarios, while customers 2, 3, 5, and 6, appear in varying order depending on the scenario sampled demands. Considering that customer 2 appears first in 2 out of 4 scenarios, by consensus it is selected as the next customer to visit. With the notations from Algorithm 3.1, the function `selectCandidates` (line 1) returns the set of unserved customers while `evaluateRequest-`

`Profit` (line. 6) returns 1 if customer r appears first in the scenario; 0, otherwise. It is worth noting that the consensus decision might recommend the vehicle to return to the depot for a preventive replenishment, that is, before the vehicle runs out of capacity.

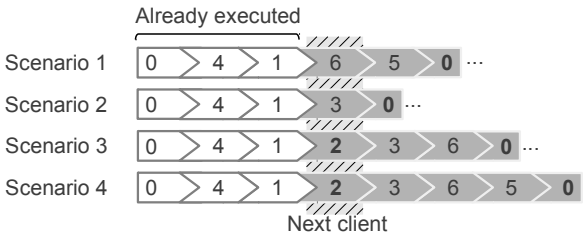

Figure 3.8: Example of the decision process by consensus in a 4-scenario pool. Each scenario contains customers who have been visited (in white) and customers yet to be visited (in gray).

3.4.3 Optimization

To optimize scenarios we use an Adaptive Variable Neighborhood Search (AVNS), which is an extension of the Variable Neighborhood Search (VNS) (Mladenovic and Hansen, 1997). The main difference between AVNS and VNS is that neighborhoods are not explored sequentially, but randomly selected with a bias depending on their previous *performance*. Our implementation uses an average ratio of the improvement to time as a metric of neighborhood performance, and maintains this information between calls to the optimization procedure. Neighborhoods with a better performance are more likely to be explored first, leading to a self-tuning algorithm. Our MSA scheme benefits from this automatic self-tuning behavior as the optimization procedure is called numerous times on similar instances (i.e., scenarios).

Algorithm 3.2 presents an outline of the AVNS algorithm. The algorithm initializes with the whole set of neighborhood structures (line. 2), then it selects a neighborhood (line. 4) to randomly perturb the current solution (line. 5), and improves it by applying a local search procedure (line. 6). If the new solution is improving (line. 8) then it becomes the current solution (line. 9), and the set of active neighborhood structures is reset (line. 10). Otherwise, the current neighborhood is removed from the set of active neighborhoods (line. 12). At each iteration, the performance of the current neighborhood is updated (line. 7). This process iterates until all neighborhoods have been explored with no improvement.

In our experiments we used the two neighborhoods structures *Or-opt* and *string-exchange* for the perturbation, and a Variable Neighborhood Descent (VND) based on *swap* and *2-opt* as local search (line. 6). A more detailed description of these neighborhoods can be found in the paper by Irnich et al. (2006). The initial solution is obtained by a Clarke and Wright (CW) heuristic (Clarke and Wright, 1964) in which the saving list is randomized, as presented in Mendoza et al. (2010), leading to the CW+AVNS algorithm.

Algorithm 3.2 The Adaptive Variable Neighborhood Search algorithm

Input: feasible solution $\mathbf{x}$, evaluation function z , and set of neighborhood structures $\mathcal{N} = \{N_1, .., N_K\}$
Output: best solution found $\mathbf{x}^*$

$\mathbf{x}^* \leftarrow \mathbf{x}$
$\mathcal{N}_c \leftarrow \mathcal{N}$ ▷ Initial neighborhood set
while $\mathcal{N}_c \neq \emptyset$ **do**
  $N \leftarrow$ `selectNeighborhood` $(\mathcal{N}_c)$ ▷ Select neighborhood
  $\mathbf{x}' \leftarrow$ `shake` $(N, \mathbf{x})$ ▷ Generate a neighbor from neighborhood N
  $\mathbf{x}' \leftarrow$ `localSearch` $(\mathbf{x}')$ ▷ Local search to improve $\mathbf{x}'$
  `updatePerformance` $(\mathcal{N}, \mathbf{x}, \mathbf{x}')$
  if $z(\mathbf{x}') < z(\mathbf{x})$ **then** ▷ $\mathbf{x}'$ is accepted as current solution
    $\mathbf{x} \leftarrow \mathbf{x}'$ ▷ Update current solution
    $\mathcal{N}_c \leftarrow \mathcal{N}$ ▷ Reset the neighborhood set
  else
    $\mathcal{N}_c \leftarrow \mathcal{N}_c \setminus \{N\}$ ▷ Remove the explored neighborhood
  end if
  if $z(\mathbf{x}') < z(\mathbf{x}^*)$ **then** ▷ An improvement has been found
    $\mathbf{x}^* \leftarrow \mathbf{x}'$ ▷ Update best solution
  end if
end while
return $\mathbf{x}^*$

3.4.4 Failure handling

A route fails when a customer demand exceeds the vehicle's remaining capacity. Thus, the MSA procedure becomes aware of a route failure as soon as a `Resource` event is raised upon the arrival at the customer location. As a consequence, the route failure handling must be defined at the event handler level, by checking if the demand of the current customer is larger than the vehicle remaining capacity, and updating the scenario pool accordingly.

3.4.5 User interface

To illustrate the use of callbacks we developed a user interface shown in Fig. 3.9. The main panel (right) presents in real time the unserved (white) and served (dark gray) customers, the vehicle destination (light gray), and the executed route (arrows). The left panel displays a log of events of jMSA and echoes the configuration settings. By means of a callback registered in the MSA procedure, all the information in the interface is updated in real time.

3.5 Computational experiments on the D-VRPSD

The benchmark instances for the D-VRPSD used in this work were initially proposed by Novoa (2005) and later used in Novoa and Storer (2009). In this work we consider the larger problems with 30, 40, and 60 customers uniformly distributed in a 1×1 square grid with discrete uniform demands. For each problem size, there are ten combinations of five different client locations and demand distributions

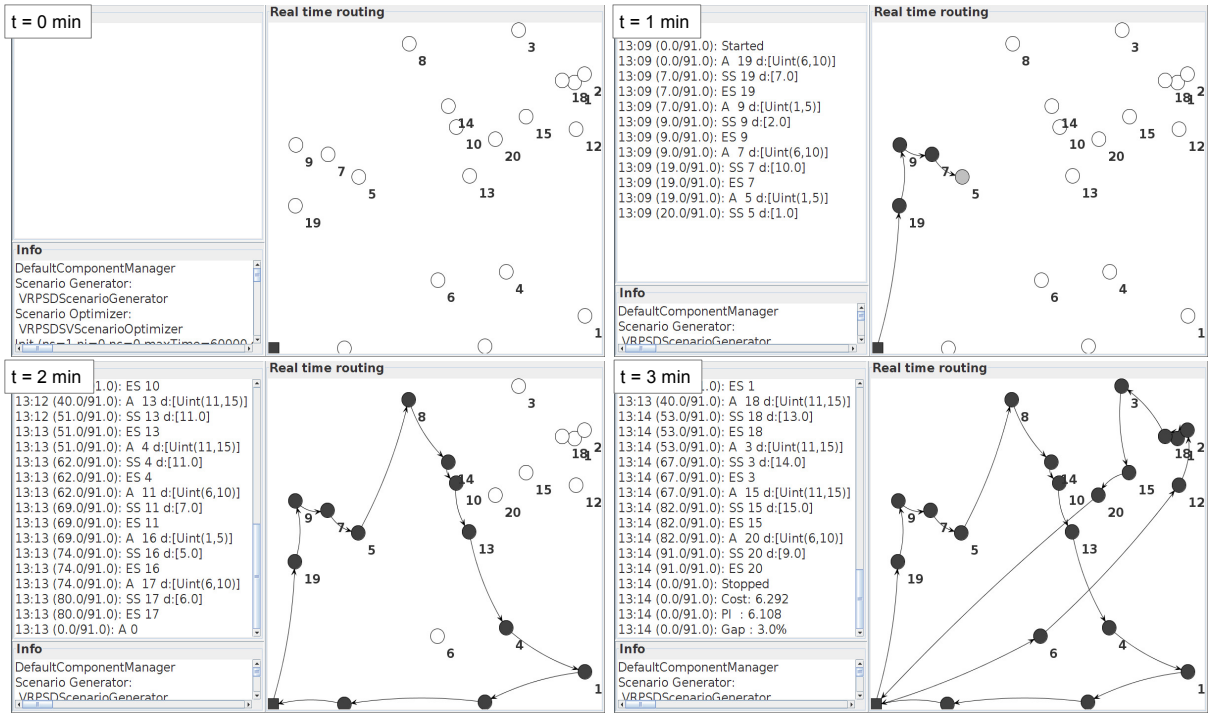

Figure 3.9: A graphical user interface for jMSA

by two vehicle capacities, leading to a complete testbed of 30 instances. Optimal values where obtained using the COIN-OR Symphony VRP solver (Ralphs, 2006; Ralphs et al., 2003).

To assess the optimization component in isolation, we conducted an experiment on 100 different demand realizations for all 30 instances. Fig. 3.10 presents the distribution of gaps to optimal values for CW+AVNS and a CW+2-opt heuristic used for comparison. Note that CW+AVNS clearly dominates CW+2-opt, with 90% of all instances solved with a gap of less than 4%. Additionally, CW+AVNS runs relatively fast, with average CPU times between 50 ms and 650 ms for the larger instances.

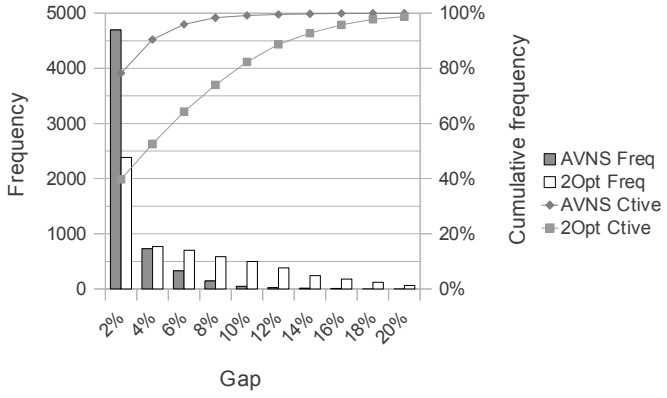

Figure 3.10: Optimal gap distribution of the CW+AVNS algorithm vs. CW+2-opt for all Novoa (2005) instances

To facilitate the comparison between approaches for the D-VRPSD, we report the results in terms

of *value of information* (Mitrović-Minić and Laporte, 2004). The value of information for instance I, namely $\mathcal{V}(I)$, is the gap between the cost of the final solution returned by the algorithm $z(I)$ and the a-posteriori optimal solution $z^*(I)$, and it is calculated as follows:

$$\mathcal{V}(I) = \frac{z(I) - z^*(I)}{z^*(I)} \tag{3.1}$$

As in Novoa and Storer (2009), we ran 100 simulations with different demand realizations for each instance, using the jMSA framework as a black box. This means that an external simulator was used to send events to the MSA procedure simulating the vehicle route execution. The results reported by Novoa and Storer (2009) being aggregated, we report the *average value of information* by using *average* solution values in Eq. 3.1.

	Instance set (size,capacity)						
Algorithm	**(30,137)**	**(30,87)**	**(40,183)**	**(40,116)**	**(60,274)**	**(60,175)**	**Average**
1s_n2_r (Secomandi, 2001)	12.3%	11.8%	11.1%	12.9%	13.9%	19.6%	13.6%
1s_stostat_r (Novoa and Storer, 2009)	4.7%	5.1%	3.7%	**5.3%**	3.5%	12.3%	5.8%
2s_stostat_r (Novoa and Storer, 2009)	3.5%	**3.6%**	**3.0**%	5.4%	**2.8%**	10.7%	4.8%
jMSA	**0.9%**	4.1%	3.5%	6.3%	2.9%	**2.0%**	**3.3%**

Table 3.2: Comparison of average value of information, bold values indicate the best performing algorithm for a subset of instances.

Table 3.2 presents results for the 30 benchmark instances, each column representing 500 runs (100 runs for each of the 5 instances with the same size and capacity). MSA dominates the algorithm proposed by Secomandi (2001) (1s_n2_r), and outperforms the best performing algorithms reported by Novoa and Storer (2009) (1s_stostat_r, 2s_stostat_r) for instances with 30 and 60 customers, and a vehicle capacity of 137 and 175. Additionally, MSA shows better overall results with an average gap of 3.3% against 4.8% for 2s_stostat_r, 5.8% for 1s_stostat, and 13.6% for 1s_n2_r. Aside from the performance in terms of value of information, it is important to stress that MSA runs continuously, and the next customer to visit is selected in a fraction of a second, while the other algorithms can take up to several minutes to make such decision, limiting their deployment and applicability in a real-world online DSS.

Aside from direct numerical comparison, the strength of our approach relies on the lack of strong assumptions on demand distributions. To illustrate this point, we adapted the testbed instances by changing the demand distribution from a discrete uniform distribution to a left-truncated normal distribution ($\mathcal{N}_{LT\geq 0}$) as follows:

$$\mathcal{U}_{int}\,(a,b) \rightarrow \mathcal{N}_{LT\geq 0}\left(\frac{a+b}{2}, \frac{b-a+2}{6}\right) \tag{3.2}$$

Note that Eq. 3.2 ensures that the demand will be between $a-1$ and $b+1$ with probability 0.997, and truncates negative values.

Table 3.3 highlights the robustness of MSA which shows consistent performance when demand distributions are changed from uniform (discrete) to normal (continuous). Furthermore, the results are as expected slightly better, with a reduction of 0.3% in the overall average value of information, which is due to the smaller variance. It is important to stress that to conduct this experiment in jMSA the

	Instance set (size,capacity)						
Algorithm	**(30,137)**	**(30,87)**	**(40,183)**	**(40,116)**	**(60,274)**	**(60,175)**	**Average**
Uniform	0.9%	3.9%	3.5%	6.3%	2.9%	2.0%	3.3%
Normal	0.7%	3.6%	3.4%	6.2%	2.2%	1.9%	3.0%

Table 3.3: Comparison of average VI for discrete uniform and normal distributions.

only change required was to use a different random number generator, which illustrates the flexibility of our approach. Other approaches based on stochastic modeling (Novoa and Storer, 2009; Novoa, 2005; Secomandi, 2001) are not as flexible and depend on distributional assumptions, thus limiting their application scope.

3.6 Conclusions

In this paper we presented the design and implementation of jMSA, an object-oriented event-driven framework for the Multiple Scenario Approach (MSA). By doing a high-level abstraction of MSA to a problem independent level, we modeled it as an event-driven process that allows high reactivity to changes occurring in online and highly dynamic operational environments. We implemented jMSA as a flexible framework that is easily embeddable in decision support systems. By design, jMSA includes a callback system that gives the user further control over MSA and allow complex interactions with third party components. Additionally, we integrated into the framework the parallelization of time consuming tasks with no compromise for the framework user, which is a key aspect considering the wide availability of multi-core personal computers.

We illustrated the use of jMSA on the Dynamic Vehicle Routing Problem with Stochastic Demands (D-VRPSD). The optimization of scenarios is performed by an Adaptive Variable Neighborhood Search (AVNS) which improves an initial solution generated with a randomized Clarke and Wright heuristic. The strength of AVNS is that it automatically adjusts its search scheme depending on the problem's structure by keeping track of the neighborhood performance throughout the execution of the MSA procedure. Computational experiments show that our approach is competitive with state-of-the-art algorithms that take full advantage of the stochastic aspects, while it provides a more flexible scheme that can be used to tackle problems with different demand distributions.

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4

Case study: the Technician Routing and Scheduling Problem

The two papers presented in this chapter are motivated by a real-world optimization problem submitted by an industrial partner. This company provides software solutions for organizations that have to route a crew of technicians to service geographically distributed customer *requests* that can be either *static* or *dynamic*. Static requests are known in advance and correspond to appointments with customers or preventive maintenance operations. On the other hand, dynamic requests appear dynamically throughout the day and are, for instance, emergencies or corrective maintenance operations. Requests may require a technician with different skills, a certain set of tools, and a number of spare parts to be serviced. In addition, technicians generally start and end their day at their home, and may visit a central depot to pickup tools and spare parts. Finally, the objectives include the minimization of the traveled distance, the minimization of the working time, the balancing of the workload between technicians, and the minimization of the constraints violations.

From this practical application, we introduced a new optimization problem, namely, the Technician Routing and Scheduling Problem (TRSP), which deals with a limited crew of technicians that serves a set of requests. In the TRSP, each technician has a set of skills, tools, and spare parts, while requests require a subset of each. The problem is then to design a set of tours of minimal total duration such that each request is visited exactly once, within its time window, by a technician with the required skills, tools, and spare parts.

A distinctive feature of this problem is that it introduces several compatibility constraints between technicians and requests. While skills are intrinsic attributes, technicians may carry different tools and spare parts over the planning horizon. Technicians start their tour from home, with a set of tools (renewable resources) and spare parts (consumed once the technician serves a request) that allow them

to serve an initial set of requests. Technicians may have the opportunity to replenish their tools and spare parts at a central depot at any time to service more requests.

The TRSP naturally arises in a wide range of applications, including telecoms, public utilities, and maintenance operations. However technician routing and scheduling problems have received limited attention until recently, and to the best of our knowledge there is no work that considers simultaneously skills, tools, spare parts, and the arrival of new requests, three important components of real-world applications. The paper in Section 4.1 introduces a parallel matheuristic able to solve the static TRSP, while the paper in Section 4.2 presents two approaches to tackle the dynamic TRSP.

4.1 The static TRSP

The paper presented in this section proposes a parallel matheuristic to solve the static TRSP. From a practical perspective, this algorithm can be used either to design an initial solution to the problem considering only static requests, or to compute an a-posteriori solution to a dynamic problem that can be used to assess the performance of a dynamic approach.

The full reference of the paper presented in this section is:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011)
A parallel matheuristic for the technician routing and scheduling problem
Optimization Letters, Accepted manuscript, doi:10.1007/s11590-012-0567-4.

Preliminary results were presented in MIC 2011 international conference:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011)
On the technician routing and scheduling problem
In Di Gaspero, L., Schaerf, A., and Stützle, T., editors, *Proceedings of the 9th Metaheuristics Conference (MIC 2011)*, pages 675–678. Università degli Studi di Udine.

A Parallel Matheuristic for the Technician Routing and Scheduling Problem

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Abstract : The Technician Routing and Scheduling Problem (TRSP) consists in routing staff to serve requests for service, taking into account time windows, skills, tools, and spare parts. Typical applications include maintenance operations and staff routing in telecoms, public utilities, and in the health care industry. In this paper, we present a formal definition of the TRSP, discuss its relation with the Vehicle Routing Problem with Time Windows (VRPTW), and review related research. From a methodological perspective, we describe a matheuristic composed of a constructive heuristic, a parallel Adaptive Large Neighborhood Search (pALNS), and a mathematical programming based post-optimization procedure that successfully tackles the TRSP. We validate the matheuristic on the Solomon VRPTW instances, where we achieve an average gap of 0.23%, and matched 44 out of 55 optimal solutions. Finally, we illustrate how the matheuristic successfully solves a set of TRSP instances extended from the Solomon benchmark.

Keywords : Vehicle routing ; Technician routing and scheduling ; Matheuristic ; ALNS ; pALNS ; VRPTW

4.1.1 Introduction

The Technician Routing and Scheduling Problem (TRSP) deals with a limited crew of technicians $\mathcal{K}$ that serves a set of requests $\mathcal{R}$. In the TRSP, each technician has a set of skills, tools, and spare parts, while requests require a subset of each. The problem is then to design a set of tours of minimal total duration such that each request is fulfilled exactly once, within its time window, by a technician with the required skills, tools, and spare parts. It is important to note that the departure of technicians may be delayed to minimize the waiting time at each visited request, thus reducing the duration of tours. The TRSP naturally arises in a wide range of settings, including telecoms, public utilities, and companies planning maintenance operations. The TRSP can be seen as an extension of the Vehicle Routing Problem with Time Windows (VRPTW), where technicians play the role of vehicles and requests are made by clients. Thus, it belongs to the class of NP-Hard problems.

A distinctive feature of this problem is the presence of compatibility constraints between technicians and requests. While skills are intrinsic attributes, technicians may carry different tools and spare parts over the planning horizon. Technicians start their tour from their home, with a set of tools and spare parts that allows them to serve an initial set of requests. They also have the opportunity to

replenish their tools and spare parts at a central depot at any time to serve more requests. Tools can be seen as renewable resources, while spare parts are non-renewable and consumed once the technician serves a request.

The remainder of this paper is organized as follows: Section 4.1.2 reviews the literature on problems related to the TRSP; Section 4.1.3 introduces the proposed matheuristic; Section 4.1.4 presents experimental results; and finally, Section 4.1.5 concludes this work and outlines directions for future research.

4.1.2 Literature review

The technician scheduling problem is closely related to the TRSP, but does not consider the routing aspects, nor the tool and spare part constraints. It was featured in the 2007 French Operational Research Society (ROADEF) challenge. We refer the reader to the work by Cordeau et al. (2010) and Hashimoto et al. (2011) for two solution approaches to a multi-day variant in which teams are assembled to serve requests. Kovacs et al. (2011) studied an extension of this problem, namely, the Service Technician Routing and Scheduling Problem (STRSP), which considers routing costs, skills, and team building.

Bredström and Rönnqvist (2008) present a generic mixed integer programming formulation for a Vehicle Routing and Scheduling Problem with Time Windows (VRSPTW) in which some clients must be visited simultaneously by two or more vehicles. The authors do not explicitly consider skills, but the proposed model accounts for compatibility constraints between vehicles and requests. Parragh (2010) also tackled a variant with synchronization between technician visits.

A practical consideration in technician routing is that it may not be possible or desirable to serve all requests. Xu and Chiu (2001) studied a variant of the TRSP in which the objective is to maximize the number of requests served while accounting for skill constraints and request urgency. Tang et al. (2007) also considered requests with different urgency levels. The authors use a multi-period maximum collection problem formulation with time-dependent rewards modeling customer preferences. Tsang and Voudouris (1997) solved a problem faced by British Telecom where technician skills affect the time required to serve a request.

Finally, home care routing and scheduling problems are related to the TRSP in the sense that they consider patients that need to be visited by staff with specific skills and within a given time frame. We refer the interested reader to the case studies by Bertels and Fahle (2006), Eveborn et al. (2006), and Akjiratikarl et al. (2007).

In summary, technician routing problems have received limited attention and to the best of our knowledge, no work considers tools or spare parts, two important components of real-world applications. The present work, based on a real problem, addresses this aspect and proposes a parallel matheuristic approach for the TRSP.

4.1.3 The proposed matheuristic

This section outlines the proposed matheuristic that comprises a fast constructive heuristic, a parallel adaptive large neighborhood search, and a mathematical programming based post-optimization.

4.1.3.1 Regret constructive heuristic

Regret heuristics (Potvin and Rousseau, 1993) are constructive heuristics that incorporate a look ahead component. At each iteration the algorithm inserts the request with the greatest *regret* value at the best position, where the regret value is an estimation of the additional cost incurred if a request is not inserted at its best position.

More formally, let $\mathcal{U}$ be the set of requests to be inserted and δ_i^k be the cost of inserting request i at its best position in its k-th best route. The *regret-q* heuristic inserts at its best position request $i^* = \arg\max_{i \in \mathcal{U}} \left\{ \sum_{k=2}^{q} \left(\delta_i^k - \delta_i^1 \right) \right\}$ (ties are broken by choosing the request with the lowest δ_i^1 value). It is worth noting that *regret-1* corresponds to the well-known best insertion heuristic.

When evaluating the insertion of a request in a tour we need to consider the possibility to plan a trip to the main depot to pick up additional tools and spare parts. The procedure first checks for the best feasible insertion without considering trips to the depot. If no feasible insertion is found, it then considers each possible combination of request and main depot insertions. Insertion feasibility and cost are evaluated in constant time using the concepts of *waiting time* and *forward time slack* introduced by Savelsbergh (1992).

We use a *regret-3* heuristic to design an initial set of K solutions that will then be improved by the parallel adaptive large neighborhood search.

4.1.3.2 Parallel Adaptive Large Neighborhood Search

Shaw (1998) introduced the Large Neighborhood Search algorithm (LNS), which works by successively *destroying* and *repairing* a current solution. Pisinger and Ropke (2007) extended LNS by using several destroy and repair operators and adding an adaptive layer to select them, leading to the Adaptive LNS algorithm (ALNS). In this work, we propose a parallel version of ALNS, namely pALNS, that takes advantage of parallel architectures to achieve significant speedups.

Algorithm 4.1 presents the outline of pALNS. The algorithm maintains a pool $\mathcal{P}$ of N promising solutions that are optimized in K subprocesses (note that $N \geq K$). For each *master* iteration, a subset of K promising solutions is selected randomly (line 4) and distributed among independent subprocesses. Then for I^p iterations, each subprocess selects destroy and repair operators with a roulette wheel mechanism that adaptively reflects their past performance (line 8). The current solution is then successively destroyed and repaired, producing a temporary solution (line 9). The temporary solution is either accepted as the subprocess current solution or rejected according to a simulated annealing criterion (line 10) The weights of the destroy and repair operators are updated depending on their performance (line 16) and the tours from the solution are stored for the post-optimization (line 17). The final current solution of each subprocess is added to the pool of promising solutions (line 19). When all subprocesses have terminated, a filtering procedure ensures that the pool contains at most N solutions, including the best solution found so far (line 21). The algorithm stops after I^m master iterations, which corresponds to $I = I^m \times I^p \times K$ ALNS iterations. What follows is a detailed description of the main components of pALNS.

Algorithm 4.1 Parallel Adaptive Large Neighborhood Search (pALNS) algorithm

Input: $\mathcal{P}$, initial solutions; z, evaluation function; Θ^-/Θ^+, set of destroy/repair operators; N, maximum size of the solution pool; Km number of subprocesses; I^m, number of master iterations; I^p, number of iterations performed in parallel.

Output: $\mathbf{\Pi}^*$, the best solution found; Ω, the pool of tours for the post-optimization.

$\Omega \leftarrow \emptyset$
$\mathbf{\Pi}^* \leftarrow \arg\min_{\mathbf{\Pi} \in \mathcal{P}} \{z(\mathbf{\Pi})\}$
for I^m iterations **do**
  $\mathcal{P}' \leftarrow \texttt{selectSubset}\,(\mathcal{P}, K)$ ▷ Select a subset of K solutions
  parallel forall $\mathbf{\Pi}$ **in** $\mathcal{P}'$ **do**
    $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}$ ▷ Current solution for this subprocess
    for I^p iterations **do**
      $d \leftarrow \texttt{select}\,(\Theta^-)\,; r \leftarrow \texttt{select}\,(\Theta^+)$ ▷ Select destroy/repair
      $\mathbf{\Pi}' \leftarrow \texttt{r}\,(\texttt{d}\,(\mathbf{\Pi}^p))$ ▷ Destroy and repair current solution
      if $\texttt{accept}\,(\mathbf{\Pi}', \mathbf{\Pi}^p)$ **then**
        $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is accepted as current solution
      end if
      if $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then**
        $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is the best solution found so far
      end if
      $\texttt{updateScore}\,(d, r, \mathbf{\Pi}')$ ▷ Update d and r scores
      $\Omega \leftarrow \Omega \cup \{\pi\}_{\pi \in \mathbf{\Pi}'}$ ▷ Add tours from $\mathbf{\Pi}'$ to the set-covering tour pool Ω
    end for
    $\mathcal{P} \leftarrow \mathcal{P} \cup \{\mathbf{\Pi}^p\}$ ▷ Add $\mathbf{\Pi}^p$ to the pool $\mathcal{P}$
  end forall
  $\mathcal{P} \leftarrow \texttt{retain}\,(\mathcal{P}, \mathbf{\Pi}^*, N)$ ▷ Retain at most N solutions in the pool $\mathcal{P}$
end for
return $\mathbf{\Pi}^*, \Omega$

Destroy Destroy operators remove a random number of requests from the current solution. We used three destroy operators originally proposed by Pisinger and Ropke (2007): *random*, *critical*, and *related*. The random destroy operator removes requests randomly from their current tours; the critical destroy operator removes requests that are among the most costly in the current solution; finally, the related destroy removes requests that share common characteristics by first selecting a seed request, and then removing related requests. It is important to note that all three destroy operators are randomized.

We propose two relatedness metrics tailored for the TRSP that define two new destroy operators. The *a priori relatedness* is a precalculated metric that does not depend on the current position of the requests in the tours and combines three components: geographic distance, difference of due dates, and number of technicians that can serve both requests. On the other hand, *time relatedness* measures the difference between the service time of two requests in the current solution.

Repair Repair operators attempt to insert requests that are currently unserved. If requests cannot be reinserted, a penalty proportional to the number of unserved requests is added to the objective function. This penalty approach allows infeasible solutions to be considered as the current solution during the search, and can be interpreted as the possible outsourcing of some requests. Our implementation is based on three repair heuristics: *best insertion*, *regret-2*, and *regret-3*.

Adaptive layer At each iteration, the pALNS algorithm selects a destroy and a repair operator using a roulette wheel mechanism. Operator θ is selected with probability w_θ. Let $\Theta^\bullet$ be either the set of destroy (Θ^-) or repair (Θ^+) operators. As in the original ALNS algorithm, probabilities are initialized with value $\frac{1}{|\Theta^\bullet|}$. However, they are then updated every l iterations as follows: $w_\theta \leftarrow (1-\rho)w_\theta + \rho\frac{s_\theta}{\sum_{\theta\in\Theta^\bullet} s_\theta}$, where $\rho \in [0,1]$ is the *reaction factor* which defines how quickly probabilities are adjusted, and s_θ is the *score* of operator θ in the last l iterations. Note that this formula ensures that $\sum_{\theta\in\Theta^\bullet} w_\theta = 1$ at all time. The scores s_θ are maintained at the master level. They are reset to 0 every l iterations and updated at the end of each iteration depending on the new solution $\mathbf{\Pi}'$: a score of σ_1 is granted for a new best solution, σ_2 for an improving solution, σ_3 for a non-improving but accepted solution, and σ_4 for a rejected solution.

Acceptance criterion The pALNS algorithm relies on a simulated annealing acceptance criterion: a new solution $\mathbf{\Pi}'$ is accepted with probability $e^{\frac{z(\mathbf{\Pi})-z(\mathbf{\Pi}')}{T}}$, where T is the *temperature* parameter. T is initialized with value T_0 and reduced at each iteration by a *cooling factor* c. Parameters T_0 and c are fixed depending on the initial solution and the target number of iterations (Pisinger and Ropke, 2007).

Promising solution pool The solution pool acts as a shared memory and allows subprocesses to collaborate efficiently. The method `retain` ensures that $\mathcal{P}$ contains at most N solutions: if $|\mathcal{P}| > N$ then the method retains the N best solutions according to the fitness function $f(\mathbf{\Pi}) = \mathrm{rank}_z(\mathbf{\Pi}) + \mathrm{rank}_d(\mathbf{\Pi})$, where $\mathrm{rank}_z(\mathbf{\Pi})$ is the rank of solution $\mathbf{\Pi}$ according to its objective value and $\mathrm{rank}_d(\mathbf{\Pi})$ is the rank of $\mathbf{\Pi}$ according to a diversity metric. For the latter metric, we use the average broken pairs distance (Prins, 2009) to measure the diversity of solution $\mathbf{\Pi}$ relative to the other solutions in $\mathcal{P}$. This fitness function is inspired by the *biased fitness* introduced by Vidal et al. (2011) in a genetic algorithm

with diversity management. It allows the preservation of solutions that are both diverse and promising in terms of cost. In addition, we ensure that $\mathcal{P}$ always contains the best solution found so far.

4.1.3.3 Set-covering based post-optimization

The pALNS algorithm generates one solution per ALNS iteration, but only keeps the best one. However, good solutions may contain poor tours, and conversely poor solutions may contain good tours. The proposed approach overcomes this limitation by solving a Set Covering model (SC) that combines the tours generated throughout the search to assemble a better solution. Note that a similar approach was for instance used by Villegas (2012) to solve the Truck and Trailer Routing Problem (TTRP) showing excellent results.

Tour pool Throughout the pALNS algorithm, we store in a pool Ω the tours π that make up the temporary solutions $\mathbf{\Pi}'$ found by the algorithm (see Algorithm 4.1, line 17). Tours are either stored in a single hash table when solving the CVRPTW, or in a separate hash table per technician for the TRSP. We associate a 32-bit integer to each tour using the hash function $\text{hash}(\pi) = \oplus_{i \in \pi} R[i]$, where R is an array associating a random 32-bit integer to each request and $\oplus$ is the `XOR` bit-wise operator. It is important to note that this hash function only considers the subset of requests in tour π, ignoring their sequence which is not relevant for the set-covering model. Preliminary experiments revealed that the probability of having a hash collision was under 10^{-3}. Therefore, we ignore hash collisions and always keep the tour with the lowest cost, without checking if tours actually contain the same requests.

Mathematical model Let $\Omega_k \subseteq \Omega$ be the subset of tours associated with technician k, c_t be the duration of tour t, and a_{ti} a binary parameter that takes the value of 1 if tour t visits request i and 0 otherwise. We denote by x_t a decision variable that takes the value of 1 if tour t is selected, and 0 otherwise. We can then formulate the TRSP on the subset Ω of all feasible tours as follows:

$$\min \quad \sum_{t \in \Omega} c_t x_t \tag{4.1}$$

$$s.t., \quad \sum_{t \in \Omega} a_{ti} \cdot x_t \geq 1 \qquad \forall i \in \mathcal{R} \tag{4.2}$$

$$\sum_{t \in \Omega_k} x_t \leq 1 \qquad \forall k \in \mathcal{K} \tag{4.3}$$

$$x_t \in \{0, 1\} \qquad \forall t \in \Omega \tag{4.4}$$

where the objective (4.1) minimizes the total routing duration, constraints (4.2) ensure that each request is served at least once, and constraints (4.3) guarantee each technician performs at most one tour.

Considering that requests must be served exactly once, one could argue that a set-partitioning formulation fits better. However, our model only contains a reduced subset of tours (columns), and therefore, we might not be able to find a good combination of tours that visit all requests exactly once. The drawback of this formulation is that the solution may visit a request more than once. In such event, the solution is repaired by removing the most costly duplicated visits.

4.1.4 Computational results

In this section we report computational results for the proposed matheuristic. All experiments were run using Java 7 and Gurobi 4.60 on an Ubuntu 11.10 64-bit machine, with an Intel i7 860 processor (4×2.8GHz) and 6GB of RAM, using $K = 8$ subprocesses. The pALNS algorithm was run for 25600 iterations ($I^p = 100$, $I^m = 32$) and a time limit of 30 minutes was enforced for the set-covering model. Because the destroy operators are randomized, pALNS is a non-deterministic algorithm, therefore we run it 10 times for each instance. The detailed parameter settings are shown in Pillac et al. (2011).

4.1.4.1 Validation on the VRPTW

The TRSP being a natural extension of the VRPTW, we validate our matheuristic on the 56 VRPTW instances from the Solomon benchmark (Solomon, 1987). The instances contain 100 requests located randomly (R), in clusters (C), or combining both (RC); with either a short (type 1) or long (type 2) planning horizon. These instances are organized combining location and horizon (i.e., C1, C2, R1, R2, RC1, and RC2), each group containing between 8 and 12 instances. For the VRPTW, we consider the minimization of the traveled distance [1] and replace constraints (4.3) from the set covering model by $\sum_{t\in\Omega} x_t \leq 25$ to model the 25-vehicle homogeneous fleet defined in the Solomon (1987) instances.

	Improvement		**Gap to BKS/Opt**		**Best known solutions**		**Time (s)**		
Group	Δ_{pALNS}	Δ_{SC}	pALNS	pALNS+SC	#Opt.	#BKS	pALNS	SC	$\lvert\Omega\rvert$
C1	37.89%	0.00%	0.00%	0.00%	9/9	-	14.6	0.4	11550
C2	26.41%	0.02%	0.02%	0.00%	8/8	-	26.5	0.2	3479
R1	24.28%	0.44%	0.59%	0.14%	10/12	-	13.1	27.2	27303
R2	32.21%	0.25%	0.76%	0.51%	5/10	1/1	24.5	2.1	14161
RC1	25.06%	1.21%	1.38%	0.15%	6/8	-	12.6	25.1	25327
RC2	36.56%	0.43%	0.99%	0.55%	6/8	-	21.3	1.3	11822
All	**30.20%**	**0.38%**	**0.62%**	**0.23%**	**44/55**	**1/1**	**18.6**	**10.1**	**16293**

Table 4.1: Computational results for the Solomon (1987) instances (average over 10 runs).

Table 4.1 summarizes the average results for each instance group. The first column defines the instance group, the second column contains the relative improvement between the initial solution and the solution returned by pALNS (Δ_{pALNS}), the third column reports the relative improvement between the pALNS solution and the pALNS+SC solution (Δ_{SC}). The fourth and fifth columns contain the average gap to the optimal or best known solution for pALNS and pALNS+SC. The sixth column reports the number of optimal solutions found (Opt.) over the number of known optimal solutions, while the seventh column reports the number of best known solutions (BKS) found over the number of heuristic BKS. Columns eight and nine show the average computational times for the pALNS and SC, and the last column reports the average size of the tour pool.

The overall average gap for pALNS+SC is just 0.23%, while Pisinger and Ropke (2007) report a value of 0.36% using an ALNS with a larger number of destroy and repair operators [2]. This illustrates

1. Note that we truncate the distances to one decimal, as it is common practice when solving the Solomon (1987) instances with the distance minimization as solely objective.

2. In addition, it is important to note that 7 optimal solutions were not known at the time of their study, using the same values the average gap for our approach is of 0.16%.

the importance of the post-optimization step of the matheuristic, which is able to divide the gap by a factor of 3.4 in 10s on average. On the other hand, the parallelization of the algorithm allowed for speedups of 3.5 times relative to a sequential implementation, leading to running times of 19s on average.

4.1.4.2 Results on the TRSP

After validating our algorithmic building blocks on the VRPTW, in this section we analyze the performance of our matheuristic on randomly generated instances of the TRSP. Our testbed is composed of 56 instances of the TRSP based on the Solomon (1987) benchmark. For each instance, we considered a crew of 25 technicians with different home locations, skills, initial set of tools and spare parts. In addition, we generated requests by adding skill, tool, and spare part information to each customer. These instances and our detailed solutions are publicly available at Pillac et al. (2011).

	Improvement	**Gap to BKS**		**Time (s)**		
Group	Δ_{SC}	pALNS	pALNS+SC	pALNS	SC	$\|\Omega\|$
C1	0.97%	1.22%	0.23%	24.0	388.9	67020
C2	0.35%	0.78%	0.42%	27.8	23.6	39334
R1	3.62%	4.96%	0.82%	28.9	500.2	30783
R2	0.23%	1.69%	1.46%	31.0	42.1	24396
RC1	3.06%	3.90%	0.68%	27.9	185.8	18638
RC2	0.49%	1.93%	1.43%	27.9	15.6	16917
All	**1.53%**	**2.54%**	**0.86%**	**28.1**	**210.1**	**32858**

Table 4.2: Computational results for 56 randomly generated TRSP instances.

Table 4.2 reports our results for the six groups of instances. Note that in this case we do not report the improvement of pALNS over the initial solution as the regret heuristic is not always able to insert all requests. In addition, the third and fourth columns report average gap to the best solution found in our experiments.

The SC post-optimization improves by 1.5% the pALNS solution, which is larger than the 0.38% improvement found for the VRPTW. This can be explained by the fact that the TRSP is harder for pALNS than the VRPTW, so further improvements can be found in the post-optimization phase. It is worth noting that on average the tour pool contains twice as many tours as in the VRPTW experiments. This can be explained by the fact that in the TRSP identical tours may be associated with different technicians. However the problem being overly constrained, it expectedly admits fewer feasible tours. In terms of running times, the post-optimization engine requires 20 times more computational effort to solve the TRSP than the VRPTW. This is due to the larger size of the tour pool and the presence of resource constraints (4.3) that destroy the set-covering structure, thus demanding more effort from the linear optimization engine which is likely to embed specific heuristics for pure set-covering models.

4.1.5 Conclusions and research perspectives

In this study we introduced a new challenging routing problem with numerous applications, namely the Technician Routing and Scheduling Problem. Distinctive features of this problem are the presence of compatibility constraints between technicians and requests; an initial set of tools and spare parts

available to the technicians; the possibility for technicians to visit a main depot to pick up additional tools and spare parts; and the scheduling aspects introduced by the objective of minimizing the total tour duration.

We proposed a parallel matheuristic, which comprises three components: a regret constructive heuristic, a parallel adaptive large neighborhood search (pALNS), and a set-covering post-optimizer (SC). The parallelization of the ALNS allows a speed increase by a factor of 3.4 on a quad-core computer, while the post-optimization phase assembles a better solution by using tours gathered during the search. The resulting matheuristic maintains the flexibility of the ALNS, while improving its performance and reducing the need for complex operators.

We validated and measured the performance of the proposed matheuristic on the Solomon VRPTW benchmark, showing a negligible gap of 0.23% to the optimal and best known solutions (BKS), and finding 44 of the 55 optimal solutions in under 30s. Results on randomly generated instances of the TRSP illustrate the improvement that pALNS and SC bring over a constructive heuristic solution.

Future work will focus on the extension of the problem to a dynamic setting, in which unexpected delays and new requests may occur. To this end, we are focusing our research efforts on developing fast optimization procedures able to react in real time to changes in the problem information.

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4.2 The dynamic TRSP

The technical report presented in this section introduces the dynamic TRSP and proposes two optimization approaches to tackle it. The first is based on the fast reoptimization framework presented in Chapter 2, and the second is an adaptation of the `jMSA` framework described in Chapter 3.

The full reference of the paper presented in this section is:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011)
On the dynamic technician routing and scheduling problem
Technical report 12/5/AUTO.

Preliminary results were presented in two international conferences:

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012)
A Multiple Plan Approach for the Dynamic Technician Routing and Scheduling Problem
In *25th European Conference on Operational Research (EURO 2012)*, Vilnius, Lithuania.

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012)
On the dynamic technician routing and scheduling problem
In *Proceedings of the 5th International Workshop on Freight Transportation and Logistics (ODYSSEUS 2012)*, Mykonos, Greece.

On the Dynamic Technician Routing and Scheduling Problem

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State : Working paper

Abstract : The Technician Routing and Scheduling Problem (TRSP) consists in routing staff to serve requests for service, taking into account time windows, skills, tools, and spare parts. Typical applications include maintenance operations and staff routing in telecoms, public utilities, and in the health care industry. In this paper we tackle the Dynamic TRSP (D-TRSP) in which new requests appear over time. We propose a fast reoptimization approach based on a parallel Adaptive Large Neighborhood Search (pALNS) and a Multiple Plan Approach (MPA). Finally, we present computational experiments on both randomly generated instances and real-world data.

Keywords : Dynamic Vehicle Routing ; Technician Routing and Scheduling ; Parallel Adaptive Large Neighborhood Search ; Multiple Plan Approach

4.2.1 Introduction

The Technician Routing and Scheduling Problem (TRSP) deals with a limited crew of technicians $\mathcal{K}$ that serves a set of requests $\mathcal{R}$. The TRSP can be seen as an extension of the Vehicle Routing Problem with Time Windows (VRPTW), where technicians play the role of vehicles and requests are made by clients. In the TRSP, each technician has a set of skills, tools, and spare parts, while requests require a subset of each. The problem is then to design a set of tours such that each request is visited exactly once, within its time window, by a technician with the required skills, tools, and spare parts. The TRSP naturally arises in a wide range of applications, including telecoms, public utilities, and maintenance operations.

This problem introduces compatibility constraints between technicians and requests. While skills are intrinsic attributes, technicians may carry different tools and spare parts over the planning horizon. Technicians usually start their tour from their home with an initial set of tools and spare parts that allows them to serve an initial set of requests. They also have the opportunity to replenish their tools and spare parts at a central depot at any time to serve more requests. Tools can be seen as renewable resources, while spare parts are non renewable and consumed once the technician serves a customer.

Figure 4.1 illustrates an instance of the TRSP with two technicians and six requests. Technician A has the green skill, while B has both green and blue skills. Technician A starts its tour at home (gray diamond) with a hammer and a screwdriver, then serves requests 1, 2, and 3, before returning home. Technician B first serves 4, then goes to the central depot (black square) to pick up a drill that allows him/her to serve request 6 after serving request 5. Note that although request 5 is close to the tour of

technician A, only technician B can serve it due to skill constraints.

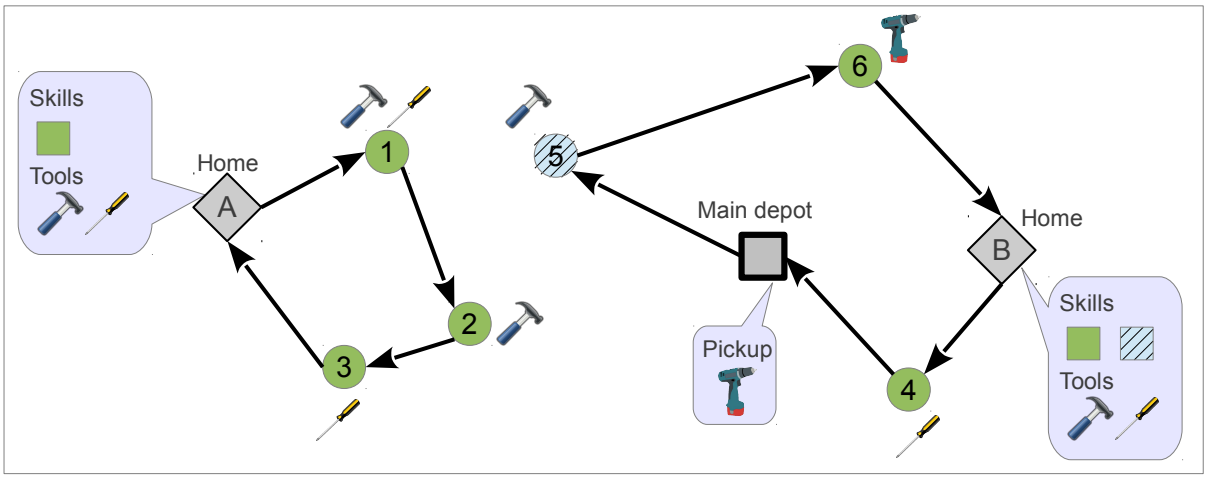

Figure 4.1: Example of a technician routing and scheduling problem with two technicians, three tools, and two skills

The static definition of the TRSP was introduced by the authors in Pillac et al. (2012b). In this work, we tackle a dynamic variant of the problem, namely the D-TRSP, in which new requests appear while the technicians are executing their routes. In this context, two types of decisions have to be taken in real time. First, whenever a technician finishes serving a request, it must be decided what will be the next request to visit. Second, whenever a request appears, the algorithm must decide whether it is possible or desirable to accept it or not. If not the request is said to be *rejected*, it leads to a cost penalty corresponding to the outsourcing/postponing of the request.

Despite its numerous practical applications and its challenging features, static technician routing and scheduling problems have received limited attention until recently, and to the best of our knowledge, no study simultaneously considers skills, tools, and spare parts. For instance, Xu and Chiu (2001) studied the Field Technician Scheduling Problem (FTSP) seen as a variant of the VRPTW, in which the objective is to maximize the number of requests served while accounting for skill constraints, request priorities, multiple depots, and overtime. The authors describe a mixed integer formulation and develop three heuristics including a GRASP algorithm. Similarly, Weigel and Cao (1999) present a software solution developed for Sears, a US retailer that serves its customers with home delivery and on-site technical assistance. The proposed solution works by first assigning technicians to requests, and then optimizing technician routes individually. Tsang and Voudouris (1997) studied the technician workforce scheduling problem faced by British Telecom. Their study does not consider skill constraints, but uses a proficiency factor that reduces the service time depending on the technician experience. They propose a Fast Local Search and a Guided Local Search to solve this problem. Borenstein et al. (2010) extended this problem accounting for dynamic requests and skill compatibility constraints. They cluster the requests using a k-mean algorithm followed by a heuristic that assigns technicians to areas. Finally, they propose a rule-based system that assigns and sequences the requests. They conclude their study by assessing the impact of soft clustering and show that it can increase sys-

tem performance under certain assumptions.

Maintenance operations planning is a problem closely related to the TRSP. Blakeley et al. (2003) present the optimization of periodic maintenance operations for Schindler Elevator Corporation in North America, a company that manufactures, installs, and maintains elevators and escalators. The problem faced by this company consists in designing a set of routes for technicians to perform periodic maintenance and repairs taking into account travel times, working regulations, and skill constraints. A similar application was studied by Tang et al. (2007) who formulate the problem as a multi-period maximum collection problem in which time-dependent rewards are granted for the completion of a request. This approach allows the modeling of soft constraints such as the desirability of performing a task in a given day (*job-to-time penalties*). The authors propose a Tabu Search (TS) algorithm that yields near-optimal solutions on real instances in reasonable time.

In 2007 the French Operations Research Society (ROADEF) organized a challenge based on a problem submitted by France Telecom. The problem consists in finding a schedule for technicians to execute a set of tasks on a multiple-day horizon. Each task requires one or more skills with different minimum proficiency levels, while technicians can have multiple skills with a given proficiency. An important aspect is the creation of teams that work together during one day, combining the skills of their members, and the possibility to outsource the execution of a task. However, this problem ignores the routing aspects. Cordeau et al. (2010) proposed a mathematical model and an Adaptive Large Neighborhood Search (ALNS), while Hashimoto et al. (2011) proposed a Greedy Randomized Adaptive Search procedure (GRASP) approach to tackle this problem.

Work regulation is an important aspect of technician routing and scheduling. Tricoire (2006) presents a technician routing problem faced by Veolia, a water distribution and treatment company. In this application, technicians have the skills to perform all requests that are divided in two categories: user requested interventions and company scheduled visits. As new requests appear on a daily basis, the routing of technicians is performed on a rolling horizon, taking into account work regulations and customer service standards. The main contributions are a column generation approach and a memetic algorithm (Bostel et al., 2008). Their approaches take advantage of partial solutions from previous plans in the rolling horizon framework to reduce computational times.

A number of technological advances have led to a renewed interest in dynamic vehicle routing problems, leading to the development of new optimization approaches. Pillac et al. (2011a) classify dynamic routing problems in two categories: *deterministic* and *stochastic*. In both cases the information available to the stackholder changes over time. In stochastic setting, data is available on the dynamically revealed information in the form of known probability distributions, while in deterministic problems, changes are simply unpredictable. The present work falls in the dynamic and deterministic category, for which approaches are based either on *periodic reoptimization* or *continuous reoptimization*.

Periodic reoptimization approaches start at the beginning of the day by producing an initial set of routes that are communicated to the vehicles. As the available information is updated along the day, or at given intervals of time, an optimization is performed using the currently available information to update the routing. Such approaches can be based on algorithms developed for static problems and are therefore relatively easy to implement, however, they may introduce delays between the update of the information and the routing plan. Such approaches include the Ant Colony Systems (ACS) proposed by

Montemanni et al. (2005) to solve the Dynamic VRP (D-VRP). A novel feature of their approach is the use of the pheromone trace to transfer characteristics of a good solution between reoptimizations. ACS was also used by Gambardella et al. (2003) and Rizzoli et al. (2007). Other heuristic approaches, such as Tabu Search (TS), were also used to tackle the Dynamic Pickup and Delivery Problem (D-PDP) (Barcelo et al., 2007; Chang et al., 2003) and the Dynamic Dial-a-Ride Problem (D-DARP) (Attanasio et al., 2004; Beaudry et al., 2010).

Continuous reoptimization approaches run throughout the day and are generally based on an adaptive memory (Taillard et al., 2001) that stores alternative solutions. The adaptive memory is then used to react to changes in the available information, thus avoiding a complete reoptimization of the problem. Gendreau et al. (1999) developed a parallel TS with adaptive memory to tackle a Dynamic VRPTW (D-VRPTW), that was later applied to the D-VRP (Ichoua et al., 2000, 2003). Bent and Van Hentenryck (2004) generalized this framework and introduced the Multiple Plan Approach (MPA) to tackle the D-VRPTW. Following a different approach, Benyahia and Potvin (1998) studied the Dynamic Pickup and Delivery Problem (D-PDP) and proposed a Genetic Algorithm (GA) that models the decision process of a human dispatcher. More recently, GAs were also used for the same problem (Cheung et al., 2008; Haghani and Jung, 2005) and for the D-VRP (Van Hemert and Poutré, 2004).

To the best of our knowledge, no work considers simultaneously skills, tools, spare parts, and dynamically arriving requests, four important components of technician routing and scheduling. The present work addresses this aspect and proposes two optimization approaches for the dynamic version of the problem, noted D-TRSP, where new requests arrive during the execution of the routes. Section 4.2.2 introduces a fast reoptimization approach based on a parallel adaptive large neighborhood search; then Section 4.2.3 introduces a continuous reoptimization algorithm based on a multiple plan approach; finally, Section 4.2.4 presents the computational results and Section 4.2.5 concludes this paper and draws directions for future research.

4.2.2 A fast reoptimization approach

The proposed approach is based on the parallel Adaptive Large Neighborhood Search (pALNS) reoptimization algorithm introduced by Pillac et al. (2012a), which is used to first compute an initial solution, and then to reoptimize the solution whenever a new customer request arrives. The pALNS extends the Adaptive Large Neighborhood Search (ALNS) algorithm (Pisinger and Ropke, 2007), which in turn is an extension of the Large Neighborhood Search (LNS) algorithm (Pisinger and Ropke, 2010; Shaw, 1998). LNS works by successively destroying (removing customers) and repairing (inserting customers back) a current solution, using *destroy* and *repair operators*. ALNS adds a layer that randomly selects operators depending on their past performance, allowing a self-adaptive version of the algorithm to the instance at hand.

Algorithm 4.2 presents the outline of pALNS as introduced in Pillac et al. (2012a). The algorithm maintains a pool $\mathcal{P}$ of N promising solutions that are optimized in K subprocesses (note that $N \geq K$). For each *master* iteration, a subset of K promising solutions is selected randomly (line 3) and distributed among independent subprocesses. Then for I^p iterations, each subprocess selects destroy and repair operators with a roulette wheel that adaptively reflects their past performance (line 7). The

resulting new solution is either accepted as the subprocess current solution or rejected according to a simulated annealing criterion (line 9), the weights of the destroy and repair operators are updated depending on their performance (line 15). The final current solution is added to the pool of promising solutions (line 17) and a filtering procedure ensures that the pool contains at most N solutions, including the best solution found so far (line 19). The algorithm stops after I^m master iterations, which corresponds to $I = I^m \times I^p$ ALNS iterations.

Algorithm 4.2 Parallel Adaptive Large Neighborhood Search (pALNS) algorithm

Input: $\mathcal{P}$, initial solutions; z, evaluation function; Θ^-/Θ^+, set of destroy/repair operators; N, maximum size of the solution pool; Km number of subprocesses; I^m, number of master iterations; I^p, number of iterations performed in parallel.
Output: $\mathbf{\Pi}^*$, the best solution found

1: $\mathbf{\Pi}^* \leftarrow \arg\min_{\mathbf{\Pi} \in \mathcal{P}} \{z(\mathbf{\Pi})\}$
2: **for** I^m iterations **do**
3: $\quad \mathcal{P}' \leftarrow \texttt{selectSubset}\,(\mathcal{P}, K)$ ▷ Select a subset of K solutions
4: $\quad$ **parallel forall** $\mathbf{\Pi}$ **in** $\mathcal{P}'$ **do**
5: $\quad\quad \mathbf{\Pi}^p \leftarrow \mathbf{\Pi}$ ▷ Current solution for this subprocess
6: $\quad\quad$ **for** I^p iterations **do**
7: $\quad\quad\quad d \leftarrow \texttt{select}\,(\Theta^-)\,; r \leftarrow \texttt{select}\,(\Theta^+)$ ▷ Select destroy/repair
8: $\quad\quad\quad \mathbf{\Pi}' \leftarrow \texttt{r}\,(\texttt{d}\,(\mathbf{\Pi}^p))$ ▷ Destroy and repair current solution
9: $\quad\quad\quad$ **if** $\texttt{accept}\,(\mathbf{\Pi}', \mathbf{\Pi}^p)$ **then**
10: $\quad\quad\quad\quad \mathbf{\Pi}^p \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is accepted as current solution
11: $\quad\quad\quad$ **end if**
12: $\quad\quad\quad$ **if** $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then**
13: $\quad\quad\quad\quad \mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is the best solution found so far
14: $\quad\quad\quad$ **end if**
15: $\quad\quad\quad \texttt{updateScore}\,(d, r, \mathbf{\Pi}')$ ▷ Update d and r scores
16: $\quad\quad$ **end for**
17: $\quad\quad \mathcal{P} \leftarrow \mathcal{P} \cup \{\mathbf{\Pi}^p\}$ ▷ Add $\mathbf{\Pi}^p$ to the pool $\mathcal{P}$
18: $\quad$ **end forall**
19: $\quad \mathcal{P} \leftarrow \texttt{retain}\,(\mathcal{P}, \mathbf{\Pi}^*, N)$ ▷ Retain at most N solutions in the pool $\mathcal{P}$
20: **end for**
21: **return** $\mathbf{\Pi}^*$

the pALNS algorithm uses three destroy operators (random, related, and critical), and three repair operators (regret-1, regret-2, regret-3). The promising solution pool $\mathcal{P}$ maintains the N best solutions according to a fitness function that considers both the cost of the solution and its diversity relative to the other solutions in the pool. The interested reader is referred to the work by Pillac et al. (2012a) and Pillac et al. (2012b) for more details on the approach.

To tackle the D-TRSP, we modified the *related destroy* operator, which attempts to remove a subset of requests that share some characteristics. We define the *relatedness* r_{ij} of requests i and j as a measure of how related two requests are (the lower the r_{ij}, the more related i and j). The procedure starts by randomly removing a *seed* request i ($\mathcal{U} = \{i\}$), then it iteratively selects a request $i \in \mathcal{U}$, and removes the most related request $j^* = \arg\min_{j \in \mathcal{R}'} \{r_{ij}\}$ from the set of unserved requests $\mathcal{R}'$. In practice the selection process is randomized and the $\lfloor y^p |\mathcal{R}'| \rfloor$-th most related request is selected, where y is a random number in $[0, 1)$ and $p \geq 1$ is a parameter that controls the level of randomness

(the lower the p, the more randomness is introduced). For the D-TRSP we introduced the a-priori relatedness, which is a precalculated metric that does not depend on the actual position of requests in the tours:

$$r_{ij}^{s} = \left(1 + \frac{c_{ij}}{M_c}\right)^{\theta_c} \left(1 + \frac{|b_i - b_j|}{M_t}\right)^{\theta_t} \left(2 - \frac{|\mathcal{K}_i \cap \mathcal{K}_j|}{\min\{|\mathcal{K}_i|, |\mathcal{K}_j|\}}\right)^{\theta_s} \tag{4.5}$$

Where M_c and M_t are scaling constants, and θ_c, θ_t, and θ_s are factors that define the weight given to each metric component. The first component, measures the geographic distance between the two requests (c_{ij}). The second is the difference of due dates b_i and b_j. The third measures the number of technicians that can serve both requests, which is modeled by the intersection of the sets $\mathcal{K}_i$ and $\mathcal{K}_j$ of technicians that can serve request i and j respectively.

The second major adaptation focuses on the objective function that considers the minimization of the total working time (i.e., the sum of traveling times, service times, and waiting times). We used the concept of forward time slack introduced by Savelsbergh (1992) to efficiently evaluate the minimal duration of a tour and the cost of inserting a request in a tour.

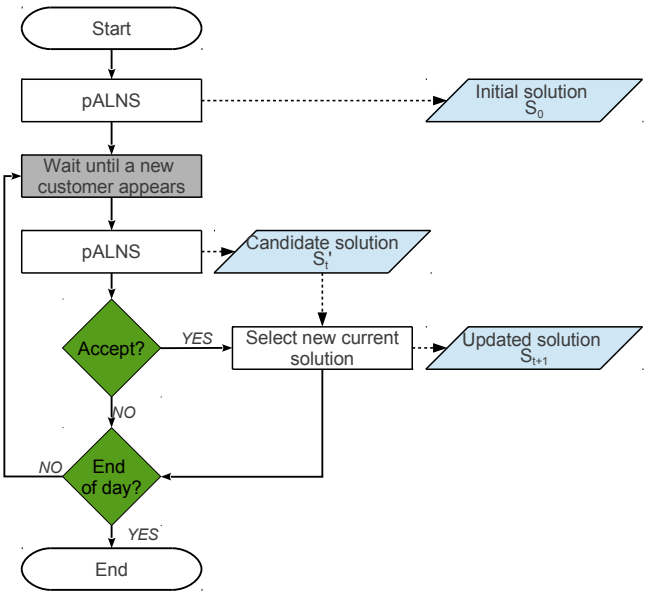

Figure 4.2: Overview of the proposed fast reoptimization approach

Figure 4.2 presents an overview of the proposed approach. The algorithm starts by producing an initial solution S_0 by using a constructive heuristic coupled with pALNS. Then each time a new customer appears, it fixes the currently executed portion of the solution, and re-runs the pALNS for a limited number of iterations, producing an updated solution S'_t. If pALNS is able to insert the new customer request, then the customer is *accepted* and S'_t becomes the new current solution, otherwise, the customer is *rejected* and S_t remains as the current solution.

4.2.3 A Multiple Plan Approach

The second proposed approach for the D-TRSP is based on the Multiple Plan Approach (MPA) introduced by Bent and Van Hentenryck (2004) to tackle the D-VRPTW. MPA is a generalization of the tabu search with adaptive memory proposed by Gendreau et al. (1999). The general idea is to populate and maintain a solution pool (the routing *plans*) that are used to generate a *distinguished solution*. Whenever a new request arrives, a procedure is called to check whether it can be served or not; if it can be served, then the request is inserted in each plan of the solution pool and incompatible solutions are discarded. Pool updates are performed periodically or whenever a vehicle finishes serving a customer. This pool-update phase is crucial and ensures that all solutions are coherent with the current state of vehicles and customers. The pool can be seen as an adaptive memory that maintains a set of alternative solutions.

The present work is based on the event-driven optimization framework for dynamic vehicle routing proposed by the authors, namely `jMSA` (Pillac et al., 2011b). By design, `jMSA` is a flexible, parallel, and event-driven Java implementation of the Multiple Scenario Approach (MSA) (Van Hentenryck and Bent, 2006), which is an extension of MPA for dynamic and stochastic routing problems. The proposed framework is designed to facilitate and accelerate the development and deployment of MSA-based algorithms embeddable in decision support systems.

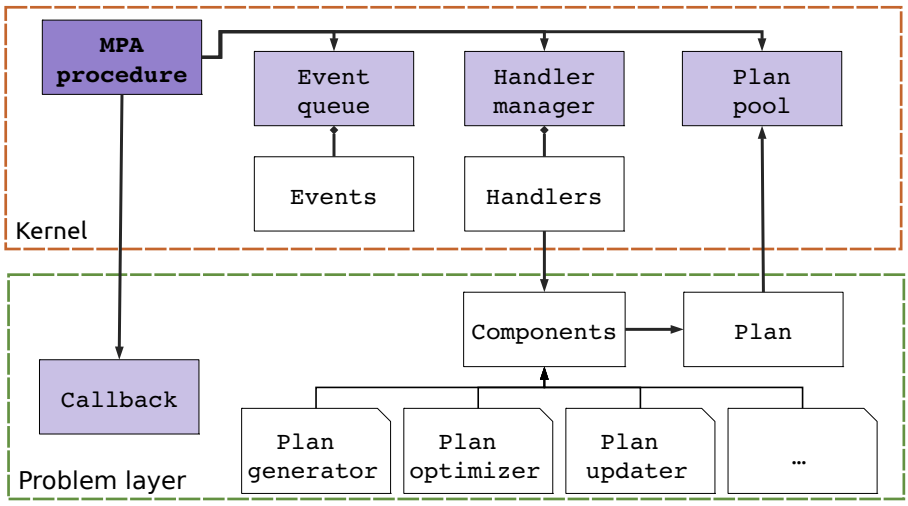

Figure 4.3: Design overview of the `jMSA` framework

Figure 4.3 outlines the main aspects of the `jMSA` framework: the *kernel* contains the components that define the event-driven behavior, and a generic definition of the *problem layer* components. To adapt the framework for a specific problem, the user needs only to implement a subset of components, mainly to generate, optimize, and update plans. The following paragraphs give more details on how `jMSA` was adapted to tackle the D-TRSP.

Figure 4.4 presents a conceptual overview of the MPA procedure as implemented in the `jMSA` framework. `jMSA` starts two subprocesses: a *main loop* and an *event loop*. The main loop is responsible for continuously generating and optimizing a set of alternative solutions (the *routing plans*) stored in the plan pool. This main loop maximizes the utilization of the computational resources when the

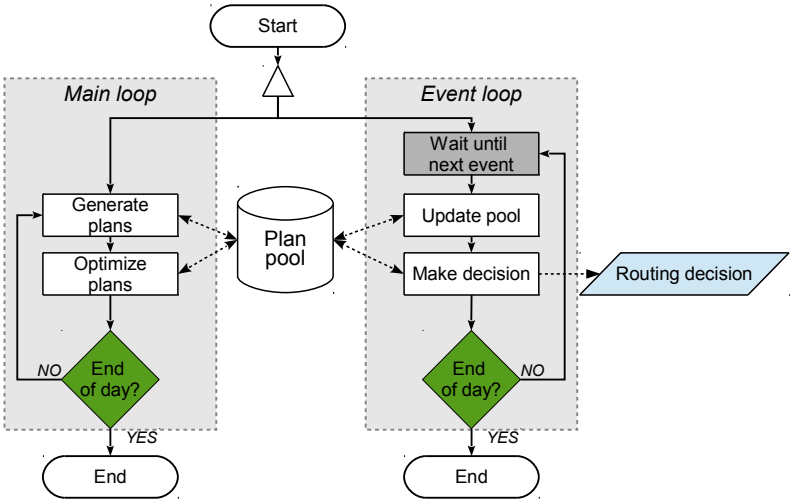

Figure 4.4: Overview of the multiple plan approach implemented with `jMSA`

system is *idle*, i.e., when no decision is required. On the other hand, the event loop reacts to events from the environment, which can be of two types: a) a customer calls in and requests a service; b) a technician finishes serving a request and becomes idle. In the first case, the algorithm looks for a feasible insertion of the new request in all the solutions in the pool. If at least a given fraction of the solutions can accommodate the request, then it is accepted, otherwise it is rejected. In the second case, the algorithm selects a solution from the pool and assigns a request to all idle technicians. The event loop is also responsible for updating the pool and ensuring that all plans are coherent with the current state of the environment.

4.2.3.1 Plan generation

The goal of the plan pool is to maintain a set of diverse solutions for the current routing problem that could be used later to cope with the arrival of new requests. It is therefore necessary to have a randomized constructive heuristic that will produce a set of solutions that are both diverse and of good quality.

Our implementation is based on a randomized *regret-3* heuristic (Potvin and Rousseau, 1993) which iteratively inserts requests at their best position. More formally let $\mathcal{U}$ be the set of requests that are currently not visited in the solution and let Δz_i^k be the cost of insertion of request $i \in \mathcal{U}$ in its k-th best route. The *regret-q* value r_i^q associated with request i is a measure of how desirable it is to insert i in the current iteration assuming that the best insertion will no longer be feasible in the next iteration. It is defined as:

$$r_i^q = \sum_{k=2}^{q} \left(\Delta z_i^k - \Delta z_i^1 \right) \tag{4.6}$$

The randomized regret-3 algorithm iteratively selects the next request to insert using a roulette wheel

in which each request is given a probability p_i:

$$p_i = \frac{r_i^3}{\sum_{j \in \mathcal{U}} r_j^3} \tag{4.7}$$

4.2.3.2 Optimization procedure

The optimization procedure continuously optimizes the pool of solutions. The fact that a solution might go through the optimization process more than once requires an algorithm able to escape from local optima to further improve a solution. Therefore, we implemente an Adaptive Large Neighborhood Search (ALNS) similar to the pALNS presented in Section 4.2.2. Note that the choice of having a sequential optimization algorithm is motivated by the fact that `jMSA` will optimize various plans in parallel.

Algorithm 4.3 outlines the ALNS algorithm. ALNS starts with an initial solution $\mathbf{\Pi}$. Then for I iterations, the algorithm selects destroy and repair operators (line 4) with a roulette wheel that reflects their past performance. The destroy operator removes a subset of requests from the current solution that are then reinserted by the repair operator (line 5). The resulting new solution is accepted as current solution according to a simulated annealing criterion (line 6). At the end of each iteration, the scores of the destroy and repair operators are updated depending on the solution they generated (line 12).

Algorithm 4.3 Adaptive Large Neighborhood Search (ALNS) algorithm

Input: $\mathbf{\Pi}_0$ initial solution, z evaluation function, Θ^-/Θ^+ set of destroy/repair operators, I number of iterations
Output: $\mathbf{\Pi}^*$ the best solution found

1: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}_0$ ▷ Initialize best solution
2: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}_0$ ▷ Initialize current solution
3: **for** I iterations **do**
4: $d \leftarrow \texttt{select}(\Theta^-); r \leftarrow \texttt{select}(\Theta^+)$ ▷ Select destroy/repair
5: $\mathbf{\Pi}' \leftarrow \texttt{r}(\texttt{d}(\mathbf{\Pi}))$ ▷ Generate a neighbor
6: **if** $\texttt{accept}(\mathbf{\Pi}', \mathbf{\Pi})$ **then** ▷ $\mathbf{\Pi}'$ is accepted as current solution
7: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}'$ ▷ Update current solution
8: **end if**
9: **if** $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then** ▷ An improvement has been found
10: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ Update best solution
11: **end if**
12: $\texttt{updateScore}(d, r, \mathbf{\Pi}')$ ▷ Update scores
13: **end for**
14: **return** $\mathbf{\Pi}^*$

4.2.3.3 Interactions with the decision maker

The decision maker interacts with MPA by raising events. In the context of the D-TRSP, there are two major events: the arrival of a new request and the end-of-service of a request.

Arrival of new requests Whenever a new request appears, a procedure attempts to insert it in all the plans in the pool. The procedure starts by trying to insert the request directly, if it fails, it removes a fraction of the requests and uses regret-3 to attempt to reinsert all requests. If at least a given fraction of the plans can accommodate the new request then it is accepted and the plans are updated accordingly, otherwise the request is marked as rejected.

Real-time routing decisions When a technician finishes serving a request and becomes idle, a decision needs to be taken on what will be his/her next assignment. To this end we use the *consensus* algorithm (Van Hentenryck and Bent, 2006) which aggregates the information contained in the plans from the pool to select a distinguished solution and assign requests to idle technicians. The intuition behind consensus is to assign to each technician the requests that appear first with the highest frequency across plans. As multiple technicians are involved, the consensus algorithm selects a solution from the pool that maximizes the consensus across all technicians. Algorithm 4.4 presents the details of the algorithm. Consensus starts by counting the number of times each request appears first in a tour across all solutions from the pool (lines 1 to 6). Then the algorithm evaluates each solution by summing the evaluations of the first request of each of its tours (line 11). Finally, the solution $\mathbf{\Pi}^*$ with the highest evaluation is returned, and the first unserved request of each tour in $\mathbf{\Pi}^*$ is the next assignment of the corresponding technician.

Algorithm 4.4 The consensus algorithm

Input: $\mathcal{P}$ a pool of alternative solutions
Output: $\mathbf{\Pi}^*$ a distinguished solution

1: $e \leftarrow [0]_{i \in \mathcal{R}}$ ▷ Initialize the evaluation of all requests
2: **for all** $\mathbf{\Pi} \in \mathcal{P}$ **do** ▷ For each solution in the pool
3: **for all** $\pi \in \mathbf{\Pi}$ **do** ▷ For each tour in the solution
4: $e[\pi_0] \leftarrow e[\pi_0] + 1$ ▷ Increment the evaluation of the first unserved request π_0
5: **end for**
6: **end for**
7: $s^* \leftarrow 0$
8: **for all** $\mathbf{\Pi} \in \mathcal{P}$ **do**
9: $s \leftarrow 0$ ▷ Initialize the evaluation of this scenario
10: **for all** $\pi \in \mathbf{\Pi}$ **do**
11: $s \leftarrow s + e[\pi_0]$ ▷ Update the evaluation of this scenario
12: **end for**
13: **if** $s > s^*$ **then**
14: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}$
15: **end if**
16: **end for**
17: **return** $\mathbf{\Pi}^*$

Waiting strategy It is important to note that the immediate commitment of idle technicians to requests may lead to difficulties when new requests appear. Figure 4.5 illustrates this with a single technician. Suppose that at time t a technician is assigned to a request i, if the technician is committed immediately to i, it will travel to i then wait at its destination until the start of the time window (black

brackets). On the other hand, if a waiting strategy is used, the technician will remain idle until the latest moment such that it will not wait at i. Assume now that at time $t+1$ a new request j appears, in the first case j cannot be served as the technician is already waiting at i (the hashed section is already executed), while in the second case it can be inserted right before i.

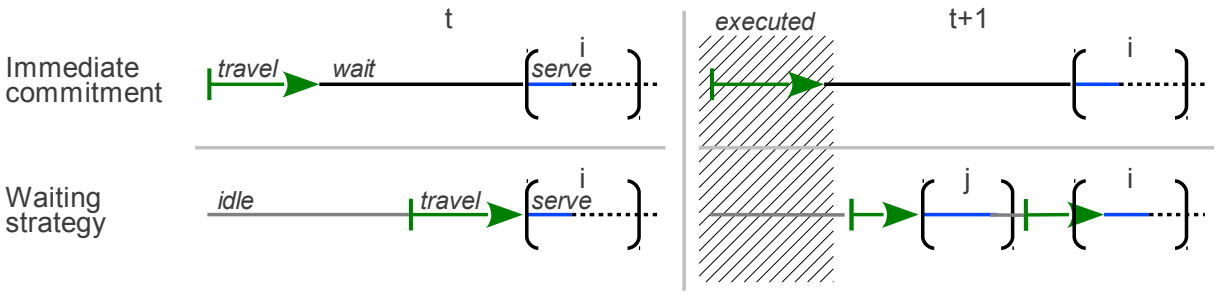

Figure 4.5: Advantage of a waiting strategy.

The proposed waiting strategy is implemented as follows: first, the procedure evaluates the latest departure time so that the technician will not have to wait at its next request. If this departure time is within a given range, then it is assumed there is not enough time to change the technician's route and the technician is committed to the next request. Otherwise, the technician remains in an idle state for a given time, after what a new decision is taken, leaving time for further changes in assignments.

4.2.4 Preliminary results

We tested the pALNS and MPA approaches on a set of 56 randomly generated instances based on the Solomon (1987) testbed. The instances contain 100 requests located randomly (R), in clusters (C), or combining both (RC); while the planning horizon is either short (type 1) or long (type 2). These instances are organized combining location and horizon (i.e., C1, C2, R1, R2, RC1, and RC2). We considered 5 skills, 5 tools, and 5 types of spare parts. For each request, we selected 1 skill, and between 0 and 2 tools and spare part types. Each of the 25 technicians has between 2 and 4 skills, and an initial set of 0 to 5 tools, and 2 to 5 spare parts. In addition, we generated release dates for either 10, 30, 50, 70, or 90 requests, leading to a complete testbed of 280 dynamic instances.

We compare the two proposed approaches with a regret-3 heuristic. This simple approach starts with the same initial solution as pALNS. Each time a new request appears, it attempts to insert it in the current solution using a regret heuristic, rejecting it if it cannot be inserted. The parameter setting for the pALNS reoptimization approach is identical to the one presented in Pillac et al. (2012a), we allowed for 25,000 iterations for the calculation of the initial solution, and 5,000 for subsequent reoptimizations. The maximum pool size for MPA was set to 50 plans, while the ALNS algorithms used the same parameters as in Pillac et al. (2012a), with a maximum of 5,000 iterations per optimization.

The same simulation procedure was used to test the three approaches. First, the simulator allows them time to either design an initial solution (pALNS and regret-3) or initialize the pool of plans (MPA). Then the procedure simulates the routing of the technicians using an average traveling speed and taking into account waiting times. Whenever a technician becomes idle, the simulator uses the

current solution (pALNS and regret-3) or distinguished plan (MPA) to select the next assignment for this technician. The simulator handles the new requests and depending on the approach response it marks them as accepted or rejected. Finally, it finds an a-posteriori solution to the problem defined by all the accepted requests using pALNS with 50,000 iterations.

4.2.4.1 Minimizing the total working time

The static TRSP problem (Pillac et al., 2012b) considers the minimization of the total working time. In a dynamic setting, this objective leads to the premature ending of tours: technicians are sent home as soon as possible to reduce the duration of their tour, ignoring the fact that additional requests may appear in the future. To prevent this behavior we define a *cutoff policy* that ensures for an instance I that technicians will no be sent back to their home until time $t_c(I)$. Considering that each instance have a different horizon $[0, T(I)]$, we define the relative cutoff $\alpha(G)$ for instance group G. The value of $\alpha(G)$ is defined such that all requests of instance $I \in G$ will be known before $\alpha(G)T(I)$ with a certain probability. In our experiments, $\alpha(G)$ corresponds to the 90-percentile of the distribution of $\left\{\frac{rd^I_{max}}{T(I)}\right\}_{I \in G}$ where rd^I_{max} is the last release date for instance I [3].

A direct consequence of this policy is that the minimal tour duration for instance I is either 0 (if the technician is not used), or $\alpha(G)T(I)$. Therefore the total duration at the end of the day is significantly longer than the one found when solving the static problem.

	pALNS		**MPA**		**regret-3**	
δ	**Gap (%)**	**R**	**Gap (%)**	**R**	**Gap (%)**	**R**
10	65.7	0.0	152.8	1.5	59.9	0.4
30	79.5	0.1	160.1	3.2	84.6	0.6
50	93.0	0.1	150.6	4.6	100.4	1.0
70	100.3	0.2	153.9	6.3	113.8	1.4
90	102.8	0.4	154.0	6.0	122.3	1.8
Avg.	**88.3**	**0.2**	**154.3**	**4.4**	**96.2**	**1.0**

Table 4.3: Average gap to a-posteriori solution and number of rejected requests for the D-TRSP instances minimizing the total duration.

Table 4.3 reports the results for the 56 instances and 5 degrees of dynamism when minimizing the total duration. The first column contains the degree of dynamism (δ) defined as the number of dynamic requests. The second and third columns report the average gap to an a-posteriori solution [4] and the average number of rejected requests (R) for the pALNS. The fourth and fifth columns contain these statistics for the MPA, and the seventh and eighth columns for the regret-3 heuristic. Note that running times for pALNS are of 12s on average for the calculation of the initial solution and 2.8s for subsequent reoptimizations, while decision times are negligible for both MPA and regret-3.

3. With this definition: $\alpha^{C1} = 0.380$, $\alpha^{C2} = 0.509$, $\alpha^{R1} = 0.357$, $\alpha^{R2} = 0.419$, $\alpha^{RC1} = 0.321$, $\alpha^{RC2} = 0.400$

4. The gap for instance I is defined as the ratio $\frac{z(I) - \underline{z}(I)}{\underline{z}(I)}$ where $z(I)$ is the value of the solution found by the algorithm for the dynamic instance, and $\underline{z}(I)$ is a lower bound obtained by solving the static a-posteriori instance with 50,000 iterations of the pALNS algorithm.

Firstly, it can be observed that gaps are large regardless of the approach. This is due to the fact that the a-posteriori solution does not consider the cutoff strategy enforced in the dynamic context. Therefore the gap should not be interpreted as an absolute performance metric, but instead as a metric that allows comparisons between approaches. Secondly, the results show that, as expected, both the gap and number of rejected requests increase with the degree of dynamism. Finally, they indicate that the pALNS approach leads to better solutions both in terms of quality of the routing (measured by the gap) and ability to cope with new requests (measured by R). In contrast, MPA performs poorly and is dominated by the simpler regret-3 reoptimization approach. This can be explained by the fact that the decision process in MPA does not take into account the cost (total duration) of plans to select the distinguished plan, while the other two approaches explicitly focus on the cost. In addition, our experiments show that MPA tends to use more technicians, starting more tours than pALNS and regret-3. Considering that technicians then have to wait until the cutoff time, this leads to a greater total duration. On the other hand, the higher number of rejected requests can be explained by the fact that MPA is more conservative than the other approaches, as it requires that a fraction of the plans can accommodate the new requests, while the other approaches only require a feasible insertion in the current solution.

4.2.4.2 Minimizing the total distance

The cutoff policy forces technicians to wait at their current location before returning home. Thus, the minimization of the working time may not be as relevant in a dynamic context as it is for the static case. To assess the validity of this objective, we performed the same experiments with the minimization of the traveled distance.

	pALNS		**MPA**		**regret-3**	
δ	**Gap (%)**	**R**	**Gap (%)**	**R**	**Gap (%)**	**R**
10	2.4	0.1	9.1	1.9	10.5	0.3
30	5.4	0.1	11.0	4.6	30.5	0.4
50	10.8	0.3	14.4	5.6	44.1	1.0
70	11.8	0.2	21.3	8.7	57.5	1.2
90	17.9	0.4	23.9	8.1	64.1	1.4
Avg.	**9.7**	**0.2**	**16.1**	**5.9**	**41.3**	**0.8**

Table 4.4: Average gap to a-posteriori solution and number of rejected requests for the D-TRSP instances minimizing the total distance.

Table 4.4 compares the different approaches when the objective only considers the minimization of the traveled distance. As before, the gap and number of rejected requests generally increases with the degree of dynamism. These results show that pALNS consistently outperforms the two other approaches, both in terms of gap and number of rejected requests. However, in this case MPA is the second best-performing approach in terms of gap, but it remains third with respect to the number of rejected requests. As before, our experiments show that MPA uses more technicians on average. However, what was a disadvantage when minimizing the total duration helps MPA in reducing the

total distance. Nonetheless, the remark regarding the number of rejected requests remains valid: the approach seems to be overly conservative.

	pALNS		MPA		regret-3	
δ	Δ_{WT}	Δ_{Dist}	Δ_{WT}	Δ_{Dist}	Δ_{WT}	Δ_{Dist}
10	-8.0	-40.9	-13.3	-58.1	-1.4	-33.6
30	-9.8	-45.5	-15.8	-57.2	-7.7	-31.7
50	-16.4	-46.5	-11.4	-55.1	-11.0	-31.4
70	-18.5	-47.6	-12.8	-54.1	-10.8	-30.2
90	-20.2	-45.4	-10.1	-52.9	-11.9	-32.0
Avg.	**-14.6**	**-45.2**	**-12.6**	**-55.4**	**-8.5**	**-31.8**

Table 4.5: Difference in total working time and distance when minimizing the total distance instead of the total working time (in %).

Finally, Table 4.5 presents the effect of the change in the objective function in both total working time (Δ_{WT}) and traveled distance (Δ_{Dist}) for the three approaches. As expected, minimizing the distance instead of the working time leads to a reduction of the total traveled distance by 45%, 55%, and 32% for pALNS, MPA, and regret-3, respectively. More surprisingly, it also leads to a reduction of the total working time by 15%, 13%, and 8%. This can be explained by the cutoff policy that is contradictory with the minimization of the working, which mainly focuses on minimizing waiting times. In contrast, focusing on the minimization of the traveled distance always leads to a reduction of the travel time, which in turn reduces the duration of tours.

4.2.5 Conclusions

In this paper we introduced a new dynamic optimization problem, namely the Dynamic Technician Routing and Scheduling Problem (D-TRSP). This problem arises in numerous practical contexts such as public utilities, telecoms, and maintenance operations.

We propose two solution methods to tackle the D-TRSP. The first is a periodic reoptimization approach based on a parallel Adaptive Large Neighborhood Search (pALNS) that produces a new routing plan each time a new request appears. The second is a continuous reoptimization approach based on the Multiple Plan Approach (MPA) that continuously optimizes a pool of routing plans that are then use to take routing decisions.

Our preliminary computational results indicate that the pALNS based reoptimization approach dominates MPA and a simpler regret-3 heuristic, by yielding high quality results in limited time. In addition, its relative simplicity makes it a good candidate for practical applications. MPA results were disappointing, but this can be attributed to the decision process which does not takes into account the plan costs, and an overly conservative request acceptance criterion.

In addition, we have demonstrated that the minimization of the total working time, although perfectly sound in a static context, does not fit well in a dynamic environment. In particular, we have shown that minimizing the total distance ultimately leads to solutions that are better both in terms of total distance and duration.

Further work will focus on improving MPA to take better decisions and reject less requests. In addition, we are testing the proposed approach on real world data from an industrial partner. Finally, the uncertainty should be modeled to better anticipate the arrival of new requests and improve the quality of the decisions.

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Conclusions

Recent technological advances provide companies with the right tools to manage their fleet in real time. Nonetheless, these new technologies also introduce more complexity in fleet management tasks, unveiling the need for decision support systems dedicated to dynamic vehicle routing. In this context, the contributions of this Ph.D. thesis are threefold: first, we presented a comprehensive review of the literature on dynamic vehicle routing; second, we designed, implemented, and made publicly available flexible optimization frameworks that can cope with a wide variety of dynamic vehicle routing problems; and third, we defined a new vehicle routing problem faced by an industrial partner and introduced new sets of instances.

In the literature review, we introduced a new taxonomy dividing vehicle routing problems in four categories, depending on whether they are static or dynamic, and deterministic or dynamic. Further, we presented several real-world applications and surveyed the current state-of-the-art solution techniques for dynamic routing. We classify approaches for dynamic and deterministic routing problems into periodic and continuous reoptimization, depending on whether the optimization algorithm is run periodically or throughout the planning horizon. Similarly, we identified two categories of approaches for dynamic and stochastic problems: stochastic modeling approaches which model accurately the stochasticity of the problem, and sampling based approaches, that rely on the generation of scenarios to capture the uncertainty of the problem at hand. Finally, we outline promising research directions for dynamic routing. In particular, we stressed the need for both parallel algorithms that make use of modern computer architectures to reduce running times, and flexible approaches able to capture the uncertainty of dynamic routing problems. In this thesis, we developed parallel and flexible approaches for both dynamic and deterministic and dynamic and stochastic vehicle routing problems.

We tackled dynamic and deterministic routing problems with a parallel Adaptive Large Neighborhood Search (pALNS). The proposed pALNS inherits the flexibility of ALNS and is therefore able to cope with a wide variety of side constraints, while its parallel architecture improves running times by a factor of 3.5 on a regular desktop machine. The proposed algorithm relies on a promising solution pool for which we designed a diversity management scheme that allows the efficient exploration of the solution space. We demonstrated the efficiency of pALNS on the reference benchmark introduced by Solomon (1987) for the Vehicle Routing Problem with Time Windows (VRPTW), achieving gaps to best known and optimal solutions of 0.5% under 12s. Then, we proposed a simple yet effective reoptimization approach for the Dynamic-VRPTW that makes use of pALNS to reoptimize the routing whenever a new customer appears, and illustrated its performance on the Lackner (2004) benchmark instances, leading to improvements of up to 12% relative to state-of-the-art approaches.

We presented a bi-objective optimization problem that arises in the context of dynamic vehicle routing. It is generally assumed that routes can be designed in an online fashion, implying that drivers do not know their next destination until the very last moment. We proposed to consider the driver inconvenience resulting from the online routing of vehicles by accounting for the route consistency throughout the planning horizon. The approach we proposed, namely pBiALNS, is an extension of the pALNS framework that maintains the set of non-dominated solutions according to the minimization of the cost function, and the minimization of the edit distance relative to a reference solution which reflects the number of changes made to the routes. Our computational results indicate that pBiALNS is able to quickly produce a set of alternative solutions for the decision maker to choose from, and illustrate the tradeoff between the two objectives, revealing that under certain conditions it may be worth sacrificing quality of routing to gain route consistency.

We addressed dynamic and stochastic routing problems with a flexible event-driven optimization framework, namely `jMSA`, that efficiently captures uncertainty. It is based on a multiple scenario approach and it is easily embeddable in decision support systems. One of its key features is that it intrinsically handles the parallelization of time consuming tasks without any intervention from the user. Besides, the fact that it is event-driven makes it reactive and application-oriented. We illustrated the flexibility and accuracy of our approach by tackling the Dynamic Vehicle Routing Problem with Stochastic Demands (D-VRPSD), producing state-of-the-art results on the Novoa (2005) benchmark instances with average gaps of 3.3%, compared to the 4.8% reported in Novoa and Storer (2009) with a specifically tailored algorithm.

Finally, we defined a novel optimization problem inspired from a real-world application, namely the Technician Routing and Scheduling Problem (TRSP). The TRSP considers the routing of a fleet of technicians that serve a set of requests, considering skills, tools, spare parts, and time windows. The TRSP objectives include the minimization of the total working time and tour balancing. We introduced two sets of instances for the TRSP, one based on the Solomon (1987) benchmark, and the other derived from real-world data [5]. To tackle the static version of the problem, we designed a parallel matheuristic (pALNS+SC) that combines the pALNS algorithm with a set-covering post-optimization. Our computational experiments indicate that pALNS+SC is competitive with state-of-the-art approaches for the VRPTW: it solves instances from the Solomon (1987) benchmark at 0.23% of the optimal or best known solution in under 30s, and is able to find 44 out of 55 optimal solutions. In addition, it solves the TRSP instances with 100 customers in under 240s. We proposed two approaches for the dynamic TRSP, the first based on the pALNS algorithm, and the second on a Multiple Plan Approach (MPA) implemented within the `jMSA` framework.

An important contribution of this work is the release as open-source software of the components and algorithms developed to support the presented results [6]. It represents 55000 lines of codes and includes a generic library for the modeling of vehicle routing problems; an implementation of commonly used heuristics such as ALNS, VNS, GRASP, and the algorithms proposed in this thesis; and the `jMSA` framework. We hope that this initiative will foster the development of other open-source projects dedicated to vehicle routing, and that it will facilitate technology transfer to industry.

5. Benchmark instances available at `http://hdl.handle.net/1992/1145`
6. Source code available at `http://victorpillac.wordpress.com/libraries-for-the-vrp`

To summarize, the present thesis brings the following contributions with respect to the current state of the art: first, pALNS is the first parallel periodic-optimization algorithm able to cope with a wide variety of D-VRP variants; second, `jMSA` is the first event-oriented description of the Multiple Scenario Approach, and we hope it will constitute a reference point for application-driven optimization frameworks for dynamic routing; third, we introduced a dynamic bi-objective routing problem that takes into account driver inconvenience and attempt to maintain route consistency throughout the day; fourth, we defined the TRSP, a new optimization problem with numerous applications; and fifth, we published a new open-source library for static and dynamic vehicle routing.

From our experience, periodic reoptimization approaches such as pALNS represent a good alternative for practical applications as they are relatively simple to implement and provide satisfactory results. In that sense, it is worth noting that pALNS is currently used by the industrial partner that motivated the definition of the TRSP. However, they suffer from two limitations: first, they transfer the computational effort at decision time, which induces potentially long response times when the size of the problem grows; second, they do not keep information on good solutions from one run to the other.

Consequently, we consider that optimization algorithms for dynamic vehicle routing problems should focus on event-driven continuous-reoptimization approaches. Although their implementation may be more complex, they are the best fit to take full advantage of modern multi-core architecture as the optimization can be spread over multiple threads. Moreover, they allow for faster interactions with the decision maker when a decision is required. Whenever possible, stochastic information should be used to better anticipate the future. In our opinion, the generation of scenarios by sampling is a promising and practical direction. In contrast to stochastic modeling approaches, sampling-based optimization handles stochasticity decoupled from the optimization algorithms, thus they are able to cope with a wider scope of business constraints.

Future work should focus on the development of simple and flexible continuous reoptimization frameworks for dynamic and deterministic routing. Such framework could be based on pALNS and optimize a set of promising and diverse solutions throughout the planning horizon. It could then be extended to include stochastic knowledge by generating scenarios. An interesting direction of research would be to find smart ways to limit the computational complexity of the resulting optimization problem, which could be achieved by putting emphasis on capturing the uncertainty on the near future, or by avoiding very unlikely scenarios. In addition, new efficient ways to aggregate information from scenarios should be developed as this appear to be a key component in such approaches.

The dynamic management of a fleet of vehicles raises numerous theoretical and practical problems that require the development of efficient and accurate algorithms. Although it has received an increasing interest in the last decades, there is still room for innovation and we hope that the present thesis will bring significant insights for further research.

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Appendices

A

Efficient implementation

This appendix provides details on the implementation of the data structures used for the VRPTW and TRSP experimentations.

A.1 Tour representation

A tour π is represented by a doubly linked list. This choice is motivated by the fact that it is generally not required to have constant time access to a node at a given index, while the majority of operations on tours consist in removing and inserting nodes, or truncating and concatenating subtours. More specifically:

$$\pi = [k, \pi_0, \pi_l, \boldsymbol{\pi}^-, \boldsymbol{\pi}^+]$$

With:

k	the technician id
$\pi_0(\pi_l)$	the first (last) node visited by the tour
$\boldsymbol{\pi}^-(\boldsymbol{\pi}^+)$	the predecessor (successor) array

For convenience, we will use the notations $i-1 = \boldsymbol{\pi}^-{}_i$ ($i-1$ is the predecessor of i) and $i+1 = \boldsymbol{\pi}^+{}_i$ ($i+1$ is the successor of i). $\boldsymbol{\pi}^-(\boldsymbol{\pi}^+)$ are implemented with two integer arrays of dimension $|\mathcal{R}| + 2|\mathcal{K}|$, initialized with an arbitrary value (noted $\square$, for instance -1), and are then updated to represent the

tour. For instance, tour $\pi = (0, 3, 4, 2, 5)$ associated with technicien 3 will be represented as follows:

$$\pi = \begin{cases} k = 3 \\ \pi_0 = 0 \\ \pi_l = 5 \\ \boldsymbol{\pi}^- = [\square, \square, 4, 0, 3, 2] \\ \boldsymbol{\pi}^+ = [3, \square, 5, 4, 2, \square] \end{cases} \tag{A.1}$$

In addition, a tour contains the following information:

Main depot visited For each node in the tour we store a boolean flag that states whether the main depot was visited before or not.

Remaining number of spare parts For each node in the tour we store the number of spare parts for each type that are still available after its service. If the main depot is visited before then this value is considered as infinite.

Earliest arrival date The earliest time at which the technician can arrive to the node.

$$A_{\pi_0} = a_{\pi_0} \tag{A.2}$$
$$A_{i+1} = \max\{A_i, a_i\} + s_i + c_{i,i+1} \qquad \forall i \in \pi, i \neq \pi_0 \tag{A.3}$$

Earliest departure time Using the earliest arrival date, we can evaluate the earliest departure time D_i at node i:

$$D_{\pi_0} = a_{\pi_0} + s_{\pi_0} \tag{A.4}$$
$$D_i = \max\{A_i, a_i\} + s_i \qquad \forall i \in \pi, i \neq \pi_0 \tag{A.5}$$

Latest feasible arrival time The latest feasible arrival time defines the latest arrival time that ensures that the rest of the tour will remain feasible:

$$l_{\pi_l} = b_{\pi_l} \tag{A.6}$$
$$l_i = \min\{b_i, l_{i+1} - s_i - c_{i,i+1}\} \qquad \forall i \in \pi, i \neq \pi_l \tag{A.7}$$

Waiting time The time the technician has to wait between the earliest arrival date and the start of the time window.

$$W_i = \max\{0, a_i - A_i\} \qquad \forall i \in \pi \tag{A.8}$$

Cumulated waiting time The cumulated waiting time between a node and the end of the tour.

$$W_i^{\pi_l} = \sum_{j=i}^{\pi_l} W_j \qquad \forall i \in \pi \quad \text{(A.9)}$$

Forward time slack The forward time slack F_i, introduced by Savelsbergh (1992), measures how much the departure from node i can be delayed without causing the route to become infeasible. By extension, F_i^j (also noted $F_i^{i,\dots,j}$) is the forward time slack at node i relative to the path (or subtour) $(i,\dots,j)$ (Note that $F_i = F_i^{\pi_l}$ and $F_i^i = +\infty$):

$$F_i^j = \min_{i<q\leq j} \left\{ b_q - \left(D_i + \sum_{i\leq p<q} c_{p,p+1} + \sum_{i<p<q} s_p \right) \right\} \quad \text{(A.10)}$$

Note that b_q is the latest feasible arrival at node q, while $D_i + \sum_{i\leq p<q} c_{p,p+1} + \sum_{i<p<q} s_p$ is the earliest arrival time at q when departing at time D_i from i. Using the theorem presented by Savelsbergh (1992), we can derive the following recursive definition for F_i^j:

$$F_i^i = +\infty \quad \text{(A.11)}$$

$$F_i^{j+1} = \min\left\{ F_i^j, b_{j+1} - A_{j+1} + W_{i+1}^j \right\} \qquad \forall i,j \in \pi, i<j \quad \text{(A.12)}$$

Proof. Theorem 1 (Savelsbergh, 1992) states that

$$F_{i_1}^{(i_1,\dots,j_1,i_2,\dots,j_2)} = \min\left\{ F_{i_1}^{j_1}, F_{i_2}^{j_2} + \sum_{i_1<q\leq j_1} W_q + D_{i_2} - (D_{j_1} + c_{j_1 i_2}) \right\} \quad \text{(A.13)}$$

With respect to the original definition and notations, we replace the time windows end l_i by $b_i + s_i$ and the travel times c_{ij} with the sum of travel time and service time $c_{ij} + s_j$. This leads to the following:

$$F_{i_1}^{(i_1,\dots,j_1,i_2,\dots,j_2)} = \min\left\{ F_{i_1}^{j_1}, F_{i_2}^{j_2} + \sum_{i_1<q\leq j_1} W_q + D_{i_2} - (D_{j_1} + c_{j_1 i_2} + s_{i_2}) \right\} \quad \text{(A.14)}$$

Therefore:

$$\begin{aligned}
F_i^{j+1} &= F_{i_1}^{(i,\dots,j,j+1\dots,j+1)} \\
&= \min\left\{ F_i^j, F_{j+1}^{j+1} + \sum_{i<q\leq j} W_q + D_{j+1} - (D_j + c_{jj+1} + s_{j+1}) \right\} \\
&= \min\left\{ F_i^j, b_{j+1} + s_{j+1} - D_{j+1} + W_{i+1}^j + D_{j+1} - D_j - c_{jj+1} - s_{j+1} \right\} \\
&= \min\left\{ F_i^j, b_{j+1} - A_{j+1} + W_{i+1}^j \right\}
\end{aligned}$$

□

	0	1	2	3
a_i	0	5	25	30
b_i	50	10	35	40
A_i	-	5	15	35
W_i	-	0	10	0
D_i	0	10	30	35
F_i^3	5	15	5	$+\infty$

Table A.1: Illustration of the forward time slack concept for a 4-nodes tour.

Table A.1 illustrates the concept of forward time slack for a tour with 4 nodes, in which traveling and service time are equal to 5. The forward time slack at node 2 F_2 is equal to 5 as delaying the departure for more than 5 time units will cause the violation of the time window of node 3. F_1 is equal to 15: if we delay the departure of 15, W_2 becomes 0 and D_2 becomes 35, which will allow for the arrival at 3 at the end of its time window. Finally, F_0 is equal to 5 as delaying the departure any longer will cause the violation of the time window at 1.

Compact representation Figure A.1 illustrates the compact representation of a solution with a single array describing 3 different tours. The use of such representation is particularly useful when solutions have to be cloned often as it minimizes the memory footprint and the time required to copy the arrays.

id	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
pred	-	-	-	0	3	4	5	1	7	8	-	9	11	-	15	16	17	18	2	6	12	14
succ	3	7	18	4	5	6	19	8	9	11	-	12	20	-	21	14	15	16	17	-	-	-
A	*0*	*100*	*50*	*60*	*110*	*190*	*350*	*130*	*250*	*400*	-	*500*	*545*	-	*65*	*95*	*150*	*250*	*300*	*410*	*600*	*450*
W	*0*	*0*	*0*	*15*	*5*	*30*	*0*	*10*	*25*	*30*	-	*0*	*0*	-	*0*	*0*	*15*	*30*	*45*	*0*	*0*	*0*
F	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure A.1: Representation of 3 tours with a unique matrix. Tours are $(0, 2, 3, 4, 5, 6, 19)$ (green), $(1, 7, 8, 9, 11, 12, 20)$ (blue), and $(2, 18, 17, 16, 15, 14, 21)$ (red). Nodes 10 and 13 are not visited.

A.2 Cost of a solution

Depending on whether we are solving the VRPTW or the TRSP, the cost of a solution is either defined as the total traveled distance z_{dis}, or the total working time z_{wt}.

A.2.1 Total distance

The total distance z_{dis} measures the total distance traveled by all vehicles:

$$z_{\text{dis}}(\mathbf{\Pi}) = \sum_{\pi \in \mathbf{\Pi}} z_{\text{dis}}(\pi) = \sum_{\pi \in \mathbf{\Pi}} \sum_{i=2}^{|\pi|} c_{\pi_{i-1}, \pi_i} \tag{A.15}$$

A.2.2 Total working time

The total working time z_{wt} evaluates the total duration of all tours, including travel, service, and waiting times. It is defined as:

$$z_{\text{wt}}(\mathbf{\Pi}) = \sum_{\pi \in \mathbf{\Pi}} z_{\text{wt}}(\pi) \tag{A.16}$$

$$z_{\text{wt}}(\pi) = \left[A_{\pi_l} - (a_{\pi_0} + \min\{F_{\pi_0}, W_{\pi_0}^{\pi_l}\})\right] \tag{A.17}$$

Where $(a_{\pi_0} + \min\{F_{\pi_0}, W_{\pi_0}^{\pi_l}\})$ models the fact that the start of tour π may be delayed to reduce its total duration.

Algorithm A.1 presents the detail of the evaluation of z_{wt}. An important difference with z_{dis} is that we need to take into account waiting times and the possible delay at the beginning of the tour.

Algorithm A.1 Algorithm for the evaluation of z_{wt}

function EVALUATEZWT(π)
  $A \leftarrow a_{\pi_0}$
  $F \leftarrow b_{\pi_0} - a_{\pi_0}$
  $W \leftarrow 0$
  for $i = 2$ **to** $|\pi|$ **do**
    $A \leftarrow \max\{A, a_{\pi_i - 1}\} + s\pi_i + c_{\pi_{i-1}, \pi_i}$
    $W \leftarrow W + \max\{0, a_i - A\}$
    $F \leftarrow \min\{F, b_i - A_i + W\}$
  end for
  return $A - (a_{\pi_0} + \min\{F, W\})$
end function

A.3 Node insertion evaluation

The efficiency of the adaptive large neighborhood search algorithms presented in this thesis depends on the ability to evaluate the cost and feasibility of an insertion in constant time. This section details how this can be achieved.

A.3.1 Simple insertion

We consider the insertion or r between i and j in tour $\pi = (\pi_0, \ldots, i, j, \ldots, \pi_l)$, which would lead to tour $\pi' = (\pi_0, \ldots, i, r, j, \ldots, \pi_l)$.

A.3.1.1 Total distance insertion cost

The cost of a simple insertion in terms of total distance $\Delta z_{\text{dis}}(\pi, r, i, j)$ is straightforward:

$$\Delta z_{\text{dis}}(\pi, r, i, j) = c_{i,r} + c_{r,j} - c_{i,j} \tag{A.18}$$

A.3.1.2 Working time insertion cost

The evaluation of the cost of an insertion in terms of working time is more complicated as it will impact the arrival time at the successors and may require an earlier departure from the depot. Nonetheless, Savelsbergh (1992) points out that it can be achieved in constant time using precalculated data as the waiting and forward time slack.

Arrival time at the last node We start by evaluating the arrival time and the waiting time at the inserted request r:

$$A_r = D_i + c_{ir} \qquad W_r = \max\{0, a_r - A_r\} \tag{A.19}$$

Then, we evaluate the arrival time at the successor j:

$$A'_j = \max\{A_r, a_r\} + s_r + c_{rn} \tag{A.20}$$

Finally, we calculate the resulting arrival time at the last node:

$$A'_{\pi_l} = A_{\pi_l} + \max\left\{0, \Delta - W_j^{\pi_l}\right\} \tag{A.21}$$

where $\Delta = A'_j - A_j$ is the change in arrival time at j, and $W_j^{\pi_l}$ is the cumulated waiting time between j and π_l that will possibly absorb the delay.

Cumulated waiting time The new cumulated waiting time is:

$$W'^{\pi_l}_{\pi_0} = W^i_{\pi_0} + W_r + \max\{0, W_j^{\pi_l} - \Delta\} \tag{A.22}$$

Forward time slack The new forward time slack F'_{π_0} is:

$$F'_{\pi_0} = \min\left\{F^i_{\pi_0}, b_r - A_r + W^i_{\pi_0}, F_j^{(j,\dots,\pi_l)} + W^i_{\pi_0} + W_r + \max\{A_j, a_j\} - A'_j\right\} \tag{A.23}$$

Cost of the insertion Finally, the cost of the insertion is:

$$\begin{aligned}
\Delta z_{\text{wt}}(\pi, r, i, j) &= z_{\text{wt}}(\pi') - z_{\text{wt}}(\pi) \\
&= (A'_{\pi_l} - (a_k + \min\{F'_{\pi_0}, W'^{\pi_l}_{\pi_0}\})) - (A_{\pi_l} - (a_k + \min\{F_{\pi_0}, W^{\pi_l}_{\pi_0}\})) \\
&= \max\left\{0, \Delta - W_j^{\pi_l}\right\} - \min\{F'_{\pi_0}, W'^{\pi_l}_{\pi_0}\} + \min\{F_{\pi_0}, W^{\pi_l}_{\pi_0}\}
\end{aligned} \tag{A.24}$$

A.3.1.3 Feasibility

If the inserted node is a request, the technician must have the required skills, tools, and spare parts to service it. In addition, the insertion must not violate time window constraints. This can be checked

in constant time using the values calculated in §A.3.1.2 by verifying that:

$$\begin{cases} A_r \leq b_r \\ A'_j \leq l_j \end{cases} \tag{A.25}$$

A.3.2 Simultaneous insertion

We consider the insertion of r between m and n and q between i and j in tour $\pi = (\pi_0, \ldots, m, n, \ldots, i, j, \ldots, \pi_l)$, which would lead to tour $\pi' = (\pi_0, \ldots, m, r, n, \ldots, i, q, j, \ldots, \pi_l)$. This case is useful when considering the simultaneous insertion of a request and a visit to the main depot.

A.3.2.1 Total distance insertion cost

Similarly to the simple insertion case, the cost of the insertion is:

$$\Delta z_{\text{wt}}(\pi, r, m, n, q, i, j) = c_{m,r} + c_{r,n} - c_{m,n} + c_{i,q} + c_{q,j} - c_{i,j} \tag{A.26}$$

In the case in which q is inserted immediately after r ($n = q$ and $i = r$), the cost of the insertion is:

$$\Delta z_{\text{wt}}(\pi, r, m, n, q, i, j) = c_{m,r} + c_{r,q} + c_{q,j} - c_{m,j} \tag{A.27}$$

A.3.2.2 Working time insertion cost

Arrival time at the last node We first evaluate the arrival and waiting time at the inserted node r:

$$A_r = D_m + c_{mr} \qquad W_r = \max\{0, a_r - A_r\} \tag{A.28}$$

Then we evaluate the new arrival time at n:

$$A'_n = \max\{A_r, a_r\} + s_r + c_{rn} \tag{A.29}$$

Next we evaluate the new earliest departure time at i:

$$D'_i = D_i + \max\{0, \Delta_n - W_n^i\} \tag{A.30}$$

Where $\Delta_n = A'_n - A_n$ is the change in the arrival time at n. We can then evaluate the arrival time at q:

$$A_q = D'_i + c_{iq} \qquad W_q = \max\{0, a_q - A_q\} \tag{A.31}$$

And the new arrival time at j

$$A'_j = \max\{A_q, a_q\} + s_q + c_{qj} \tag{A.32}$$

And the new arrival time at the last node:

$$A'_{\pi_l} = A_{\pi_l} + \max\{0, \Delta_j - W_j^{\pi_l}\} \tag{A.33}$$

Where $\Delta_j = A'_j - A_j$.

Total waiting time Similarly to the analysis made for the single insertion case, the new total waiting time can be computed as follows:

$$W'^{\pi_l}_{\pi_0} = W^m_{\pi_0} + W_r + \max\{0, W^i_n - \Delta_n\} + W_q + \max\{0, W_j^{\pi_l} - \Delta_j\} \tag{A.34}$$

Note that $\max\{0, W^i_n - \Delta_n\}$ is the waiting time on the path $(n, \dots, i)$, which absorbs the change in arrival time at n, and $\max\{0, W_j^{\pi_l} - \Delta_j\}$ is the waiting time on the path $(j, \dots, \pi_l)$ which will absorb the change in arrival time at j.

Forward time slack We consider five paths: $(\pi_0, \dots, m)$, (r), $(n, \dots, i)$, (q), and $(j, \dots, \pi_l)$.

From Equation (A.23):

$$F^{(\pi_0,\dots,m,r,n,\dots,i)}_{\pi_0} = \min\left\{F^m_{\pi_0}, b_r - A_r + W^m_{\pi_0}, F^{(n,\dots,i)}_n + W^m_{\pi_0} + W_r + \max\{A_n, a_n\} - A'_n\right\} \tag{A.35}$$

And for the whole new path:

$$F'_{\pi_0} = \min\begin{cases} F^i_{\pi_0}, \\ b_r - A_r + W^m_{\pi_0}, \\ F^{(n,\dots,i)}_n + W^m_{\pi_0} + W_r + \max\{A_n, a_n\} - A'_n, \\ b_q - A_q + W'^i_{\pi_0}, \\ F^{(j,\dots,\pi_l)}_j + W'^i_{\pi_0} + W_q + \max\{A_j, a_j\} - A'_j \end{cases} \tag{A.36}$$

Where $W'^i_{\pi_0}$ is the new waiting time between π_0 and i:

$$W'^i_{\pi_0} = W^m_{\pi_0} + W_r + \max\{0, W^i_n - \Delta_n\} \tag{A.37}$$

Cost of the insertion The cost of the insertion is equal to

$$\begin{aligned} \Delta z_{\text{wt}}(\pi, r, m, n, q, i, j) &= z_{\text{wt}}(\pi') - z_{\text{wt}}(\pi) \\ &= (A'_{\pi_l} - (a_k + \min\{F'_{\pi_0}, W'^{\pi_l}_{\pi_0}\})) - (A_{\pi_l} - (a_k + \min\{F_{\pi_0}, W^{\pi_l}_{\pi_0}\})) \\ &= \max\left\{0, \Delta_j - W_j^{\pi_l}\right\} - \min\{F'_{\pi_0}, W'^{\pi_l}_{\pi_0}\} + \min\{F_{\pi_0}, W^{\pi_l}_{\pi_0}\} \end{aligned} \tag{A.38}$$

Special case A special case of the simultaneous insertion is when the second node is the successor of the first ($i = r$ and $n = q$)). The resulting tour would then be $(\pi_0, \dots, m, r, q, j, \dots, \pi_l)$, and this case must be treated separately. We chose to *merge* r and q into a single node R and to adapt the formulas from the single insertion case. In particular the waiting time at R is $W_R = W_r + W_q$, and the second term of Equation (A.23) becomes $\min\{b_r - A_r + W^n_{\pi_0}, b_q - A_q + W^n_{\pi_0} + W_r\}$.

A.3.2.3 Feasibility

The feasibility of a simultaneous insertion is similar to the single insertion case, in particular, we ensure that time windows are not violated by making sure that the solution verifies:

$$\begin{cases} A_r \leq b_r \\ A'_n \leq l_n \\ A_q \leq b_q \\ A'_j \leq l_j \end{cases} \tag{A.39}$$

A.4 Preprocessing

The algorithms can be speed up by performing some preprocessing on the data. This section details the main procedures used.

A.4.1 Infeasible arcs

During the preprocessing we remove from the graph $\mathcal{A}$ the edges (i, j) such that j cannot be visited after i without violating time window constraints. This is achieved by ensuring that:

$$a_i + s_i + c_{ij} \leq b_j \qquad \forall (i,j) \in \mathcal{A} \tag{A.40}$$

A.4.2 Technician-request compatibility

This procedure checks for each technician k and request r if the technician has the required skills to serve the request. In addition, it also checks if it can serve the request without violating time windows, in other words if $a_k + c_{kr} \leq a_r$ and $a_r + c_{rk} \leq b_k$.

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B

A library for the modeling of vehicle routing problems

`VroomModeling` is a flexible library that has been developed to model a wide range of instances of vehicle routing problems. The general idea is to clearly separate the problem information (nodes, locations, fleet, requests) from the routing logic (cost calculation, route optimization); but also to ensure a high flexibility in the model. This is achieved with the definition of node, request and vehicle objects as a combination of base properties (e.g. a node necessarily has a geographic location) and attributes that are mapped to attribute keys. For instance in this representation a node can also have a time window or a compatibility constraint with vehicles (some vehicles may not be able to access the node). An important design characteristic is the separation between the *node*, which represents a physical location, for instance a client, and a *request* which is associated with one (pickup/delivery) or two nodes (pickup and delivery), and represent a request for service.

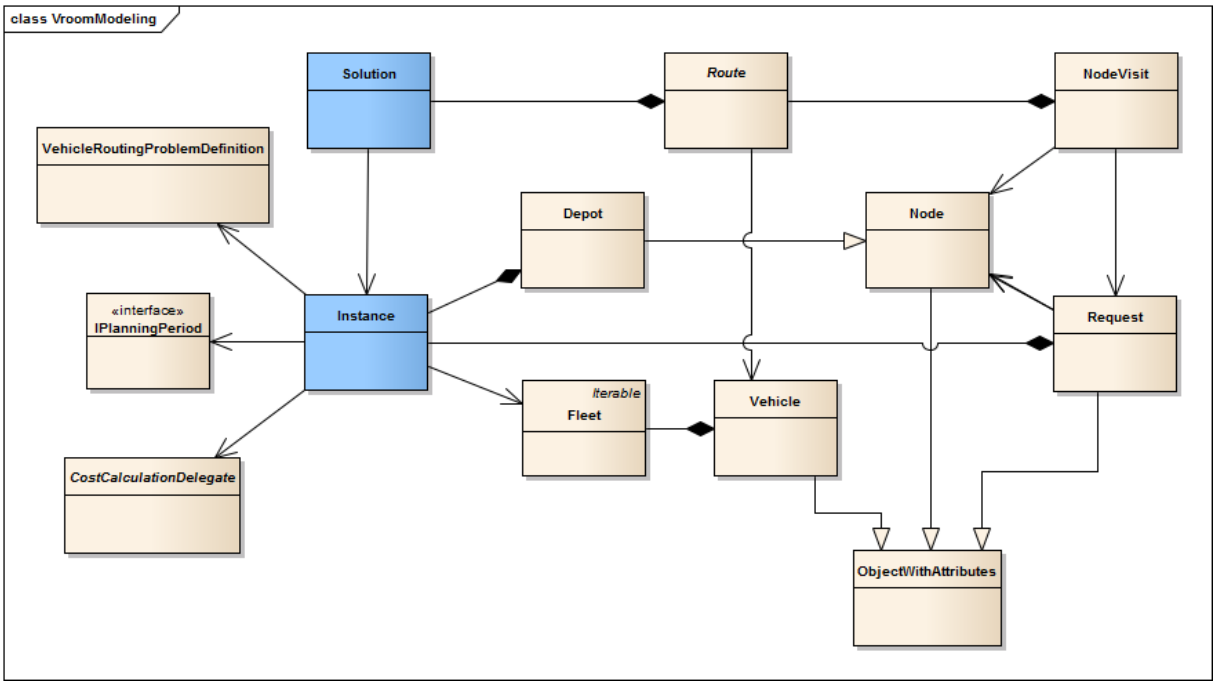

Figure B.1: Overview of the `VroomModeling` library.

Figure B.1 presents an overview of the `VroomModeling` library. The root object is the instance (`Instance`), it contains a reference to a problem definition (`VehicleRoutingProblemDefinition`), a planning period (`PlanningPeriod`), a fleet (`Fleet`) composed by one or more vehicles (`Vehicle`), and a list of requests (`Request`). It is important to note that the calculation of distances and costs is delegated to an instance of `CostCalculatorDelegate`, separating this logic from the representation of routes. On the other hand, a solution (`Solution`) contains a reference to an instance, and a set of routes (`Route`). A route is associated with a vehicle, and contains a sequence of node visits (`NodeVisit`) that model the visit of a node associated with a given request. It is worth noting that the three classes `Vehicle`, `Node`, and `Request`, inherits from `ObjectWithAttributes` which allows for the definition of any number of additional attributes such as time windows or compatibility constraints.

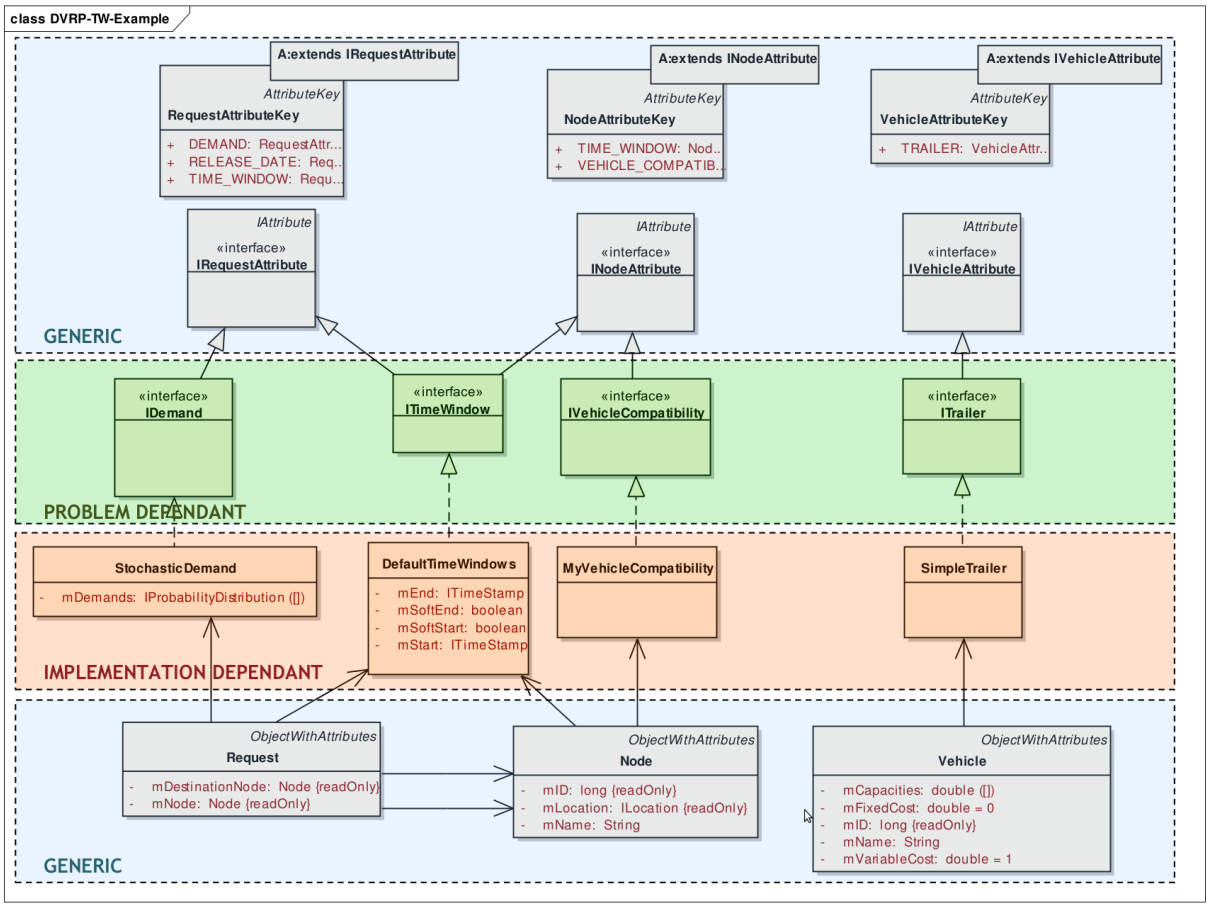

Figure B.2: Illustration of a possible use of the `VroomModeling` library.

Figure B.2 illustrates how a complex VRP problem could be modeled using the `VroomModeling` library. In this example, vehicles have trailers, nodes have a time window and compatibility constraints with vehicles, and requests have a time window and a stochastic demand.

C

A library of heuristics for vehicle routing problems

`VroomHeuristics` is a library of common heuristics and metaheuristics. Although they were implemented to tackle vehicle routing problems, the design of the algorithms in this library is flexible enough to solve other optimization problems.

Figure C.1 presents an overview of the library. There are two top-level interfaces that define two types of heuristics: `IInitialization` and `ILocalSearch`. The first defines algorithms that will design a solution (`ISolution`) from scratch, while the second take an initial solution as input and attempt to improve it. We implemented two initialization procedure: a Clarke and Wright (CW) savings algorithm (`ClarkeAndWrightHeuristic`), and a Versatile Local Search (VLS) algorithm that combines GRASP, ELS, and ILS (`VersatileLocalSearch`). The main local search component is the `LocalSearchBase` class, which contains a reference to both a stopping and acceptance criterion (`IStoppingCriterion` and `IAcceptanceCriterion`). The library contains two local search algorithms: Variable Neighborhood Search (VNS - `VariableNeighborhoodSearch`), and Adaptive Large Neighborhood Search (ALNS - `AdaptiveLargeNeighborhoodSearch`). The library also provide a generic definition of a neighborhood (`INeighborhood`) that can either be used to find a move (`IMove`) that will lead to a neighbor of a solution, or as a local search procedure to find the local optima starting with a given solution. In addition, `VroomHeuristics` contains a generic definition of a component handler (`IComponentHandler`) that can be used to handle components such as neighborhoods in VNS or destroy/repair operators in ALNS. Finally, constraints are defined and handled separately with the interface `IConstraint` and the class `ConstraintHandler`. All constraint implementations should be able to check the feasibility of both a solution and a move relative to a solution.

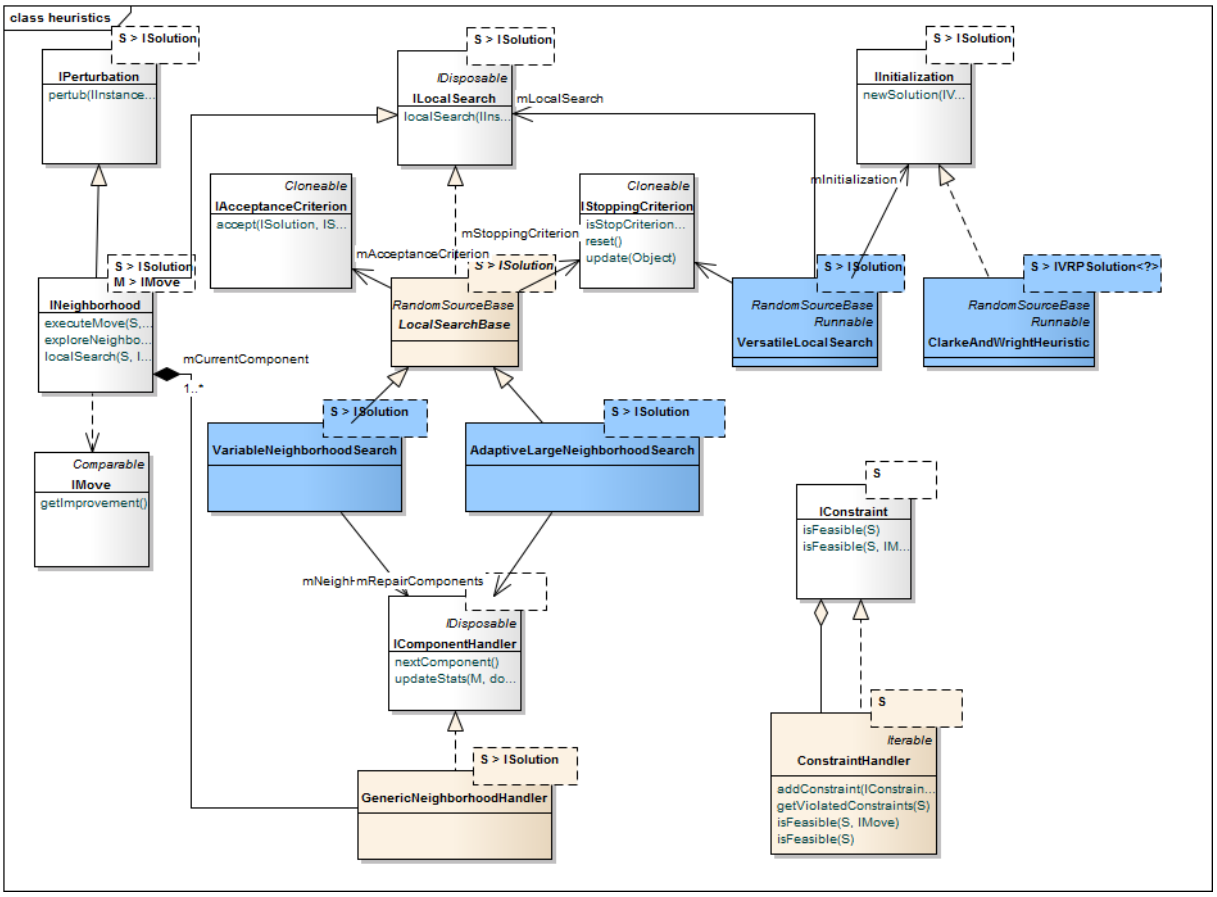

Figure C.1: Design overview of the `VroomHeuristics` framework.

C.1 Clarke and Wright

The savings algorithm, or Clarke and Wright heuristic (CW) (Clarke and Wright, 1964), is a constructive heuristic for vehicle routing problems. It starts by creating one route for each customer, and then iteratively merges routes using the notion of savings.

Algorithm C.1 presents an outline of the CW heuristic. The algorithm starts by initializing a list of candidate mergings, which savings are calculated line 6 and correspond to the decrease in cost resulting from the removal of arcs $(0, i)$ and $(0, j)$ while adding arc (i, j). Then the algorithm considers all possible mergings between routes in order of decreasing savings. For each candidate merging (i, j), the `mergingFeasible` function (line 11) checks if i) both nodes i and j are either first or last in their routes π_i and π_j; ii) the route that would result from the merging satisfy all constraints. The latter is achieved within the `VroomHeuristics` framework using a `ConstraintHandler` and modeling the merging as a move (`IMove`). If the merging is feasible, then it is executed and route π_j is appended to π_i (line 12). The algorithm terminates when there is no additional feasible merging.

Figure C.2 presents an overview of the proposed implementation of the CW algorithm, namely `jCW`. The main component is the `ClarkeAndWrightHeuristic` that uses a generic definition of a saving algorithm (`ISavingAlgorithm`) and relies on global parameters for its setup (`CWParameters`). The

Algorithm C.1 Outline of the Clarke and Wright savings heuristic

Input: $\mathcal{V}$ a set of vertices, $\mathcal{A}$ a set of arcs, 0 the central depot
Output: $\mathbf{\Pi}$ a feasible solution

1: **for all** $i \in \mathcal{V}$ **do** ▷ Initialize routes
2: $\pi_i \leftarrow (0, i, 0)$ ▷ Associate a singleton route with node i
3: **end for**
4: $M \leftarrow []$ ▷ The list of candidate mergings
5: **for all** $(i, j) \in \mathcal{A}$ **do**
6: $s_{ij} \leftarrow c_{0i} + c_{0j} - c_{ij}$ ▷ The saving for arc (i, j)
7: $M \leftarrow M + (i, j, s_{ij})$ ▷ Append to the list of mergings
8: **end for**
9: $S \leftarrow \text{sort}(M)$ ▷ Sort the merging list in decreasing savings value
10: **for all** $(i, j, s_{ij}) \in M$ **do**
11: **if** `mergingFeasible` $(\pi_i, \pi_j, (i, j))$ **then**
12: $\pi_i \leftarrow$ `merge` $(\pi_i, \pi_j, (i, j))$ ▷ Merge the two routes with arc (i, j)
13: $\pi_j \leftarrow \pi_i$
14: **end if**
15: **end for**
16: $\mathbf{\Pi} \leftarrow \{\pi_i\}_{i \in \mathcal{V}}$ ▷ The solution contains all the final routes
17: **return** $\mathbf{\Pi}$

saving algorithms use instances of `IJCWArc` to represent candidate savings and instances of `RouteMergingMove` to model the corresponding merging of two routes. The framework provides two concrete savings algorithm implementations: `BasicSavingHeuristic` that corresponds to Algorithm C.1, and `RandomizedSavingsHeuristic` which introduces some randomization while sorting the merging list.

The Clarke and Wright savings heuristic was used to generate scenarios in the multiple scenario approach presented in Chapter 3.

C.2 Adaptive Variable Neighborhood search

In this section we propose an extension of Variable Neighborhood Search *(VNS)* (Mladenovic and Hansen, 1997), namely Adaptive Variable Neighborhood Search (AVNS), that was used as optimization component of the multiple plan approach for the DVRPSD presented in Chapter 3. The original VNS iteratively improves a solution by exploring sequentially neighborhoods of increasing complexity or size. AVNS in contrast does not impose any order on the exploration of neighborhoods, leading to a higher level of modularity.

Algorithm C.2 presents an overview of the AVNS procedure. The algorithm starts with an initial solution $\mathbf{\Pi}$ and generates a neighbor $\mathbf{\Pi}'$ from the current neighborhood (`shake` line 6), which is then improved by a local search procedure (line 7). If the new solution is accepted (line 8), it replaces the current solution and a new iteration is performed using the whole set of neighborhoods (line 10); otherwise, the neighborhood is marked as explored (line 12) and a new iteration is done with the unchanged current solution. Iterations are performed until either all neighborhoods have been explored or a *stop criterion* is met (usually a maximum time or number of iterations). The key difference

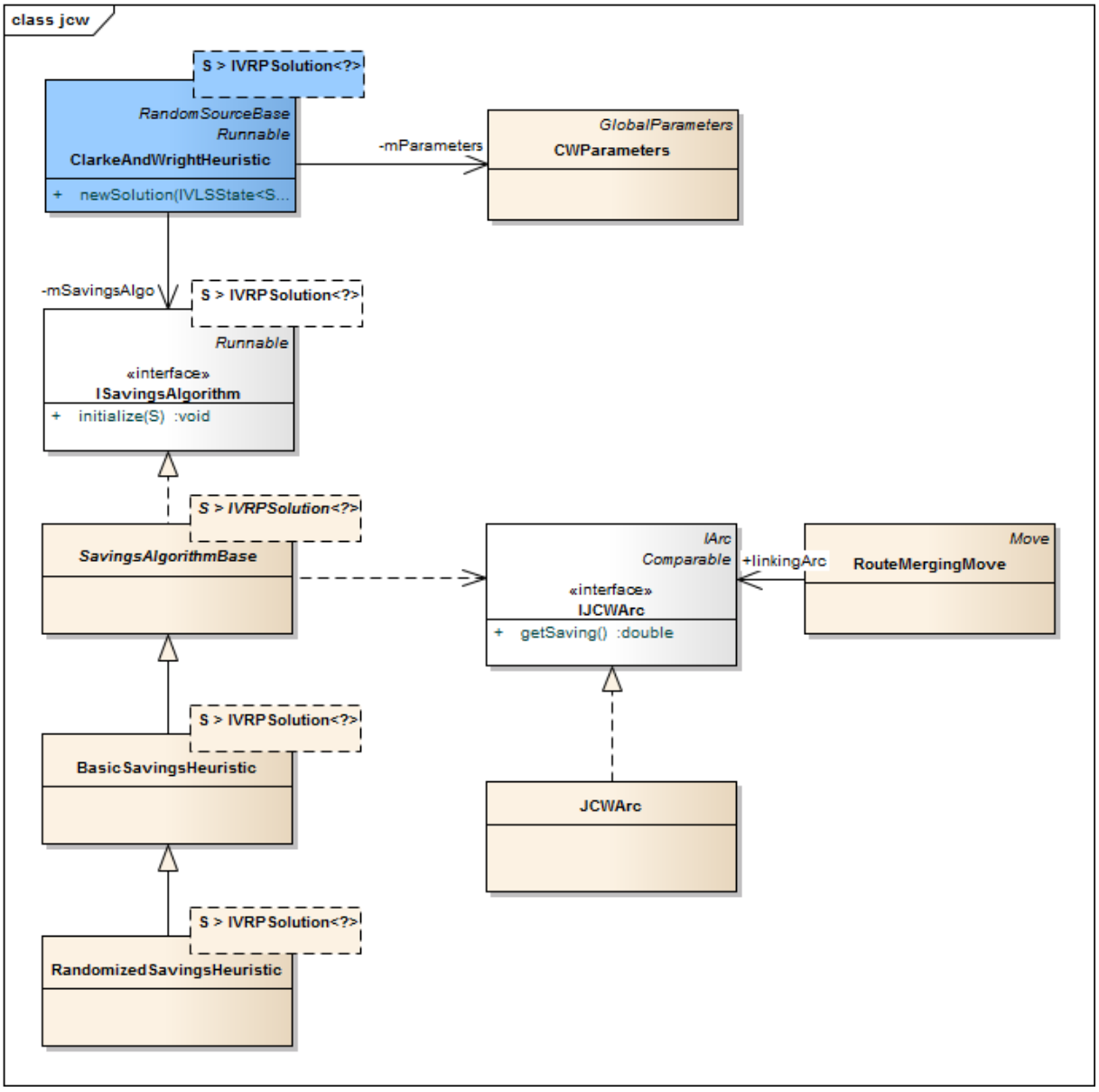

Figure C.2: Design overview of the Clarke and Wright heuristic framework.

with respect to the original VNS algorithm is the call to the `selectNeighborhood` function at line 5. It allows for non-sequential exploration of neighborhoods, with the goal of exploring the best neighborhoods first.

Algorithm C.2 The Adaptive Variable Neighborhood Search algorithm.

Input: $\mathbf{\Pi}$ a feasible solution, z an evaluation function and $\mathcal{N} = \{N_1, .., N_K\}$ a set of neighborhood structures
Output: $\mathbf{\Pi}^*$ the best solution found

1: **function** VNS($\mathbf{\Pi}$)
2: $\quad\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}$
3: $\quad\mathcal{N}_c \leftarrow \mathcal{N}$ ▷ Initial neighborhood set
4: $\quad$**while** $\mathcal{N}_c \neq \emptyset$ **and** stop condition not met **do**
5: $\quad\quad N \leftarrow selectNeighborhood(\mathcal{N}_c)$ ▷ Select neighborhood
6: $\quad\quad\mathbf{\Pi}' \leftarrow shake(N, \mathbf{\Pi})$ ▷ Generate a neighbor from neighborhood N
7: $\quad\quad\mathbf{\Pi}' \leftarrow ls(\mathbf{\Pi}')$ ▷ Local search to improve $\mathbf{\Pi}'$
8: $\quad\quad$**if** $accept(\mathbf{\Pi}', \mathbf{\Pi})$ **then** ▷ $\mathbf{\Pi}'$ is accepted as current solution
9: $\quad\quad\quad\mathbf{\Pi} \leftarrow \mathbf{\Pi}'$ ▷ Update current solution
10: $\quad\quad\quad\mathcal{N}_c \leftarrow \mathcal{N}$ ▷ Reset the neighborhood set
11: $\quad\quad$**else**
12: $\quad\quad\quad\mathcal{N}_c \leftarrow \mathcal{N}_c \setminus \{N\}$ ▷ Remove the explored neighborhood
13: $\quad\quad$**end if**
14: $\quad\quad$**if** $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then** ▷ An improvement has been found
15: $\quad\quad\quad\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ Update best solution
16: $\quad\quad$**end if**
17: $\quad$**end while**
18: $\quad$**return** $\mathbf{\Pi}^*$
19: **end function**

C.2.1 Implementation

Figure C.3 presents a UML diagram of the VNS implementation. The key classes are the following: `VariableNeighborhoodSearch` is the class containing the implementation of Algorithm C.2, where the *shake*, *local search* and *neighborhood selection* are delegated to instances of other classes (template method pattern); `ILocalSearch` is the generic definition of local search, an instance of this class is responsible for the local search in the VNS algorithm (`ls` line 7); `INeighborhood` is a generic definition of a neighborhood structure. `IComponentHandler` is an interface for classes responsible of the neighborhood selection strategy.

It is worth noting that the following variants (Hansen et al., 2003) can be easily implemented in this framework:

	Shake	**Local search**
VND	Best neighbor	None
RVNS	Random neighbor	None
BVNS	Random neighbor	Any
GVNS	Random neighbor	VND

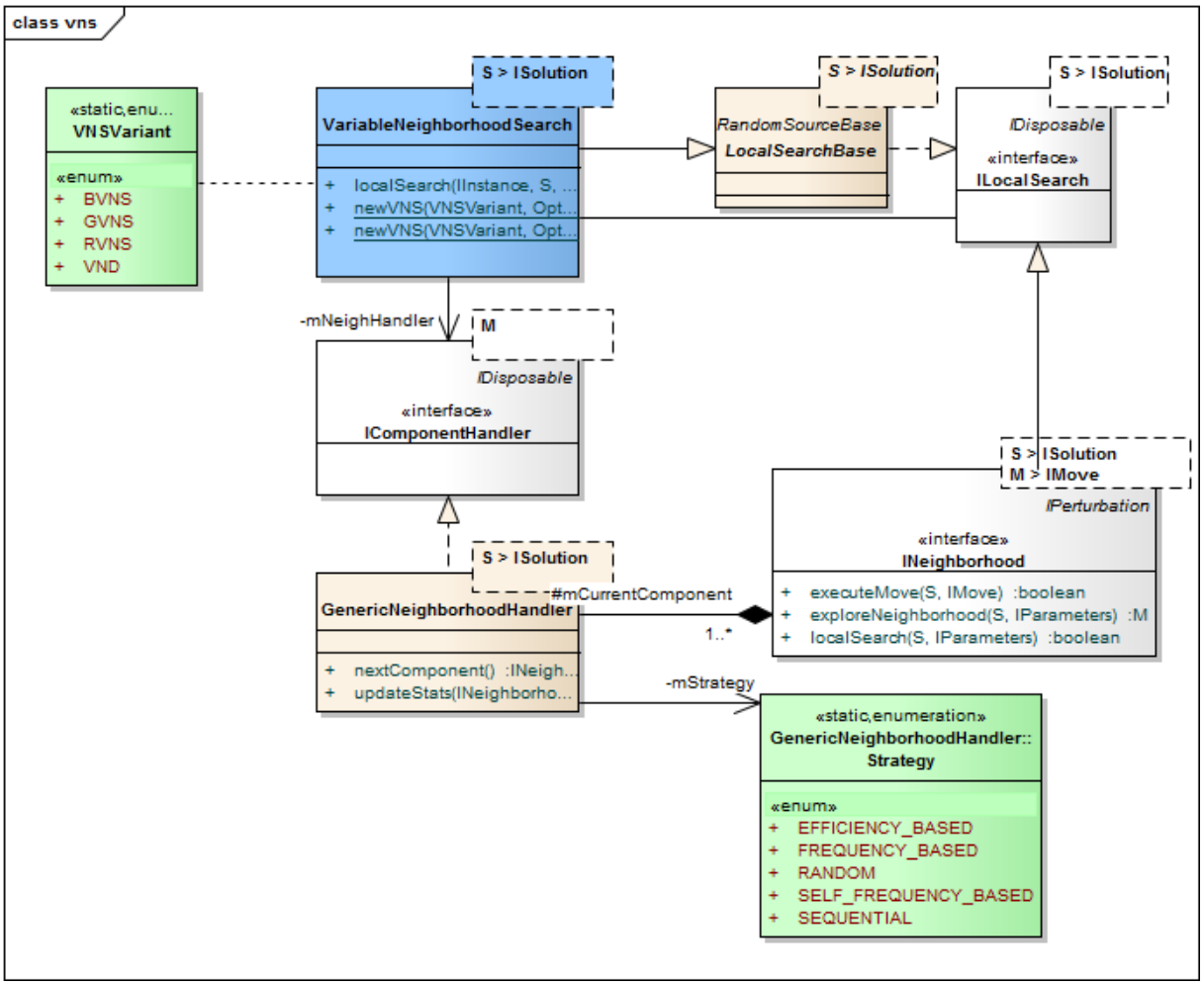

Figure C.3: Design overview of the VNS implementation.

C.2.2 Neighborhoods

We implemented four neighborhoods for the VRP, all considering intra and inter-route moves: swap, 2-opt, Or-opt, and string-exchange. The swap neighborhood swaps two nodes from possibly different routes; 2-opt removes two non-adjacent edges and reconnect the segments; Or-opt relocates a segment of 1 to k nodes, possibly by reversing its order, in the best possible position (in our implementation $k = 3$); and finally string-exchange exchanges two segments of length 1 to k, possibly by reversing their orders (we set $k = 4$). We refer the interested reader to the paper by Irnich and Villeneuve (2006) for a more detailed description of these neighborhoods.

We provide a general purpose implementation of `INeighborhoodHandler` in the class `Generic-NeighborhoodHandler` which defines 4 strategies: sequential *(SEQ)*, frequency-based *(FRE)*, efficiency based *(EFF)* and random *(RAN)*. The simplest selection strategy (FRE) explores neighborhoods sequentially, as in the original VNS algorithm. FRE stores the success count for each neighborhood, i.e. the number of times that its exploration yields an improvement in the objective function. The selection of the next neighborhood is then performed using a roulette wheel based on the success count. EFF uses a efficiency metric equal to the average ratio $\frac{\text{improvement}}{\text{time}}$ to select the next neighborhood with a roulette wheel. Finally, RAB is used as a comparison basis and select any neighborhood with equal probability.

C.2.3 Computational experiments

The AVNS was designed to tackle the Vehicle Routing Problem with Stochastic Demands (VRPSD) within the `jMSA` framework. Therefore, we tested it on the Novoa (2005) testbed, later used in Novoa et al. (2006) and Novoa and Storer (2009). The customer demands are given as probability distributions, however, the routing problems solved in the MSA procedure are deterministic, thus we used the expected value of the demands. The benchmark contains instances of 5, 8, 20, 40 and 60 customers, randomly distributed on a 1 per 1 square, the depot being at the origin (0,0). There are 10 instances of each size

We tested the four strategies presented above, in two variants: for the sequential strategy we used an increasing complexity ordering of neighborhoods (swap, 2-opt, Or-opt, string-exchange), denoted *SEQ*, as well as a reversed order, denoted *SEQ-Rev*; for the frequency (respectively efficiency) we did a set of run in which the neighborhood handler is reset between each run, denoted *FRE-R* (*EFF-R*), and a second where the performance information (success count or efficiency) is kept between runs, noted *FRE-NR* (*EFF-NR*).

Each strategy was run 10 times on each instance, each run starting with the initial solutions obtained by running a randomized savings based heuristic. We used a Variable Neighborhood Descent variant in order to have a better understanding of the neighborhood selection impact on performance.

Table C.1 presents the average gaps to the optimal solutions for the different strategies. It can be noted that there is apparently no difference between strategies at this point, although *SEQ-Rev* appears to perform slightly better.

Table C.2 reports average CPU running times. They reveal a strong dominance of *EFF-NR* over all instances sizes. *SEQ* performs quite poorly on small instances but it is competitive on larger instances,

while the tendency reverses for *SEQ-Rev*. This last observation can be explained by the fact that this last strategy will explore first the more complex neighborhoods (string-exchange and Or-opt), which are of complexity $O(k^2n^2)$ and $O(kn^2)$, thus requiring a quadratically increasing time to explore. As expected, we can note that preserving the performance information from one run to another (R vs. NR) slightly improves the performance.

Finally, Table C.3 shows that the *EFF-NR* strategy also have a lower CPU time standard deviation, meaning that it is the most stable in terms of running times. A similar analysis has been done for the gap standard deviation but no tendency can be drawn.

C.3 Versatile Local Search

The Versatile Local Search package (VLS) contains an implementation of the Greedy Randomized Adaptive Search Procedure (GRASP) with multi-start evolutionary local search proposed by Prins (2009) and Villegas et al. (2010). This approach is an hybrid between GRASP, Iterated Local Search (ILS), and Evolutionary Local Search (ELS), and was initially designed as optimization component for the `jMSA` framework.

Algorithm C.3 presents the outline of the approach which comprises three nested loops. The GRASP loop (lines 1–20) builds a solution with a randomized constructive heuristic (line 2) and then improves the solution with a local search (line 3). The resulting solution is passed to the ILS loop (lines 4–16), and the ELS loop (lines 6–12). The ELS randomly modifies the current solution (line 5) and then apply a local search to it (line 6). The best solution from the ELS iteration is then taken as current solution for the next ILS iteration.

Figure C.4 illustrates the implementation of the VLS algorithm withing the `VroomHeuristics` framework. The central component is the `VersatileLocalSearch` class which is configured via `VLSGlobalParameters` and contains a reference to an initialization (`IInitialization`), local search (`ILocalSearch`), and perturbation (`IVLSPerturbation`).

C.4 Adaptive Large Neighborhood Search

Figure C.5 presents an overview of the implementation of the Adaptive Large Neighborhood Search (ALNS) and parallel ALNS (pALNS) algorithms described in Chapter 2. The main component is the `AdaptiveLargeNeighborhoodSearch` class, which is configured via (`ALNSGlobalParameters`). It relies on two component handlers (`ALNSComponentHandler`) that are responsible for the evaluation and selection of the destroy and repair operators (`IDestroy` and `IRepair`). `ParallelALNS` provides the parallel implementation and uses an abstract definition of a solution pool (`IPALNSSolutionPool`) to manage the pool of solutions.

The pALNS and ALNS algorithms were used in Chapter 2 and 4 to tackle both static and dynamic routing problems.

Size	SEQ	SEQ-Rev	FRE-R	FRE-NR	EFF-R	EFF-NR	RAN-R
5	4.60	4.60	4.60	4.60	4.60	4.60	4.60
8	4.76	4.75	4.75	4.75	4.76	4.76	4.75
20	6.48	6.45	6.45	6.48	6.45	6.46	6.46
40	7.33	7.28	7.31	7.28	7.28	7.33	7.30
60	8.15	8.12	8.15	8.14	8.14	8.13	8.14

Table C.1: Average gap to the optimal solution (in %).

Algorithm C.3 The Versatile Local Search algorithm.

Input: I an instance, `initialization` a randomized constructive heuristics, `localSearch` a local search procedure, `perturbation` a randomized perturbation procedure., z an evaluation function.
Output: $\mathbf{\Pi}^*$ the best solution found

for $i = 1$ **to** n_s **do** ▷ GRASP loop
  $\mathbf{\Pi} \leftarrow$ `initialization`(I) ▷ Build a new solution
  $\mathbf{\Pi} \leftarrow$ `localSearch`(S) ▷ Apply a local search
  for $j = 1$ **to** n_i **do** ▷ ILS loop
    $\mathbf{\Pi}' \leftarrow \mathbf{\Pi}$ ▷ Starting solution for the ELS
    for $k = 1$ **to** n_c **do** ▷ ELS loop
      $\mathbf{\Pi}'' \leftarrow$ `perturbation`$(\mathbf{\Pi}')$ ▷ Randomly perturb the solution
      $\mathbf{\Pi}'' \leftarrow$ `localSearch`$(\mathbf{\Pi}'')$ ▷ Apply a local search
      if $z(\mathbf{\Pi}'') < z(\mathbf{\Pi}')$ **then**
        $\mathbf{\Pi} \leftarrow \mathbf{\Pi}''$ ▷ Store the best solution produced by ELS
      end if
    end for
    if $z(\mathbf{\Pi}') < z(\mathbf{\Pi})$ **then**
      $\mathbf{\Pi} \leftarrow \mathbf{\Pi}'$ ▷ Update the current solution with the best ELS solution
    end if
  end for
  if $z(\mathbf{\Pi}) < z(\mathbf{\Pi}^*)$ **then**
    $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}$ ▷ Update the overall best solution
  end if
end for
return $\mathbf{\Pi}^*$

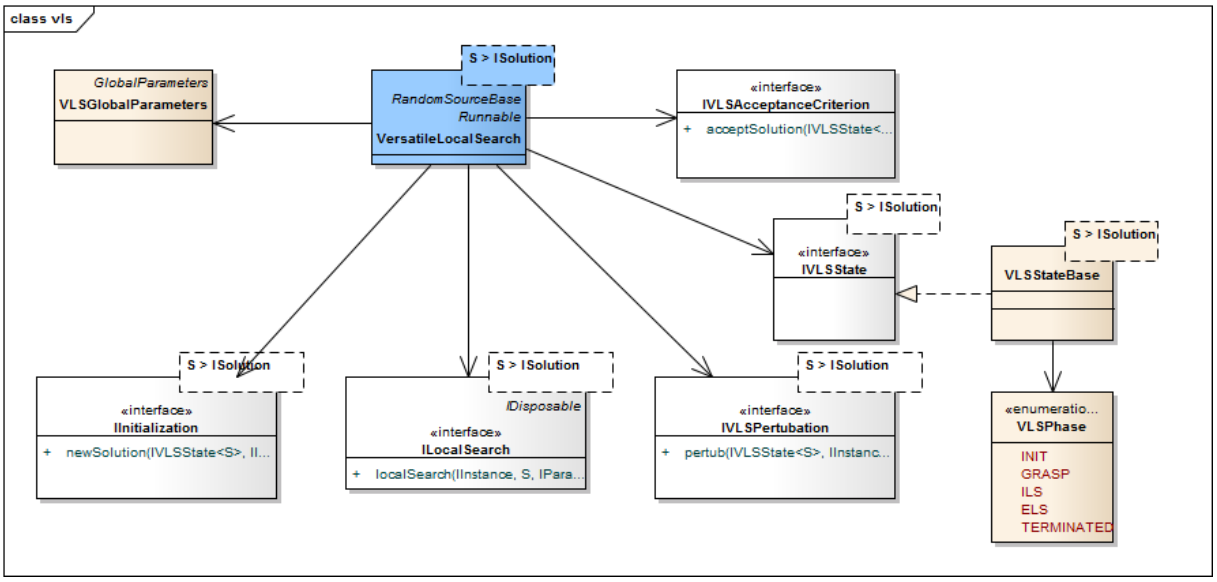

Figure C.4: Design overview of the Versatile Locale Search framework.

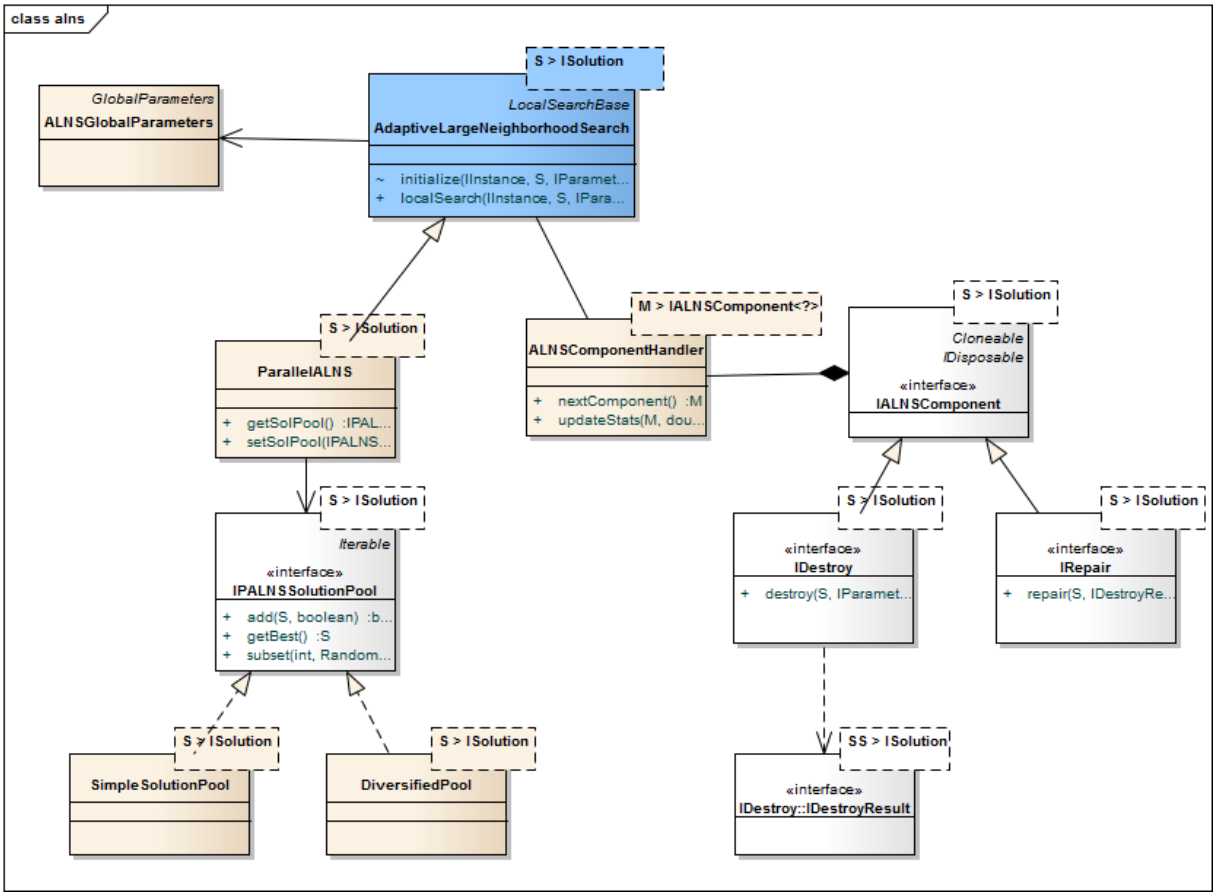

Figure C.5: Design overview of the Adaptive Large Neighborhood Search framework.

Size	SEQ	SEQ-Rev	FRE-R	FRE-NR	EFF-R	EFF-NR	RAN-R
5	2	0	1	0	0	0	0
8	4	1	1	1	1	1	1
20	18	58	22	**14**	20	15	19
40	142	575	232	273	190	**120**	212
60	485	2385	861	603	656	**430**	812

Table C.2: Average CPU running times (ms).

Size	SEQ-R	SEQ-Rev	FRE-R	FRE-NR	EFF-R	EFF-NR	RAN-R
5	64.6	140.7	92.2	67.8	61.7	37.9	56.3
8	4.5	0.7	0.9	0.7	0.6	0.5	1.3
20	0.8	0.8	0.8	0.8	0.8	0.8	0.8
40	64.6	140.7	92.2	67.8	61.7	37.9	56.3
60	135.8	674.5	362.8	157.6	187.5	158.3	193.6

Table C.3: Standard deviation of CPU running times (ms).

C.5 Multi-space sampling with heuristic concentration

This section describes an approach based on the work of Mendoza and Villegas (2011), namely Multiple Space Sampling with Heuristic Concentration (MSSHC), which generates feasible routes using randomized constructive heuristics, and then builds a solution by solving a set-covering problem.

Algorithm C.4 presents an overview of the method. For each constructive heuristic, the algorithm generates a number of giant TSP-like tours (line 5), that are then split into a set of feasible routes (line 6). Finally, a set-covering model is solved to select a subset of routes conforming a solution of minimal cost (line 10).

Algorithm C.4 The MSSHC algorithm

Input: $\mathcal{H}$ a set of constructive heuristics, I number of iterations
Output: $\mathbf{\Pi}^*$ the best solution that can be built from the generated routes

1: $\mathcal{P} \leftarrow \emptyset$ ▷ Initialize route pool
2: $I^H \leftarrow \left\lceil \frac{I}{|\mathcal{H}|} \right\rceil$ ▷ Number of samples per heuristic
3: **for all** $H \in \mathcal{H}$ **do**
4: **for** $i = 1$ **to** I^H **do**
5: $\bar{\pi} \leftarrow \texttt{generateGiantTour}(H)$ ▷ Generate a giant tour
6: $\mathcal{P}' \leftarrow \texttt{split}(\bar{\pi})$ ▷ Split the giant tour into multiple feasible routes
7: $\mathcal{P} \leftarrow \mathcal{P} \cup \mathcal{P}'$ ▷ Add the routes to the pool
8: **end for**
9: **end for**
10: $\mathbf{\Pi}^* \leftarrow \texttt{solveSC}(\mathcal{P})$ ▷ Solve the set covering problem
11: **return** $\mathbf{\Pi}^*$

We tested this approach on the TRSP but it appeared that pALNS+SC was clearly dominating both in terms of objective function and computational time. Our intuition is that the presence of time windows makes it more difficult to generate good routes during the split procedure. However this method has shown very good results on the VRPSD and its simplicity makes it a good candidate for problems without time windows.

C.5.1 Implementation

Figure C.6 presents an overview of the MSSHC framework. The main class is `RCHSCSolver` which uses a collection of randomized constructive heuristics (`TRSPRndConstructiveHeuristic`) and a set covering solver (`SCGurobiSolver`). Note that at present time this implementation is tied with the data model used for the experiments on the TRSP.

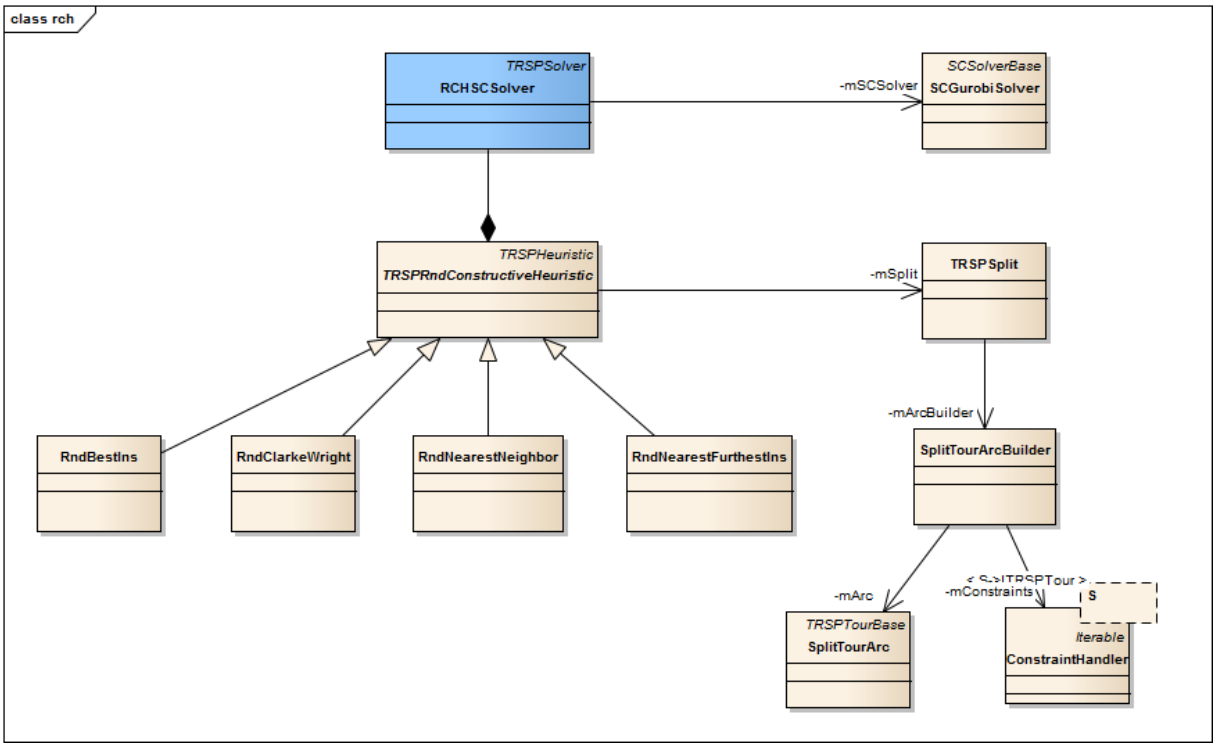

Figure C.6: Design overview of the MSSHC framework.

C.5.2 Constructive heuristics

Giant tours are generated using a randomized variant of four well known heuristics for the TSP, that draw a random number χ between 0 and the number of unvisited customers. Random Nearest Neighbor (RNN) selects the χ-th closest customer to the last customer of the tour and appends it to the tour. Random Nearest (Furthest) Insertion (RNI/RFI) selects the χ-th closest (furthest) customer to any of the customers currently in the tour and inserts it in the best position. Random Best Insertion (RBI) selects and inserts the χ-th best insertion for all unserved customers.

C.5.3 Split procedure

Algorithm C.5 presents the split procedure as introduced by Prins (2004), which is basically a labeling algorithm that finds the shortest path on an auxiliary graph representing all the feasible partitions of the giant tour into routes.

Algorithm C.5 The `split` procedure

Input: $\bar{\pi}$ a giant tour of length n, z an evaluation function
Output: $\mathcal{P}'$ the optimal splitting of $\bar{\pi}$ into a set of routes

$\mathcal{P}' \leftarrow \emptyset$
$L \leftarrow [+\infty]_{i=1..n}$ ▷ Initialize labels to $+\infty$
$L_1 \leftarrow 0$ ▷ Initialize labels of the first node to 0
$P \leftarrow [\emptyset]_{i=1..n}$ ▷ Initialize the predecessor array
for $i = 1$ **to** n **do**
    $j \leftarrow i$
    $f \leftarrow$ `true`
    while f **and** $j \leq n$ **do**
        $f \leftarrow$ `isFeasible` $\left(\bar{\pi}_{[i,j]}\right)$ ▷ Check route feasibility
        if f **and** $L_i + z(\bar{\pi}_{[i,j]}) < L_j$ **then** ▷ We found an improving feasible arc
            $L_j \leftarrow L_i + z(\bar{\pi}_{[i,j]})$ ▷ Update j's label
            $P_j \leftarrow \bar{\pi}_{[i,j]}$ ▷ Update j's predecessor
        end if
        $j \leftarrow j + 1$
    end while
end for
$i \leftarrow n$
while $i \neq 1$ **do**
    $\mathcal{P}' \leftarrow \mathcal{P}' \cup \{P_i\}$ ▷ Add the route to the set of optimal routes
    $i \leftarrow P_i^0$ ▷ Move to the first node of the route
end while
return $\mathcal{P}'$

C.5.4 Heuristic concentration

The heuristic concentration consists in selecting a subset of routes that constitutes a minimal cost feasible solution of the problem at hand. This can be modeled as the following set-covering problem:

$$\text{Min} \quad \sum_{t \in \mathcal{P}} c_t x_t \tag{C.1}$$

$s.t.$

$$\sum_{t \in \mathcal{P}} x_t a_{ti} \geq 1 \qquad \forall i \in \mathcal{R} \tag{C.2}$$

$$x_t \in \{0, 1\} \qquad \forall t \in \mathcal{P} \tag{C.3}$$

Where $\mathcal{P}$ is the set of generated routes and a_{ti} a parameter taking the value of 1 if route t visits node i.

Constraint C.2 ensures that each customer is visited at least once. Considering that customers must be visited exactly once, one could argue that a set-partitioning formulation would fit better our purpose. Nonetheless, our model only contains a limited subset of columns, and therefore we may not be able to find a good combination of columns that ensures the unique covering of all customers. As a result, the final solution may visit a customer more than once. This is easily dealt with by removing the most costly visits. In all cases we are ensured that the repaired solution x^*_{SC+rep}, is at least as good as the optimal solution x^*_{SC} of the set-covering, and by transitivity of the set-partitioning x^*_{SP},

as illustrated in Equation C.4

$$z(x^*_{SC}) \leq z(x^*_{SP}) \wedge z(x^*_{SC+rep}) \leq z(x^*_{SC}) \Rightarrow z(x^*_{SC+rep}) \leq z(x^*_{SP}) \tag{C.4}$$

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D

An instance generator for the TRSP

We adapted the VRPTW instances proposed by Solomon (1987) by adding skills, tools, and spare parts information. The instances contain 100 requests located randomly (R), in clusters (C), or combining both (RC); while the planning horizon is either short (type 1) or long (type 2). These instances are organized combining location and horizon (i.e., C1, C2, R1, R2, RC1, and RC2). For all instances the crew size is fixed, and the traveling speed of technicians is assumed to be unitary.

D.1 Parameters

The parameters of the generator are the following:

$|\mathcal{S}|, |\mathcal{T}|, |\mathcal{P}|$ number of skills, tools, and spare parts types;

$\mathcal{D}t_S$ distribution of the number of skills per technician;

$\mathcal{D}t_T$ distribution of the number of tools available to each technician;

$\mathcal{D}t_P$ distribution of the number of different spare part types available to each technician;

$\mathcal{D}t_{PC}$ distribution of the number of spare parts of any available type available to each technician;

$\mathcal{D}r_S$ distribution of the number of skills required by each request;

$\mathcal{D}r_T$ distribution of the number of tools required by each request;

$\mathcal{D}r_P$ distribution of the number of different spare part types required by each request;

$\mathcal{D}r_{PC}$ distribution of the number of spare parts of any required type required by each request.

We then numerate skills, tools and spare parts in a natural order (e.g., $\mathcal{S} = \{0, 1, ..., |\mathcal{S}| - 1\}$).

D.2 Tools and spare parts

To ensure a certain coherence between skills and spare parts, we define for each skill a subset of associated tools/spare parts. For instance the skill *screw* will be associated with the tools (*drill, screw driver*) and spare parts (*screw, rawplug*). We therefore have:

T_s the set of tools associated with skill s,
$T_s = \left\{ t| : s * \lceil \frac{|\mathcal{T}|}{|\mathcal{S}|} \rceil \leq t < (s+1) * \lceil \frac{|\mathcal{T}|}{|\mathcal{S}|} \rceil \right\}$

P_s the set of spare parts associated with skill s,
$P_s = \left\{ p| : s * \lceil \frac{|\mathcal{P}|}{|\mathcal{S}|} \rceil \leq p < (s+1) * \lceil \frac{|\mathcal{P}|}{|\mathcal{S}|} \rceil \right\}$

D.3 Technicians

We associate to each vehicle of the original instance a technician k, and generate additional information to match the TRSP definition.

Home depot We randomly generate a home depot h_k for each technician k in a 100×100 square.

Skills We sample the $\mathcal{D}t_S$ distribution to generate a random number η_s, and then pick η_s skills from the skill set $\mathcal{S}$ to form $\mathcal{S}_k$, the skill set of technician k.

Tools We sample the $\mathcal{D}t_T$ distribution to generate a random number η_t, and then pick η_t tools from the union of the tool subsets $\bigcup_{s \in \mathcal{S}_k} T_s$.

Spare parts We sample the $\mathcal{D}t_P$ distribution to generate a random number η_p, and then pick η_p spare part types from the union of the spare part types subsets $\bigcup_{s \in \mathcal{S}_k} P_s$; then for each selected spare part type p we generate the number of parts of type p available to the technician by sampling the $\mathcal{D}t_{PC}$ distribution.

D.4 Requests

We associate to each customer of the original instance a request i, and generate additional information to match the TRSP definition.

Skills We sample the $\mathcal{D}r_S$ distribution to generate a random number η_s, and then pick η_s skills from the skill set $\mathcal{S}$ to form $\mathcal{S}_i$, the skill set of request i.

Tools We sample the $\mathcal{D}r_T$ distribution to generate a random number η_t, and then pick η_t tools from the union of the tool subsets $\bigcup_{s \in \mathcal{S}_i} T_s$.

Spare parts We sample the $\mathcal{D}r_P$ distribution to generate a random number η_p, and then pick η_p spare part types from the union of the spare part types subsets $\bigcup_{s \in \mathcal{S}_i} P_s$; then for each p we generate the number of parts of type p required by the request by sampling the $\mathcal{D}r_{PC}$ distribution.

Release dates For the dynamic instances we generate release date for a proportion δ of the requests. The release date for request r is selected randomly in the interval $[0, b_r - 1.5c_{0r}]$, where b_r is the time window end for request r, and c_{0r} is the travel time between the central depot and r. The interval upper bound is an estimate of the latest feasible time for a technician to start traveling to the request.

D.5 File format

Figure D.1 illustrates the file format used which is an extension of the original Solomon's format. The first line contains the instance name; then follows a description of the instance with the number of technicians, skills, tools and spare part types; and the rest of the file contains a list of nodes. The first corresponds to the main depot, while the $|\mathcal{K}|$ following are a description of each technician with its home depot, set of skills, tools and available spare parts (from node 1 to 25 in this example). Finally, the remaining lines describe the instance requests (from node 26 to 125 in this example). Filename follows the pattern $|\mathcal{R}|$-name_$|\mathcal{S}|$-$|\mathcal{T}|$-$|\mathcal{P}|$ where name is the name of the original instance.

```
100-C101_5-5-5

INFO
CREW COUNT  SKILLS  TOOLS   SPARE PARTS
25          5       5       5

DEPOT TECHNICIANS AND REQUESTS
ID   X     Y     TWS    TWE    Serv   SKILLS   TOOLS    SPARE PARTS
0    40    50    0      1236   0      []       []       []
1    51    19    0      1236   0      [2,3,4]  [3,4]    [0,0,2,5,0]
2    16    73    0      1236   0      [0,1,2]  [2]      [0,3,2,3,5]
...
26   45    68    912    967    90     [4]      [1]      [0,1,0,1,0]
27   45    70    825    870    90     [1]      [2]      [0,0,0,0,0]
...
125  60    85    561    622    90     [1]      []       [0,0,0,1,0]
```

Figure D.1: Illustration of the file format used to store Solomon based instances.

D.6 Generated instances

The parameters used to generate instances are recapitulated in Table D.1

Bibliography

Solomon, M. M. (1987). Algorithms for the vehicle-routing and scheduling problems with time window constraints. *Operations Research*, 35(2):254–265.

Parameter	**Value**
$\lvert\mathcal{S}\rvert$	5
$\lvert\mathcal{T}\rvert$	5
$\lvert\mathcal{P}\rvert$	5
$\mathcal{D}t_S$	$\mathcal{U}_{int}(2,4)$
$\mathcal{D}t_T$	$\mathcal{U}_{int}(0,5)$
$\mathcal{D}t_P$	$\mathcal{U}_{int}(2,5)$
$\mathcal{D}t_{PC}$	$\mathcal{U}_{int}(2,5)$
$\mathcal{D}r_S$	1
$\mathcal{D}r_T$	$\mathcal{U}_{int}(0,2)$
$\mathcal{D}r_P$	$\mathcal{U}_{int}(0,2)$
$\mathcal{D}r_{PC}$	1

Table D.1: Parameter setting for the instance generation

E

Best known solutions for the TRSP

This appendix presents the value of the best known solutions for the TRSP instances introduced in this thesis.

E.1 Summary of best known solutions

Tables E.1, E.2, and E.3 present a summary of the best known solutions for instances from group C, R, and RC respectively. Note that the objective function only considers the minimization of the duration, the distance is reported for reference only.

The interested reader is referred to the webpage `http://hdl.handle.net/1992/1152` for the detailed solutions.

Instance	Duration	Distance
C101.100_25-5-5-5	10717.516	1665.946
C102.100_25-5-5-5	10239.040	1206.218
C103.100_25-5-5-5	10281.862	1281.862
C104.100_25-5-5-5	10107.440	1107.440
C105.100_25-5-5-5	10584.062	1584.062
C106.100_25-5-5-5	10322.596	1322.329
C107.100_25-5-5-5	10356.556	1353.632
C108.100_25-5-5-5	10251.215	1250.821
C109.100_25-5-5-5	10107.331	1107.331
C201.100_25-5-5-5	10192.975	1162.608
C202.100_25-5-5-5	10001.521	1001.521
C203.100_25-5-5-5	10001.169	999.590
C204.100_25-5-5-5	9890.558	890.558
C205.100_25-5-5-5	10208.442	1208.442
C206.100_25-5-5-5	9983.137	983.137
C207.100_25-5-5-5	9849.688	849.688
C208.100_25-5-5-5	9981.063	981.063

Table E.1: Best known solutions for group C

Instance	Duration	Distance
R101.100_25-5-5-5	3134.863	1950.115
R102.100_25-5-5-5	3039.234	1962.761
R103.100_25-5-5-5	2421.778	1399.052
R104.100_25-5-5-5	2285.773	1285.773
R105.100_25-5-5-5	2975.424	1945.165
R106.100_25-5-5-5	2626.378	1618.301
R107.100_25-5-5-5	2134.362	1119.964
R108.100_25-5-5-5	2116.046	1116.046
R109.100_25-5-5-5	2512.891	1512.891
R110.100_25-5-5-5	2359.424	1359.424
R111.100_25-5-5-5	2550.500	1550.500
R112.100_25-5-5-5	2145.758	1145.758
R201.100_25-5-5-5	2639.699	1616.663
R202.100_25-5-5-5	2382.865	1375.446
R203.100_25-5-5-5	2334.581	1333.116
R204.100_25-5-5-5	1931.190	931.190
R205.100_25-5-5-5	2254.816	1254.816
R206.100_25-5-5-5	2082.799	1082.799
R207.100_25-5-5-5	1981.760	981.760
R208.100_25-5-5-5	1879.491	879.491
R209.100_25-5-5-5	2130.504	1130.504
R210.100_25-5-5-5	2111.923	1111.923
R211.100_25-5-5-5	1975.420	975.420

Table E.2: Best known solutions for group R

Instance	Duration	Distance
RC101.100_25-5-5-5	2856.488	1804.244
RC102.100_25-5-5-5	2843.178	1825.804
RC103.100_25-5-5-5	2495.567	1494.851
RC104.100_25-5-5-5	2162.514	1162.514
RC105.100_25-5-5-5	2711.491	1684.443
RC106.100_25-5-5-5	2761.863	1761.863
RC107.100_25-5-5-5	2570.403	1570.403
RC108.100_25-5-5-5	2354.422	1354.422
RC201.100_25-5-5-5	2686.012	1685.053
RC202.100_25-5-5-5	2487.727	1486.713
RC203.100_25-5-5-5	2310.010	1303.007
RC204.100_25-5-5-5	2064.163	1064.163
RC205.100_25-5-5-5	2588.166	1560.131
RC206.100_25-5-5-5	2359.699	1350.841
RC207.100_25-5-5-5	2233.678	1233.678
RC208.100_25-5-5-5	1914.536	914.536

Table E.3: Best known solutions for group RC

F

List of contributions

F.1 International peer-reviewed journal papers

Pillac, V., Guéret, C., Medaglia, A. L. (2012), An event-driven optimization framework for dynamic vehicle routing, *Decision Support Systems*, *Accepted manuscript*, doi:10.1016/j.dss.2012.06.007

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F.3 Peer-reviewed conference proceedings

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F.4 Conference presentations

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F.5 Software libraries

We released the libraries under the GNU General Public License version 3 (GPL3) [1] to allow their use in non-commercial applications only. This choice is motivated by two aspects: first, the libraries depend to a certain extent on the Stochastic Simulation in Java (SSJ) [2] which is itself released under GPL 3; second the libraries may be included in the near future in an open-source project with a broader scope and a more permissive license, therefore we wanted to restrict the use of the present libraries in favor of the broader project. All the cited libraries are publicly available at:
`http://victorpillac.wordpress.com/libraries-for-the-vrp`

Pillac, V., Guéret, C., Medaglia, A. L., `VroomModeling`: A general purpose modeling library for vehicle routing problems.

Pillac, V., Guéret, C., Medaglia, A. L., `VroomHeuristics`: A set of general heuristics for vehicle routing problems.

Pillac, V., Guéret, C., Medaglia, A. L., `jMSA`: An event-driven optimization framework for dynamic vehicle routing.

1. GNU General Public License v.3 - `http://www.gnu.org/licenses/gpl.html`
2. SSJ library - `http://www.iro.umontreal.ca/~simardr/ssj/`

G

Résumé en français

Les activités de transport jouent un rôle crucial tant dans le domaine de la production que dans celui des services. En particulier, elles permettent d'assurer la distribution de biens et de services entre fournisseurs, unités de production, entrepôts, distributeurs, et clients finaux. Le transport a également un fort impact sur l'économie et sur l'environnement. Selon Hesse and Rodrigue (2004), le coût total des activités logistiques était de 10% du Produit Intérieur Brut (PIB) aux États Unis en 2010, et le transport à lui seul représentait 5.9% du PIB. Par ailleurs, un rapport récent de la la Energy Information Administration (EIA, 2011) indique que le transport était responsable de 27% des émissions de gaz à effet de serre en 2009 (toujours aux États Unis), alors que la European Environment Agency estime cette part à 24% pour l'Union Européenne (EEA, 2011).

En conséquence, améliorer l'efficacité des activités de transport est une étape critique pour augmenter la compétitivité et réduire l'impact environnemental des organisations. Dans ce sens, l'opération d'une flotte de véhicules constitue un problème clef qui apparaît autant dans les entreprises de services, avec entre autres le transport de personnes handicapées, la planification des tournées de bus scolaires, ou les activités de maintenance sur site, que dans l'industrie avec, par exemple, le transport de matières premières entre fournisseurs et usines, le repositionnement de camions dans les sociétés de transport longue distance, ou la collecte et la livraison de produits dans les societés de vente par correspondance.

Plus particulièrement, les problèmes de tournées de véhicules (Vehicle Routing Problems - VRPs) considèrent la conception d'un ensemble de tournées de coût minimal servant les demandes en produits ou services d'un ensemble de clients distribués géographiquement, tout en respectant un ensemble de contraintes opérationnelles. Depuis sa définition par Dantzig and Ramser (1959), le nombre de publications sur le VRP a augmenté exponentiellement. L'étude récente de Eksioglu et al. (2009) est une preuve de cette évolution : elle reporte environ 1500 publications indexées traitant des tournées de véhicules

(à la date de la rédaction de l'article). Le volume de publications est intimement lié à la grande diversité de problèmes de tournées, et la variété des approches proposées pour les traiter.

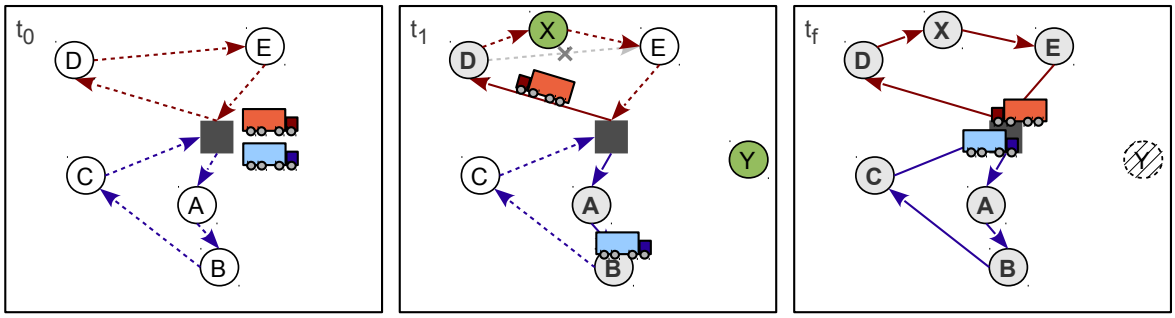
La formulation originale du problème de tournées de véhicules avec capacité (CVRP ou simplement VRP) est une généralisation du problème du voyageur de commerce (Travelling Salesman Problem - TSP) proposé par Flood (1956). Le VRP est défini sur un graphe $G = (\mathcal{V}, \epsilon, \mathbf{C}, \mathbf{q})$, où $\mathcal{V} = \{v_0, \ldots, v_n\}$ est l'ensemble des nœuds, ϵ est l'ensemble des arcs, $\mathbf{C} = (c_e)_{e\in\epsilon}$ est une matrice de coûts définie sur les arcs, et $\mathbf{q} = (q_i)_{i\in\mathcal{V}}$ est un vecteur de demandes pour un certain produit. Traditionnellement, le nœud v_0 est appelé *dépôt*, alors que les nœuds restants représentent des *clients* qui requièrent une certaine quantité du produit considéré. Le VRP consiste à concevoir un ensemble de tournées de coût minimal pour une flotte illimitée de véhicules de capacité Q, commençant et finissant au dépôt, de telle sorte que chaque client soit visité exactement une fois, tout en respectant la capacité des véhicules.

Cette définition a été étendue sous diverses formes pour modéliser une variété d'applications pratiques. Parmi les contraintes additionnelles les plus étudiées se trouvent la prise en compte de fenêtres de temps qui imposent de visiter un client durant une certaine période ; la prise en compte simultanée des opérations de collecte et de livraison qui impose qu'un produit soit d'abord collecté à une certaine position pour être ensuite livré à une autre, les contraintes de distances ou durées maximales qui limitent le nombre de clients visités dans une tournée ; ou les contraintes d'accessibilité qui réduisent l'ensemble des véhicules pouvant desservir un client. Par ailleurs, les variantes communes de la définition originale du problème incluent la prise en compte de multiples dépôts, avec des véhicules pouvant commencer et terminer leur tournées à des dépôts distincts ; des flottes de véhicules hétérogènes et/ou limitées. Finalement, d'autres problèmes proches considèrent des horizons multi-périodes ; la prise en compte simultanée de la gestion de stocks ; les tournées à niveaux multiples dans lesquelles certains véhicules alimentent des hubs desquels partent d'autres tournées de livraison ; des véhicules avec une remorque pouvant être détachée pour servir des clients avec des contraintes d'accessibilité ; et des problèmes de tournées sur les arcs dans lesquels la demande est localisée sur les arcs.

En parallèle de cette multitude de variantes, de nombreuses méthodes d'optimisation ont été proposées pour résoudre les problèmes de tournées de véhicules. Nous renvoyons le lecteur vers les études de la littérature de Baldacci et al. (2007), Cordeau et al. (2007), Laporte (2009), et Toth and Vigo (2002) pour un panorama complet des méthodes exactes et approchées. La majorité des algorithmes et logiciels de tournées de véhicules reposent sur l'hypothèse que toute l'information est connue avec certitude. Cependant, dans certaines applications, une partie ou l'ensemble des informations sont incertaines. Un exemple fréquent est l'incertitude sur les temps de transport qui varient grandement, en fonction des conditions météorologiques et de trafic, en particulier dans les zones urbaines. Ces problèmes sont qualifiés de statiques et stochastiques et des exemples communs incluent des clients présents avec une certaine probabilité, des temps de trajet et de service stochastiques, et enfin des demandes stochastiques lorsque la demande des clients n'est connue que sous forme de probabilité.

Par ailleurs, les avancés récentes des moyens de communication et de géolocalisation permettent aux entreprises de suivre et d'interagir avec leur flotte en temps réel. Ces nouvelles technologies ont amené à la création des systèmes de transport intelligents (Intelligent Transport Systems - ITS), et plus précisément des système de gestion avancée de flotte (Advanced Fleet Management Systems - AFMS), qui combinent des solutions matérielles et logicielles pour présenter en temps réel l'information dis-

ponible sur la flotte, les clients, et les réseaux routiers. Le développement des ITS et AFMS crée de nouveaux défis et opportunités pour la recherche opérationnelle. Les tournées de véhicules ne sont plus limitées à une conception a-priori de tournées ne pouvant être modifiées par la suite. À l'inverse, les véhicules peuvent désormais être orientés en temps réel, définissant une nouvelle catégorie de problème de tournées *dynamiques*.



a. Tournées initiales b. Nouveaux clients c. Tournées finales

FIGURE G.1 – Illustration d'un problème de tournées de véhicules dynamique.

La figure G.1 illustre le routage dynamique de deux véhicules. Initialement (G.1a.), deux tournées sont définies pour servir l'ensemble des clients actuellement connus : (A, B, C) et (D, E). À l'instant t_1 et alors que les véhicules ont commencé leurs tournées (G.1b.), deux nouveaux client X et Y apparaissent. A ce stade, deux décisions doivent être prises : la première consiste a décider si les nouveaux clients doivent être *acceptés* ou *rejetés*, la seconde a pour but d'insérer les clients acceptés dans les tournées. Par exemple, le client X est proche de la seconde tournée et peut donc être accepté et inséré entre D et E. En revanche, le client Y est éloigné des tournées et de la position actuelle des véhicules, il est donc potentiellement impossible de le servir, ou son service impliquerait un coût trop important (détour). En conséquence, la décision est prise de le rejeter. Enfin, les tournées finales sont (A, B, C) et (D, X, E) (G.1c.). La qualité du routage dynamique des véhicules peut se mesurer en comparant les tournées finales avec les tournées qui auraient pu être conçues en supposant connu l'ensemble des clients acceptés. Cette solution, dite *statique*, est obtenue en résolvant le problème de tournées défini par les clients A, B, C, D, E, et X.

Le but de cette thèse est d'étudier l'état de l'art des approches dédiées aux tournées dynamiques ; de concevoir des algorithmes innovants pour cette catégorie de problèmes ; d'implémenter des composant logiciels génériques à la fois réutilisables, extensibles, et applicables à un grand nombre de variantes ; d'appliquer les algorithmes proposés à un cas d'étude réel ; et, finalement, de rendre publique l'ensemble des contributions sous forme de librairies open-source pour accélérer les transferts de technologies entre l'académie et l'industrie.

G.1 État de l'art sur les tournées dynamiques

Dans ce premier chapitre nous présentons une étude détaillée de la littérature traitant des problèmes de tournées de véhicules dynamiques. Dans un premier temps nous définissons une classification des problèmes de tournées suivant deux axes : l'évolution et la qualité de l'information, ce qui

conduit aux quatre catégories de problèmes identifiés dans le tableau G.1.

		Qualité de l'information	
		Données déterministes	Données stochastiques
Évolution de l'information	Données connues à l'avance	Statique et déterministe	Statique et stochastique
	Données changeantes	Dynamique et déterministe	Dynamique et stochastique

TABLE G.1 – Classification des problèmes de tournées de véhicules suivant l'évolution et la qualité de l'information.

Les problèmes de la catégorie *statique et déterministe* correspondent aux variantes de la définition originale du VRP dans lesquelles l'ensemble de l'information est connue de façon certaine a-priori. Les problèmes *statiques et stochastiques* sont caractérisés par des données partiellement connues sous forme de variables aléatoires dont la réalisation est révélée lors de l'exécution des tournées. Par ailleurs, ils supposent que seules des modifications mineures peuvent être apportées aux tournées une fois les véhicules partis, avec par exemple un retour anticipé au dépôt ou le non-service d'un client.

Les problèmes *dynamiques et déterministes* considèrent qu'une partie ou l'ensemble des données est inconnu et révélé dynamiquement et de façon non-prévisible lors de l'exécution des tournées. Pour ces problèmes, les tournées sont définies en temps réel, ce qui suppose la possibilité de communiquer en temps réel avec les véhicules. Les problèmes *dynamiques et stochastiques* supposent eux qu'il est possible de prévoir les changement dynamiques, par exemple en les modélisant sous forme de variables aléatoires avec des distributions connues.

Ce chapitre se focalise sur les problèmes dynamiques et déterministes et dynamiques et stochastiques. Dans un premier temps, nous étudions les différences avec les tournées de véhicules statiques ainsi que différentes mesures pour évaluer le dynamisme d'un problème, et nous listons les applications les plus communes dans les domaines du transport de personnes, transport de marchandises, et les services. Dans un second temps, nous dressons l'inventaire des méthodes proposées pour les problèmes dynamiques ainsi que des mesures de performance permettant leur comparaison. Enfin nous concluons sur le panorama général de ce domaine et dessinons des directions de recherche.

G.1.1 Mesures de dynamisme

Différentes mesures ont été proposées pour évaluer le degré de dynamisme d'un problème.

Degré de dynamisme Lund et al. (1996) définissent *le degré de dynamisme* (degree of dynamism) δ comme le ratio entre le nombre de clients dynamiques n_d et le nombre total de clients n_{tot} :

$$\delta = \frac{n_d}{n_{tot}} \tag{G.1}$$

Degré de dynamisme effectif Remarquant que la date à laquelle les nouveaux clients apparaissent est également important, Larsen (2001) propose le *degré de dynamisme effectif* (effective degree of dy-

namism) δ^e. Soit T la longueur de l'horizon de planification, $\mathcal{R}$ l'ensemble des clients, et t_i l'heure d'apparition du client $i \in \mathcal{R}$. En supposant que les clients connus à l'avance ont une heure d'apparition égale à 0, δ^e peut s'exprimer de la façon suivante :

$$\delta^e = \frac{1}{n_{tot}} \sum_{i \in \mathcal{R}} \frac{t_i}{T} \tag{G.2}$$

Dynamisme et urgence Larsen (2001) a également étendu le degré effectif de dynamisme à des problèmes avec fenêtres de temps afin de refléter le niveau d'urgence des demandes. Il définit le temps de réaction comme la différence entre la date d'apparition t_i et la fin de la fenêtre de temps correspondante l_i, soulignant que les temps de réaction plus longs introduisent une plus grande flexibilité pour insérer la demande dans les tournées actuelles. Ainsi, le degré de dynamisme est étendue comme suit :

$$\delta^e_{TW} = \frac{1}{n_{tot}} \sum_{i \in \mathcal{R}} \left(1 - \frac{l_i - t_i}{T}\right) \tag{G.3}$$

Il est à noter que ces trois mesures prennent leurs valeurs dans l'intervalle $[0, 1]$ et augmentent avec le niveau de dynamisme d'un problème. Larsen et al. (2002, 2007) utilisent le degré effectif de dynamisme pour classer les D-VRP entre problèmes faiblement, moyennement et fortement dynamiques, avec des valeurs de δ^e inférieures à 0.3, comprise entre 0.3 et 0.8, et supérieures à 0.8 respectivement.

G.1.2 Approches pour les problèmes dynamiques et déterministes

Cette section présente les approches qui ont été appliquées avec succès au routage dynamique, en l'absence d'information stochastique. Dans ce contexte, des données critiques sont révélées au fil du temps, ce qui signifie que l'instance complète n'est connue qu'à la fin de l'horizon de planification. En conséquence, les méthodes exactes ne fournissent une solution optimale que pour l'état actuel, mais ne garantissent pas que la solution reste optimale lorsque de nouvelles données deviennent disponibles. Par conséquent, la majorité des approches dynamiques s'appuient sur des heuristiques qui permettent de calculer rapidement une solution à l'état actuel du problème. Les approches pour les problèmes dynamiques et déterministes peuvent être divisés en deux catégories : celles basées sur une *réoptimisation périodique*, et celles basées sur une *réoptimisation continue* des tournées.

Réoptimisation périodique La figure G.1.2 présente un aperçu des approches réoptimisation périodique : l'algorithme commence au début de la journée par première optimisation produisant une solution initiale S_0. Ensuite, la procédure attend soit jusqu'au prochain changement dans les données disponibles, soit pour une période de temps déterminée, puis réalise une nouvelle optimisation qui conduit à mise à jour de la solution S_{t+1}. L'avantage des approches de réoptimisation périodiques est qu'elles peuvent être basées sur des algorithmes développés pour les problèmes de tournées statiques. Leur principal inconvénient est que l'optimisation doit être effectuée avant la mise à jour de la solution, ce qui peut augmenter les délais pour le preneur de décision, tandis que la puissance de calcul est inutilisée pendant les temps d'attente.

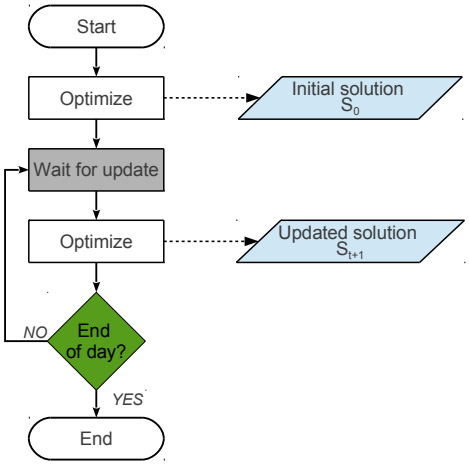


FIGURE G.2 – Approches de réoptimisation périodique

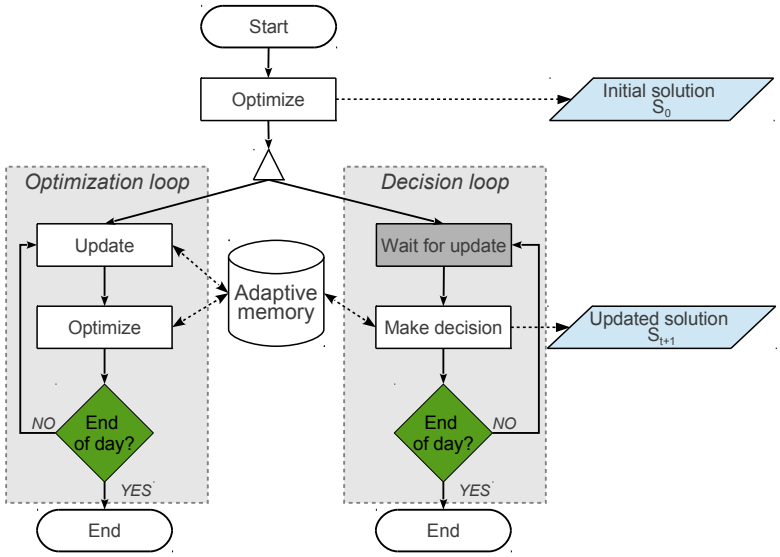


FIGURE G.3 – Approches de réoptimisation continue

Réoptimisation continue Les approches dites de réoptimisation continue sont basées sur un algorithme d'optimisation qui s'execute tout au long de la journée. Comme l'illustre la Figure G.1.2, la boucle d'optimisation stocke ses résultats dans une mémoire adaptative. En parallèle, une seconde boucle utilise les données de la mémoire adaptative pour prendre des décisions, par exemple pour décider si un nouveau client peut être servi ou non, ou pour sélectionner le prochain client à affecter à un véhicule. L'avantage de ces approches est que l'utilisation de la puissance de calcul est maximisée, au prix d'une implémentation plus complexe.

G.1.3 Approches pour les problèmes dynamiques et stochastiques

Les problèmes de tournées dynamiques et stochastiques peuvent être vus comme une extension de leurs homologues déterministes, dans lesquels les données dynamiquement révélées peuvent être modelées comme un processus stochastique. Les approches pour cette classe de problèmes peuvent être

divisées en deux catégories : celles basées sur l'*échantillonnage* et celles basées sur la *modélisation stochastique*. Comme leur nom l'indique, les stratégies d'échantillonage incorporent les informations stochastiques en générant des *scénarios* basés sur une réalisation possible des variables aléatoires. Chaque scénario est ensuite optimisé par la résolution du problème statique et déterministe qu'il définit. Les approches basées sur la modélisation stochastique intègrent quant à elles les informations stochastiques analytiquement. L'avantage de l'échantillonnage est sa relative simplicité et sa flexibilité, tandis que son inconvénient est qu'il peut requérir de générer un grand nombre de scénarios pour refléter fidèlement la réalité. Alternativement, les stratégies de modélisation stochastique saisissent formellement la nature stochastique du problème, mais leur formulation et les algorithmes d'optimisation sous-jacents sont plus complexes.

Référence de l'article présenté dans ce chapitre :

- Pillac, V., Gendreau, M., Guéret, C., and Medaglia, A. L. (2011) A review of dynamic vehicle routing problems *European Journal of Operational Research*, Accepted manuscript, doi :10.1016/j.ejor.2012.08.015.

Des versions précédentes de cet article ont été publiées comme rapports techniques avec références :

- Pillac, V., Gendreau, M., Guéret, C., and Medaglia, A. L. (2011) A review of dynamic vehicle routing problems Technical report, CIRRELT. CIRRELT-2011-62.
- Pillac, V., Guéret, C., and Medaglia, A. L. (2010) Dynamic Vehicle Routing : State of the Art and Prospects Technical report, École des Mines de Nantes, France. Report 10/4/AUTO.

G.2 Tournées dynamiques et déterministes

Dans ce chapitre nous proposons une méthode de réoptimisation rapide pour les tournées de véhicules dynamiques et nous étudions des aspects bi-objectifs liés à la prise en compte de la constance des tournées au cours de la journée.

G.2.1 Méthode de réoptimisation rapide

La méthode de réoptimisation proposée est basée sur l'algorithme de recherche adaptative à voisinage large ALNS (Adaptive Large Neighborhood Search) proposée par Pisinger and Ropke (2007), lui même une extension de la recherche à voisinages larges LNS (Large Neighborhood Search) introduite par Shaw (1998). LNS consiste a successivement *détruire* puis *réparer* une solution courante. ALNS rajoute une couche adaptive qui sélectionne aléatoirement les opérateurs de destruction et de réparation en fonction de leur performance antérieure.

L'algorithme G.1 présente l'approche ALNS. ALNS part d'une solution initiale $\mathbf{\Pi}_0$, puis, pour I itérations l'algorithme choisit un opérateur de destruction et un opérateur de réparation (ligne 4) avec une roulette qui reflète leur performance passée. Les opérateurs de destruction enlèvent un sous-ensemble de clients de la solution courante, alors que les opérateurs de réparation les réinsèrent en utilisant

Algorithm G.1 Adaptive Large Neighborhood Search (ALNS)

Input: $\mathbf{\Pi}_0$ initial solution, z evaluation function, Θ^-/Θ^+ set of destroy/repair operators, I number of iterations
Output: $\mathbf{\Pi}^*$ the best solution found

1: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}_0$ ▷ Initialize best solution
2: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}_0$ ▷ Initialize current solution
3: **for** I iterations **do**
4: $d \leftarrow \texttt{select}(\Theta^-)\,; r \leftarrow \texttt{select}(\Theta^+)$ ▷ Select destroy/repair
5: $\mathbf{\Pi}' \leftarrow \texttt{r}(\texttt{d}(\mathbf{\Pi}))$ ▷ Generate a neighbor
6: **if** $\texttt{accept}(\mathbf{\Pi}', \mathbf{\Pi})$ **then** ▷ $\mathbf{\Pi}'$ is accepted as current solution
7: $\mathbf{\Pi} \leftarrow \mathbf{\Pi}'$ ▷ Update current solution
8: **end if**
9: **if** $z(\mathbf{\Pi}') < z(\mathbf{\Pi}^*)$ **then** ▷ An Amélioration has been found
10: $\mathbf{\Pi}^* \leftarrow \mathbf{\Pi}'$ ▷ Update best solution
11: **end if**
12: $\texttt{updateScore}(d, r, \mathbf{\Pi}')$ ▷ Update scores
13: **end for**
14: **return** $\mathbf{\Pi}^*$

différentes heuristiques (ligne 5). La solution obtenue est acceptée comme solution courante en fonction d'un critère de recuit simulé (ligne 6). À la fin de chaque itération, les scores des opérateurs de destruction et de réparation sont mis à jour en fonction de la solution qu'ils ont générée (ligne 12).

Cet algorithme a montré d'excellentes performances sur une grande variété de problèmes de tournées (Pisinger and Ropke, 2010), le rendant particulièrement intéressant dans l'optique de développer des approches génériques. Cependant, son caractère séquentiel fait qu'il n'utilise qu'une fraction des ressources disponibles sur la majorité des ordinateurs modernes. Par conséquent, nous proposons un schéma de parallélisation permettant d'utiliser au mieux ces ressources et de réduire ainsi les temps de calcul. L'algorithme proposé, ou recherche adaptive parallèle à voisinages larges pALNS, repose sur l'utilisation d'un ensemble de solutions prometteuses.

L'algorithme G.2 présente les grandes lignes de pALNS. L'algorithme maintient un ensemble $\mathcal{P}$ de N solutions prometteuses qui sont optimisées par K sous-processus (notez que $N \geq K$). Pour chaque *itération maître*, un sous-ensemble de K solutions prometteuses est choisi au hasard (ligne 2) et répartis entre les sous-processus indépendants. Chaque sous-processus exécute I^p ALNS itérations (lignes 3-14) en détruisant et en réparant la solution actuelle $\mathbf{\Pi}^p$ comme dans l'algorithme original ALNS. La solution finale actuelle de chaque sous-processus est ajoutée à l'ensemble de solutions prometteuses (ligne 13) et une procédure de filtrage assure que cet ensemble contient au plus N solutions, y compris la meilleure solution trouvée jusqu'alors (ligne 15). L'algorithme s'arrête après I^m itérations maitres, ce qui correspond à $I = I^m \times I^p$ itérations ALNS. Notez que l'implémentation de pALNS assure qu'aucune synchronisation n'est nécessaire entre les sous-processus pour éviter les deadlocks.

Le tableau G.2 présente les valeurs agrégées sur les 53 instances, avec dix tests par instance et 25000 itérations ALNS [1]. La première colonne correspond à l'algorithme séquentiel original (SEQ), et les suivantes aux implémentations parallèles avec de 1 à 8 threads. Les première et deuxième lignes

1. Pour que $I = I^m I^p K \simeq 25000$, nous avons utilisé $I^m = \lceil \frac{25000}{40K} \rceil$

Algorithm G.2 Parallel Adaptive Large Neighborhood Search (pALNS)

Input: $\mathcal{P}$ initial solutions, z evaluation function, Θ^-/Θ^+ set of destroy/repair operators, N maximum size of the solution pool, K number of subprocesses, I^m number of master iterations, I^p number of iterations performed in parallel.
Output: $\mathbf{\Pi}^*$, the best solution found

for I^m iterations **do**
  $\mathcal{P}' \leftarrow \texttt{selectSubset}\,(\mathcal{P}, K)$ ▷ Select a subset of K solutions
  parallel forall $\mathbf{\Pi}$ **in** $\mathcal{P}'$ **do**
    $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}$ ▷ Current solution for this subprocess
    for I^p iterations **do**
      $d \leftarrow \texttt{select}\,(\Theta^-)\,; r \leftarrow \texttt{select}\,(\Theta^+)$ ▷ Select destroy/repair
      $\mathbf{\Pi}' \leftarrow \texttt{r}\,(\texttt{d}\,(\mathbf{\Pi}^p))$ ▷ Destroy and repair current solution
      if $\texttt{accept}\,(\mathbf{\Pi}', \mathbf{\Pi}^p)$ **then**
        $\mathbf{\Pi}^p \leftarrow \mathbf{\Pi}'$ ▷ $\mathbf{\Pi}'$ is accepted as current solution
      end if
      $\texttt{updateScore}\,(d, r, \mathbf{\Pi}')$ ▷ Update d and r scores
    end for
    $\mathcal{P} \leftarrow \mathcal{P} \cup \{\mathbf{\Pi}^p\}$ ▷ Add $\mathbf{\Pi}^p$ to the pool $\mathcal{P}$
  end forall
  $\mathcal{P} \leftarrow \texttt{retain}\,(\mathcal{P}, N)$ ▷ Retain at most N solutions in the pool $\mathcal{P}$
end for
return $\mathbf{\Pi}^* = \arg\min_{\mathbf{\Pi} \in \mathcal{P}} \{z(\mathbf{\Pi})\}$

contiennent la moyenne et l'écart-type des écarts aux meilleures solutions connues ou solutions optimales. Enfin, les troisième et quatrième lignes indiquent la moyenne et l'écart type des temps de calcul. Notez que l'augmentation du nombre de threads a un impact limité sur l'écart avec les meilleures solutions connues, lequel est toujours autour de 0,6%, mais elle permet une réduction des temps d'exécution par un facteur 3,3.

		Parallèle - Nombre de Threads							
	Seq.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Ecart	0.74%	0.72%	0.55%	0.69%	0.54%	0.70%	0.52%	0.66%	0.48%
Ecart (dev. st.)	0.87%	0.88%	0.76%	0.89%	0.70%	0.86%	0.74%	0.82%	0.66%
Temps (s)	36.58	37.32	22.07	17.60	14.70	14.69	13.39	12.37	11.32
Temps (s, dev. st.)	6.27	6.33	4.06	3.17	2.72	2.57	2.50	2.27	2.15

TABLE G.2 – Comparaison de l'écart avec les meilleurs et temps de calcul pour différents niveaux de parallélisation.

La figure G.4 illustre l'approche de réoptimisation proposée : l'algorithme commence par produire une solution initiale S_0 en utilisant une heuristique constructive couplé avec l'algorithme pALNS décrit dans la section précédente. Ensuite, chaque fois qu'un nouveau client apparaît, il fixe la partie en cours d'exécution des tournées, et réexécute pALNS pour un nombre limité d'itérations pour produire une solution mise à jour S'_t. Si pALNS est capable d'insérer la demande de nouveaux clients, le client est *accepté* et S'_t devient la nouvelle solution courante, sinon le client est *rejeté* et S_t est maintenue comme solution actuelle.

Le tableau G.3 présente l'écart moyen entre la solution produite par la méthode de réoptimisation

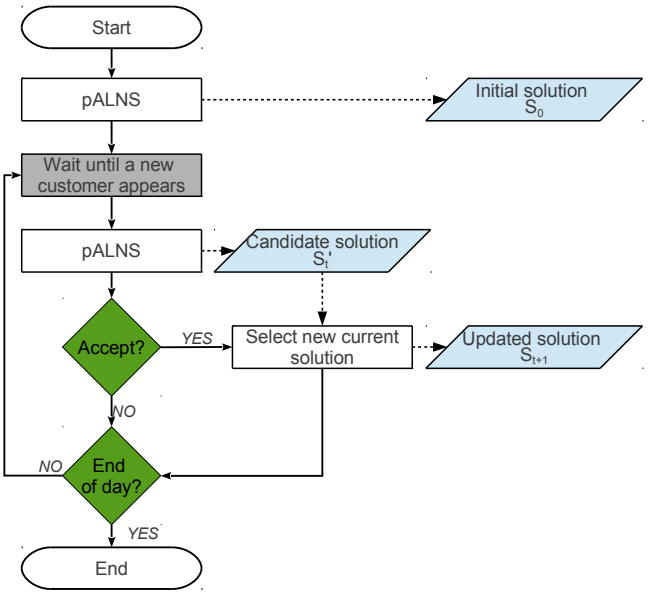


FIGURE G.4 – Approche de réoptimisation proposée

proposée et la solution optimale a-posteriori. Par ailleurs, le tableau G.4 compare l'approche proposée avec la méthode proposée par Lackner (2004) et celle présentée par Hong (2012). Ces résultats expérimentaux montrent que l'approche proposée produit des résultats proches de la solution optimale a-posteriori et meilleurs que ceux rapportés par les études précédentes.

δ	R1	C1	RC1	R2	C2	RC2	Moy.
10	2.05%	2.89%	3.06%	1.70%	1.66%	1.61%	**2.14%**
30	4.67%	5.83%	5.83%	4.34%	1.74%	4.70%	**4.54%**
50	6.41%	9.28%	9.03%	8.15%	2.82%	5.38%	**6.93%**
70	8.29%	11.18%	10.24%	10.17%	5.41%	8.60%	**9.03%**
90	9.33%	12.49%	11.84%	11.83%	6.51%	12.33%	**10.71%**

TABLE G.3 – Valeur de l'information moyenne pour les instances Lackner (2004)

G.2.2 Constance des tournées - une approche bi-objective

La plupart des études sur les tournées dynamiques considèrent que les tournées sont conçues en temps réel, ce qui signifie que les conducteurs de véhicules ne connaissent leur prochaine destination qu'à la fin du service du client actuel. Bien que cette hypothèse permette une meilleure optimisation de la fonction de coût, elle peut ne pas être souhaitable si les conducteurs sont habitués à connaître leurs itinéraires au début de la journée. Dans la pratique, avoir un ensemble de tournées connues a priori et ensuite modifiées peut être souhaitable. Il y a donc un besoin pour des approches capables de maintenir une cohérence dans les tournées des véhicules tout au long de la journée, tout en minimisant le coût total.

Les études sur les tournées dynamiques considèrent l'optimisation d'un critère unique, comme

		pALNS		Hong (2012)		Lackner (2004)	
Groupe	δ	**Dist.**	**Rej.**	**Dist.**	**Rej.**	**Dist.**	**Rej.**
R1	**10**	1197.4	0.25	1257.1 (4.99%)	0.17	1278.1 (6.74%)	0.47
	30	1212.9	0.80	1286.6 (6.08%)	0.58	1337.9 (10.30%)	0.72
	50	1225.0	1.25	1295.8 (5.78%)	0.67	1330.0 (8.57%)	0.78
	70	1237.3	1.71	1331.3 (7.60%)	1.75	1336.1 (7.98%)	0.94
	90	1230.1	2.55	1335.9 (8.60%)	2.33	1278.3 (3.92%)	0.75
C1	**10**	850.6	0.11	895.8 (5.31%)	0.22	996.4 (17.14%)	0.00
	30	874.9	0.11	962.1 (9.97%)	0.33	1066.9 (21.95%)	0.00
	50	903.4	0.11	1001.2 (10.82%)	0.22	1236.1 (36.82%)	0.00
	70	919.1	0.11	1031.7 (12.25%)	0.22	1261.3 (37.24%)	0.00
	90	929.9	0.11	1039.8 (11.81%)	0.22	1479.6 (59.11%)	0.00
RC1	**10**	1389.4	0.04	1436.2 (3.37%)	1.13	1426.9 (2.70%)	0.46
	30	1421.5	0.28	1492.2 (4.98%)	1.13	1439.7 (1.28%)	0.42
	50	1463.4	0.23	1514.7 (3.50%)	1.38	1448.1 (-1.05%)	0.46
	70	1470.1	0.58	1511.3 (2.80%)	1.88	1488.4 (1.25%)	0.58
	90	1495.5	0.51	1513.9 (1.23%)	2.00	1475.2 (-1.36%)	0.42
R2	**10**	893.0	0.00	950.0 (6.39%)	0.09	1052.9 (17.90%)	0.03
	30	915.6	0.00	985.5 (7.63%)	0.00	1085.4 (18.54%)	0.15
	50	948.6	0.00	1016.5 (7.17%)	0.00	1138.8 (20.05%)	0.21
	70	967.7	0.00	1032.0 (6.65%)	0.09	1116.9 (15.42%)	0.30
	90	981.7	0.00	1047.8 (6.73%)	0.09	1193.3 (21.55%)	0.52
C2	**10**	597.2	0.00	594.7 (-0.42%)	0.00	629.1 (5.35%)	0.00
	30	597.6	0.00	651.4 (9.01%)	0.00	632.3 (5.81%)	0.04
	50	604.0	0.00	605.0 (0.17%)	0.00	689.3 (14.12%)	0.13
	70	619.2	0.00	636.5 (2.79%)	0.00	743.8 (20.12%)	0.21
	90	625.7	0.00	636.8 (1.78%)	0.00	792.5 (26.66%)	0.29
RC2	**10**	1024.4	0.00	1103.3 (7.70%)	0.00	1220.9 (19.18%)	0.00
	30	1053.1	0.00	1166.0 (10.73%)	0.25	1244.9 (18.21%)	0.04
	50	1060.5	0.00	1190.5 (12.26%)	0.13	1244.9 (17.38%)	0.00
	70	1091.4	0.00	1239.5 (13.57%)	0.00	1269.3 (16.30%)	0.00
	90	1130.3	0.00	1257.2 (11.23%)	0.13	1346.8 (19.16%)	0.13
Moyenne			**0.29**	**(+6.75%)**	**0.50**	**(+15.61%)**	**0.27**

TABLE G.4 – Comparaison des approches pour les instances Lackner (2004).

la minimisation de la distance totale parcourue ou la maximisation du nombre de clients desservis. D'autre part, un nombre croissant d'études sur les tournées statiques prend en compte des objectifs multiples dans le but de mieux répondre aux différents contextes opérationnels (Jozefowiez et al., 2008).

Dans cette section, nous présentons une étude préliminaire qui prend en compte la gêne des conducteurs. L'approche proposée est une adaptation de l'algorithme pALNS qui minimise simultanément une fonction de coût et maximise la constance des tournées tout au long de la journée. Les résultats expérimentaux préliminaires montrent que pour les instances faiblement dynamiques il semble intéressant de favoriser la constance des tournées, alors que pour les instances fortement dynamiques il est plus profitable de ne considerer que la minimisation de la fonction de coût.

Référence de l'article présenté dans ce chapitre :
- Pillac, V., Guéret, C., and Medaglia, A. L. (2012) A fast re-optimization approach for dynamic vehicle routing Technical report, École des Mines de Nantes, France. Report 12/6/AUTO.

Des résultats préliminaires sur le cas bi-objectifs ont été présentés à la conférence ROADEF 2012 :
- Pillac, V., Guéret, C., and Medaglia, A. L. (2012) Route stability in dynamic vehicle routing : a bi-objective approach In *ROADEF 2012*, Angers, France.

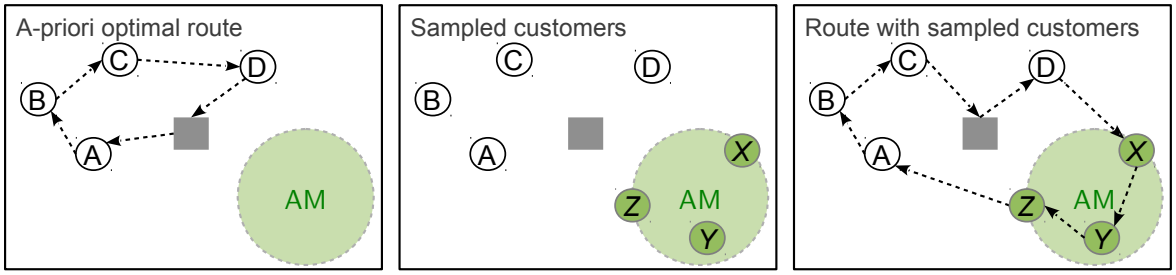
G.3 Tournées dynamiques et stochastiques

Dans les problèmes de tournées dynamiques et stochastiques, tout ou partie des données n'est pas connue initialement et est révélée dynamiquement au cours de l'exécution des tournées. Cependant, à la différence des problèmes dynamiques et déterministes, des informations stochastiques exploitables sont disponibles et permettent de prévoir les changements. Notre accent étant mis sur le développement de composants logiciels qui peuvent être utilisés pour une large gamme d'applications, nous avons choisi de développer un framework (`jMSA`) orienté évènements basé sur l'approche multiples scénarios MSA (Multiple Scenario Approach) proposé par Van Hentenryck and Bent (2006). Dans ce chapitre, nous présentons le framework `jMSA`, son implémentation, puis nous illustrons la validité de cette approche en abordant le problème de tournées dynamiques avec demandes stochastiques (D-VRPSD).

G.3.1 Multiple Scenario Approach

MSA est une méthode de réoptimisation continue qui capture l'incertain en générant des scénarios ensuite utilisés pour prendre les décisions.

La figure G.5 illustre la génération d'un scénario. En ne considérant que les clients connus actuellement (G.5a.) la tournée optimale a-priori s'éloigne d'une région où des clients sont susceptibles d'apparaître en début de matinée (zone verte). L'échantillonnage (G.5b.) génère des clients fictifs dans cette zone et permet d'orienter l'optimisation vers une tournée qui visite en premier cette région (G.5c.). Une fois un nombre suffisant de scénarios généré, une procédure de décision est utilisée pour agréger l'information contenue dans chacun des scénario afin de prendre des décisions qui tiennent compte de la stochasticité du problème.



a. Tournées a-priori b. Echantillonage c. Tournées résultantes

FIGURE G.5 – Génération de scenarios dans MSA

G.3.2 Framework proposé

La figure G.6 présente une vue d'ensemble du framework proposé. Le composant central est `MSA-Procedure` qui contient la logique générale de la méthode, et dont les paramètres sont définis dans `GlobalParameters`. Notre implémentation repose sur une file d'évènements `EventQueue`. La procédure principale extrait le premier évènement de la file et sélectionne le *handler* correspondant dans le `EventHandlerManager`. Le handler contient la logique nécessaire au traitement de l'évènement à un niveau indépendant du problème considéré. Afin d'assurer la généricité du framework, la logique spécifique à un problème est déléguée aux implémentations des différents composants, lesquels sont gérés par le `ComponentManager`. Dans cet exemple, la logique relative à la génération d'un scenario est définie par la classe concrète `DVRPScenarioGenerator`, qui implémente l'interface `Scenario Generator`. Enfin, un système de *callbacks* permet à l'utilisateur d'interagir avec la méthode sans devoir modifier le code du framework, via le `CallbackManager` et des implémentations de l'interface `Callback`.

Un aspect important du framework est la parallélisation transparente des opérations les plus exigeantes en temps de calcul. La figure G.7 illustre les interactions entre threads (fils d'exécution) dans le framework `jMSA`. À l'instant t_0, le thread MSA défile un évènement `OptimizePool`, et le traite avec le handler `OptimizeHandler` correspondant. En parallèle du thread MSA, deux nouveaux threads sont créés par le `ComponentManager` pour optimiser les scénarios. À l'instant t_1, un évènement préemptif `NewCustomer` et un évènement `Decision` sont enfilés par l'environnement, causant l'arrêt prématuré de l'optimisation. Enfin, la procédure défile et traite l'évènement `NewCustomer`, lequel a une priorité plus élevée que l'évènement `Decision`.

G.3.3 Résultats expérimentaux

La différence fondamentale entre le VRP classique et le VRP avec demandes stochastiques (VRPSD) est que dans ce dernier les demandes des clients sont modélisées par des variables aléatoires. Le caractère aléatoire du VRPSD implique que la réalisation de la demande des clients peut dépasser la capacité restante du véhicule, conduisant à l'échec de la tournée. Il est important de souligner que, dans ce contexte, tous les clients sont connus à l'avance et la seule information révélée dynamique est la réalisation de la demande des clients. Le VRPSD dynamique (D-VRPSD) est une extension du VRPSD dans laquelle il est possible de rediriger les véhicules librement suivant la réalisation des demandes.

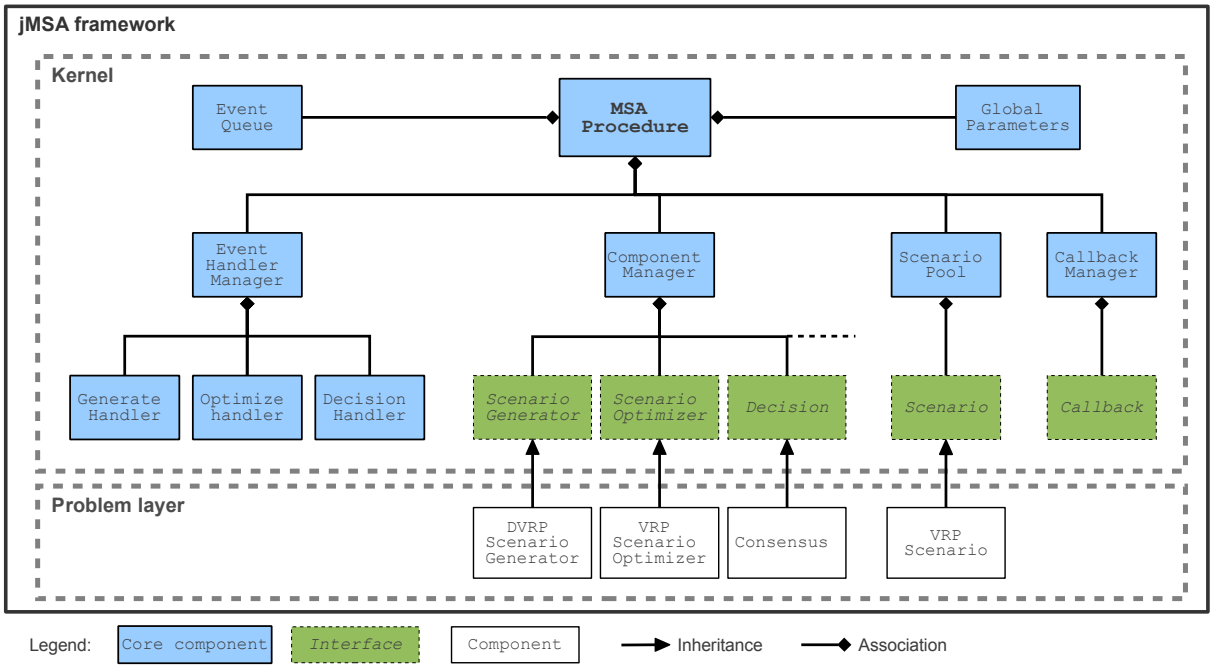


FIGURE G.6 – Vue d'ensemble du framework `jMSA`

La littérature sur le D-VRPSD est limitée, avec comme contributions principales les études de Novoa (2005), Novoa and Storer (2009), Secomandi (2001), et Secomandi and Margot (2009).

	Groupee d'instances (taille,capacité)						
Algorithme	**(30,137)**	**(30,87)**	**(40,183)**	**(40,116)**	**(60,274)**	**(60,175)**	**Moyenne**
1s_n2_r (Secomandi, 2001)	12.3%	11.8%	11.1%	12.9%	13.9%	19.6%	13.6%
1s_stostat_r (Novoa and Storer, 2009)	4.7%	5.1%	3.7%	**5.3%**	3.5%	12.3%	5.8%
2s_stostat_r (Novoa and Storer, 2009)	3.5%	**3.6%**	**3.0%**	5.4%	**2.8%**	10.7%	4.8%
`jMSA`	**0.9%**	4.1%	3.5%	6.3%	2.9%	**2.0%**	**3.3%**

TABLE G.5 – Comparaison des valeurs d'information moyennes.

Le tableau G.5 présente les résultats pour les 30 instances de référence proposées par Novoa (2005), chaque colonne représentant la moyenne sur 500 essais (100 essais pour chacune des 5 instances avec la même taille et la même capacité). MSA domine l'algorithme proposé par Secomandi (2001) (1s_n2_r), et surpasse les meilleurs algorithmes rapportés par Novoa and Storer (2009) (1s_stostat_r, 2s_stostat_r) pour les instances avec 30 et 60 clients et une capacité de 137 véhicules et 175. En outre, la MSA montre de meilleurs résultats globaux avec un écart moyen de 3,3% contre 4,8 % pour 2s_stostat_r, 5,8 % pour 1s_stostat, et 13,6 % pour 1s_n2_r. Mises à part les performances en termes de valeur de l'information, il est important de souligner que MSA fonctionne en continu, et le prochain client à visiter est sélectionné en une fraction de seconde, tandis que les autres algorithmes peuvent prendre jusqu'à plusieurs minutes pour prendre une telle décision, ce qui limite leur déploiement et leur applicabilité dans un système d'aide à la décision.

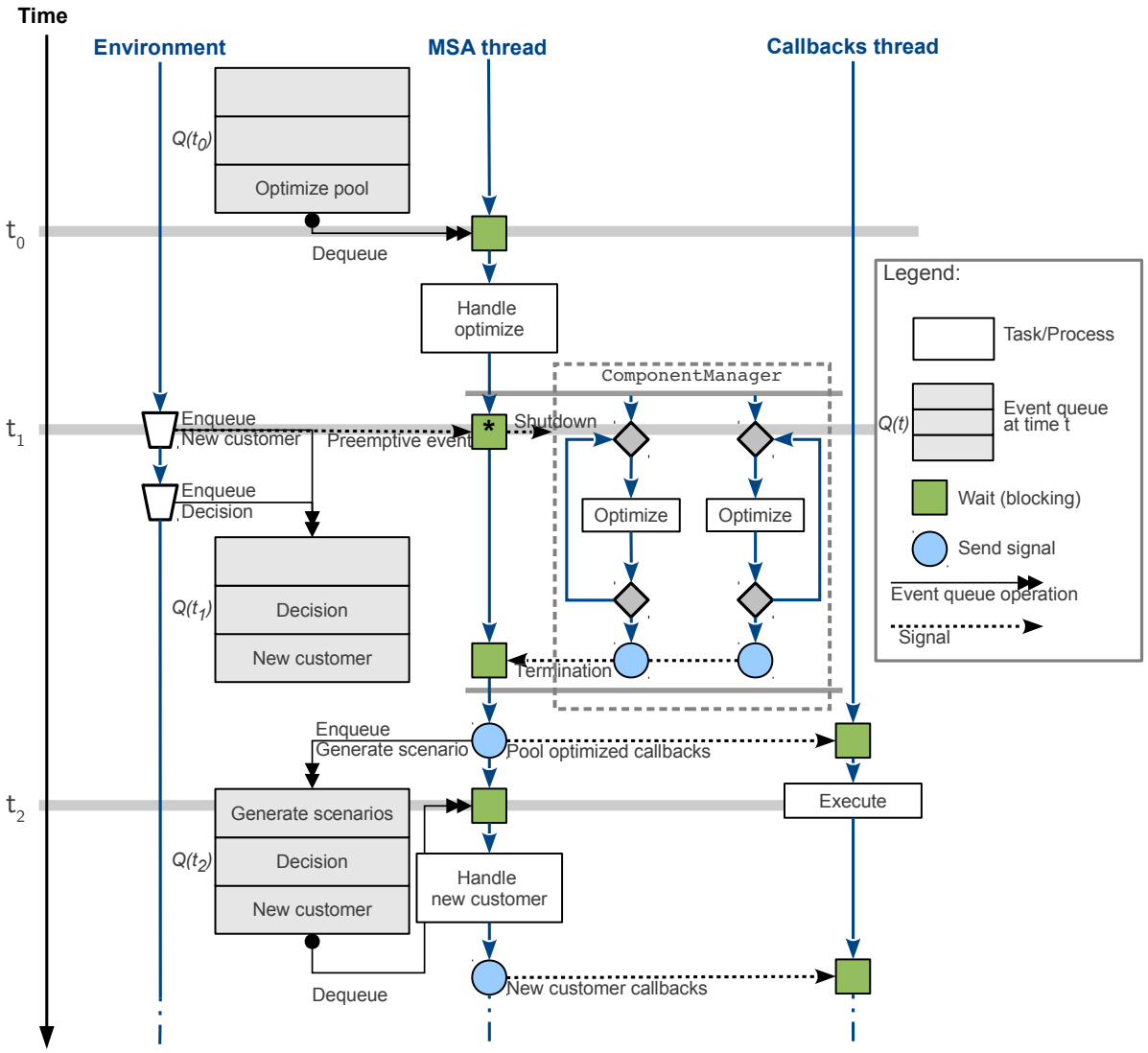


FIGURE G.7 – Parallelisation dans `jMSA`

Référence de l'article présenté dans ce chapitre :

– Pillac, V., Guéret, C., and Medaglia, A. L. (2012) An event-driven optimization framework for dynamic vehicle routing *Decision Support Systems*, Accepted manuscript doi :10.1016/j.dss.2012.06.007.

Une version précédente de cet article a été publiée comme rapport technique :

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011) An event-driven optimization framework for dynamic vehicle routing Technical report, École des Mines de Nantes, France. Report 11/2/AUTO.

Des résultats préliminaires ont été présentées dans deux conférences :
- Pillac, V., Guéret, C., and Medaglia, A. L. (2011) A dynamic approach for the vehicle routing problem with stochastic demands In *ROADEF 2011*, St Etienne, France.
- Pillac, V., Guéret, C., and Medaglia, A. L. (2010) Solving the vehicle routing problem with stochastic demands with a multiple scenario approach
  In *ALIO-INFORMS 2010*, Buenos Aires (Argentina).

G.4 Application au problème de tournées de techniciens

Les deux articles présentées dans ce chapitre sont motivés par un problème d'optimisation réel présenté par un partenaire industriel. Cette société fournit des solutions logicielles à destination d'organisations gèrant une équipe de techniciens pour servir un ensemble de requêtes distribuées géographiquement. Ces requêtes peuvent être soit statiques soit dynamiques. Les requêtes statiques sont connues à l'avance et correspondent aux rendez-vous avec des clients ou des opérations de maintenance préventive. Les demandes dynamiques apparaissent dynamiquement tout au long de la journée et sont, par exemple, les situations d'urgence ou des opérations de maintenance corrective. Les requêtes peuvent nécessiter un technicien avec des compétences différentes, un certain ensemble d'outils, et un certain nombre de pièces de rechange. En outre, les techniciens commencent et terminent généralement leur journée à leur domicile, et peuvent visiter un dépôt central pour récupérer des outils et des pièces de rechange. Enfin, les objectifs comprennent la minimisation de la distance parcourue, la minimisation du temps de travail, l'équilibrage de la charge de travail entre les techniciens, et la minimisation des violations de contraintes.

A partir de cette application pratique, nous avons introduit un nouveau problème d'optimisation, à savoir, le problème de planification de tournées de technicien (TRSP - Technician Routing and Scheduling Problem) qui considère une équipe de techniciens $\mathcal{K}$ qui sert un ensemble de requêtes $\mathcal{R}$. Le TRSP peut être vu comme une extension du problème de tournées de véhicules avec fenêtres de temps (VRPTW), où les techniciens jouent le rôle de véhicules et les requêtes sont faites par les clients. Comme illustré par la figure G.8, dans le TRSP, chaque technicien dispose d'un ensemble de compétences, d'outils et de pièces de rechange, tandis que les requêtes nécessitent un sous-ensemble de chaque. Le problème est alors de concevoir un ensemble de tournées tels que chaque requête soit visitée dans sa fenêtre de temps, par un technicien ayant les compétences, outils, et pièces de rechange requises.

Un trait distinctif de ce problème est qu'il introduit plusieurs contraintes de compatibilité entre les techniciens et les demandes. Si les compétences sont des attributs intrinsèques, les techniciens peuvent disposer de différents outils et pièces de rechange sur l'horizon de planification. Les techniciens commencent leur tournée à leur domicile, avec un ensemble d'outils (ressources renouvelables) et de pièces de rechange (consommées une fois que le technicien sert une requête) qui leur permettent de servir une première série de requêtes. Les techniciens ont alors l'opportunité de renouveler leurs outils et pièces de rechange dans un dépôt central à tout moment pour servir plus de requêtes.

Le TRSP se pose naturellement dans une large gamme d'applications, avec entre autres les télécommunications, les services publics, et les opérations de maintenance. Cependant ce problème n'a

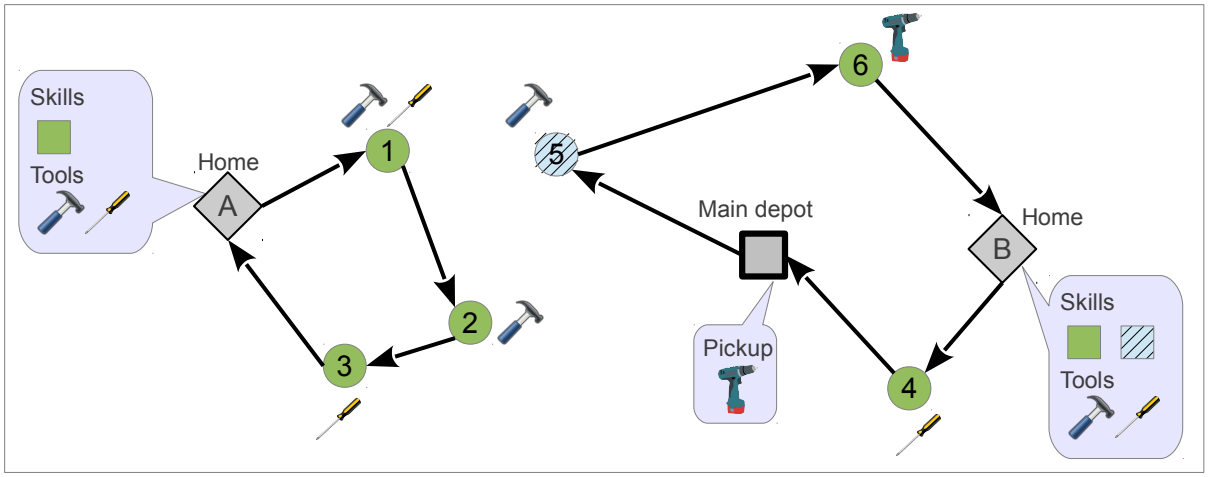


FIGURE G.8 – Exemple d'un problème de tournées et planification de techniciens.

reçu que peu d'attention jusqu'à récemment, et les compétences, les outils, les pièces de rechange, et l'arrivée de nouvelles demandes, trois composantes importantes des applications réelles, n'ont pas été simultanément prises en compte. L'article de la section G.4.1 introduit une matheuristique parallèle capable de résoudre le TRSP statique, tandis que l'article de la section G.4.2 présente deux approches pour attaquer le TRSP dynamique

G.4.1 Cas statique

La matheuristique proposée pour résoudre le TRSP est basée sur l'algorithme pALNS présenté dans la section G.2.1, couplé avec un problème de recouvrement (SC - Set Covering) qui permet d'assembler une solution à partir des tournées trouvées tout au long de l'exécution de pALNS. Le tableau G.6 présente des résultats expérimentaux sur les instances du VRPTW de Solomon (1987), et illustre la performance de l'approche proposée qui est capable d'atteindre un écart de seulement 0,23% en moins de 30s en moyenne.

	Amélioration		**Ecart MSC/Opt**		**Meilleures solutions**		**Temps (s)**		
Groupe	Δ_{pALNS}	Δ_{SC}	pALNS	pALNS+SC	#Opt.	#MSC	pALNS	SC	$\|\Omega\|$
C1	37.89%	0.00%	0.00%	0.00%	9/9	-	14.6	0.4	11550
C2	26.41%	0.02%	0.02%	0.00%	8/8	-	26.5	0.2	3479
R1	24.28%	0.44%	0.59%	0.14%	10/12	-	13.1	27.2	27303
R2	32.21%	0.25%	0.76%	0.51%	5/10	1/1	24.5	2.1	14161
RC1	25.06%	1.21%	1.38%	0.15%	6/8	-	12.6	25.1	25327
RC2	36.56%	0.43%	0.99%	0.55%	6/8	-	21.3	1.3	11822
Total	**30.20%**	**0.38%**	**0.62%**	**0.23%**	**44/55**	**1/1**	**18.6**	**10.1**	**16293**

TABLE G.6 – Résultats expérimentaux pour les instances de Solomon (1987) (moyenne sur 10 essais), MSC : meilleures solutions connues, Opt : solutions optimales..

Par ailleurs, le tableau G.7 présente les résultats expérimentaux pour un ensemble de 56 instances du TRSP générées aléatoirement à partir des instances de Solomon (1987). Les résultats mettent en évidence l'apport de la post-optimisation (SC) qui permet de réduire l'écart de 1.7% en moyenne. Il est

également à noter que les temps de calcul pour la post-optimisation (SC) sont nettement supérieurs à ceux observés pour le VRPTW, ce qui peut être attribué à des contraintes additionnelles dans le problème de recouvrement.

	Amélioration	**Ecart MSC**		**Temps (s)**		
Groupe	Δ_{SC}	pALNS	pALNS+SC	pALNS	SC	$\|\Omega\|$
C1	0.97%	1.22%	0.23%	24.0	388.9	67020
C2	0.35%	0.78%	0.42%	27.8	23.6	39334
R1	3.62%	4.96%	0.82%	28.9	500.2	30783
R2	0.23%	1.69%	1.46%	31.0	42.1	24396
RC1	3.06%	3.90%	0.68%	27.9	185.8	18638
RC2	0.49%	1.93%	1.43%	27.9	15.6	16917
Total	**1.53%**	**2.54%**	**0.86%**	**28.1**	**210.1**	**32858**

TABLE G.7 – Résultats expérimentaux pour 56 instances générées aléatoirement.

Référence de l'article présenté dans ce chapitre :

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011) A parallel matheuristic for the technician routing and scheduling problem *Optimization Letters*, Accepted manuscript, doi :10.1007/s11590-012-0567-4.

Des résultats préliminaires de ce travail ont été présentés à la conférence MIC 2011 :

– Pillac, V., Guéret, C., and Medaglia, A. L. (2011) On the technician routing and scheduling problem In Di Gaspero, L., Schaerf, A., and Stützle, T., editors, *Proceedings of the 9th Metaheuristics Conference (MIC 2011)*, pages 675–678. Università degli Studi di Udine.

G.4.2 Cas dynamique

Nous avons traité le cas dynamique du TRSP avec trois approches : la réoptimisation rapide basée sur pALNS proposée dans la section G.2.1 ; une approche par plans multiples MPA (Multiple Plan Approach), qui est une réduction au cas déterministe de MSA, implémentée dans le framework `jMSA` ; et une heuristique simple (regret-3) permettant de modéliser le comportement d'un preneur de décision humain.

	pALNS		**MPA**		**regret-3**	
δ	**Ecart (%)**	**Rej.**	**Ecart (%)**	**Rej.**	**Ecart (%)**	**Rej.**
10	2.4	0.1	9.1	1.9	10.5	0.3
30	5.4	0.1	11.0	4.6	30.5	0.4
50	10.8	0.3	14.4	5.6	44.1	1.0
70	11.8	0.2	21.3	8.7	57.5	1.2
90	17.9	0.4	23.9	8.1	64.1	1.4
Moy.	**9.7**	**0.2**	**16.1**	**5.9**	**41.3**	**0.8**

TABLE G.8 – Ecart moyen avec la solution a-posteriori et nombre de requêtes rejetées (Rej.) pour les instances du D-TRSP en minimisant la distance totale.

Le tableau G.8 présente une comparaison de ces trois méthodes. Il apparaît que pALNS domine clairement les deux autres approches tant en termes d'écart avec la solution a-posteriori, qu'en termes de nombre de requêtes rejetées. Il est à noter cependant que les résultats de MPA sont à un stade préliminaire, et donc perfectibles.

Référence de l'article présenté dans ce chapitre :

- Pillac, V., Guéret, C., and Medaglia, A. L. (2011) On the dynamic technician routing and scheduling problem Technical report 12/5/AUTO.

Des travaux préliminaires ont été présentés aux conférences suivantes :

- Pillac, V., Guéret, C., and Medaglia, A. L. (2012) A Multiple Plan Approach for the Dynamic Technician Routing and Scheduling Problem In *25th European Conference on Operational Research (EURO 2012)*, Vilnius, Lithuania.
- Pillac, V., Guéret, C., and Medaglia, A. L. (2012) On the dynamic technician routing and scheduling problem In *Proceedings of the 5th International Workshop on Freight Transportation and Logistics (ODYSSEUS 2012)*, Mykonos, Greece.

G.5 Conclusions

Les progrés technologiques récents fournissent aux organisations les outils adaptés pour gérer leur flotte en temps réel. Cependant, ces nouvelles technologies introduisent également plus de complexité dans la gestion des flottes de véhicules, révélant un besoin pour des systèmes d'aide à la décision dédiés aux problèmes de tournées de véhicules dynamiques. Dans ce contexte, les contributions de la présente thèse sont les suivantes : premièrement, nous avons présenté une étude exhaustive de la littérature ; deuxièmement, nous avons conçu, implémenté, et rendu publiques des frameworks d'optimisation à la fois flexibles et extensibles capables de traiter une grande variété de problèmes de tournées dynamiques ; et troisièmement, nous avons défini et attaqué un problème de tournées rencontré par un partenaire industriel.

Nous estimons que les travaux futurs devraient se centrer autour du développement d'approches de réoptimisation continue simples et flexibles, par exemple en étendant l'algorithme pALNS présenté dans cette thèse. Il serait également intéressant de trouver des stratégies pour limiter la complexité des problèmes d'optimisation sous-jacents, par exemple en mettant plus d'effort sur l'optimisation du futur proche, ou en éliminant des scénarios trop pessimistes. Enfin, une attention particulière devrait être mise sur la conception de nouvelles procédures permettant de consolider l'information contenue dans un ensemble de scénarios pour prendre de meilleurs décisions en un temps plus court.

La gestion en temps réel d'une flotte de véhicules soulève de nombreux problèmes, tant théoriques que pratiques, et nécessite le développement d'algorithmes rapides et efficaces. Bien que ce domaine ait reçu un intérêt croissant au cours des dernières décennies, il existe toujours de nombreuses opportunités de recherche et nous espérons que la présente thèse sera une source de réflexion pour des travaux futurs.

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PÔLE DE RECHERCHE ET D'ENSEIGNEMENT SUPÉRIEUR

Universidad de los Andes

ECOLE DES MINES DE NANTES

Thèse de Doctorat

Victor Pillac

Dynamic vehicle routing:
solution methods and computational tools

Méthodes de résolution et outils informatiques
pour les tournées de véhicules dynamiques

Résumé

Les activités de transport jouent un rôle crucial autant dans le domaine de la production que dans celui des services. En particulier, elles permettent d'assurer la distribution de biens et de services entre fournisseurs, unités de production, entrepôts, distributeurs, et clients finaux. Plus spécifiquement, les problèmes de tournées de véhicules (VRP) considèrent la mise au point d'un ensemble de tournées de coût minimal servant la demande en biens ou en services d'un ensemble de clients distribués géographiquement, tout en vérifiant un ensemble de contraintes opérationnelles. Alors qu'il s'agissait d'un problème statique, des avancées technologiques récentes permettent aux organisations de gérer leur flotte de véhicules en temps réel. Cependant, ces nouvelles technologies introduisent également une plus grande complexité dans les tâches de gestion de flotte, révélant une demande pour des outils d'aide à la décision dédiés aux problèmes de tournées de véhicules dynamiques. Dans ce contexte, les contributions de la présente thèse de doctorat s'organisent autour de trois axes : (i) elle présente un état de l'art détaillé des problèmes de tournées dynamiques ; (ii) elle introduit des frameworks d'optimisation génériques adaptés à une grande variété de problèmes ; (iii) elle définit un problème de tournées novateur et aux nombreuses applications.

Mots clés

Tournées de véhicules dynamiques ; optimisation bi-objectif ; optimisation combinatoire en temps réel ; tournées de techniciens

Abstract

Within the wide scope of logistics management, transportation plays a central role and is a crucial activity in both production and service industry. Among others, it allows for the timely distribution of goods and services between suppliers, production units, warehouses, retailers, and final customers. More specifically, Vehicle Routing Problems (VRPs) deal with the design of a set of minimal-cost routes that serve the demand for goods or services of a set of geographically spread customers, satisfying a group of operational constraints. While it was traditionally a static problem, recent technological advances provide organizations with the right tools to manage their vehicle fleet in real time. Nonetheless, these new technologies also introduce more complexity in fleet management tasks, unveiling the need for decision support systems dedicated to dynamic vehicle routing. In this context, the contributions of this Ph.D. thesis are threefold : (i) it presents a comprehensive review of the literature on dynamic vehicle routing ; (ii) it introduces flexible optimization frameworks that can cope with a wide variety of dynamic vehicle routing problems ; (iii) it defines a new vehicle routing problem with numerous applications.

Key Words

Dynamic vehicle routing ; bi-objective optimization ; online combinatorial optimization ; optimization framework ; technician routing and scheduling ; open source