Opportunistic predictive maintenance for multi-component systems with multiple dependences

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Opportunistic Predictive Maintenance for Multi-Component Systems with Multiple Dependences

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Abstract

Recently, maintenance modeling for multi-component systems with dependences (economic, stochastic, and/or structural dependences) has been extensively studied. However, most of the existing studies only consider one type of dependence since combining more than one makes the models too complicated to analyze and solve. However, in practice, several types of dependences, especially, the economic and structural dependences, may exist together in the system. To face this issue, the main objective of this thesis is to consider both economic and structural dependences in maintenance modeling and optimization for multi-component systems in framework of predictive maintenance. For this purpose, the impacts of economic and structural dependences on the maintenance cost, duration and the degradation process of the components are firstly investigated. Mathematical models for quantifying the impacts of the economic and structural dependences are then developed. Finally, a multi-level opportunistic maintenance policy is proposed to consider the impacts of these dependences between components. To evaluate the performance of the proposed maintenance policy, a cost model is developed. Particle swarm optimization algorithm is then implemented to find the optimal decision variables. Finally, the proposed opportunistic maintenance policy is illustrated through a conveyor system to show its feasibility and added value in maintenance optimization framework.

Keywords : Predictive maintenance; multi-component system; economic dependence; structural dependence; opportunistic maintenance; particle swarm optimization algorithm.

Résumé

De nombreux travaux en maintenance prédictive de systèmes multi-composants avec des dépendances (économiques, stochastiques et/ou structurelles) entre composants ont été récemment faits. Cependant, la plupart des modèles de maintenance prédictive existants ne permettent de prendre en compte qu'un seul type de dépendances. Cependant, dans les cas réels de systèmes industriels, plusieurs types de dépendances peuvent exister ensemble, notamment les dépendances économiques et structurelles. L'objectif de cette thèse est d'intégrer les dépendances économiques et structurelles dans le processus de modélisation de la dégradation et le processus de décision en maintenance d'un système à composants multiples dans le cadre de la maintenance prédictive. Plus précisément, cet objectif repose sur deux axes scientifiques majeurs. Le premier consiste à étudier l'impact des dépendances structurelles et économiques sur le processus de dégradation des composants et les coûts de maintenance. Le deuxième a pour objet d'intégrer les impacts des dépendances économiques et structurelles dans les processus de décision et d'optimisation de la maintenance. Face à ces problématiques, nous avons proposé trois contributions principales : (1)-Formalisation et proposition de modèles mathématiques permettant de modéliser les dépendances structurelles et économiques entre composants; (2)-Développement d'un modèle de dégradation considérant les impacts de la dépendance structurelle entre composants; (3)-Développement d'une politique de maintenance prédictive opportuniste adaptée permettant de prendre en considération les impacts ces dépendances. Enfin, pour évaluer la faisabilité et la valeur ajoutée ainsi que les limites des modèles proposées dans un cadre d'optimisation de la maintenance, une étude numérique sur un convoyeur industriel est investiguée.

Mots clés : Maintenance prédictive ; maintenance opportuniste ; système à composants multiples ; dépendance économique ; dépendance structurelle ; optimisation par essaims particulaires.

Notations

n	Number of components
$R_s(t)$	Reliability of the system at time *t*
$R_i(t)$	Reliability of component *i* at time *t*
$X_i(t)$	Degradation level of component *i* at time *t*
$X_{Hi}(t)$	Degradation level of component *i* at time *t* considering the disassembly impact
x_i^z	Degradation level of component *i* at the z^{th} inspection
$\Delta X_i(t-s)$	Increment of degradation level of component *i* between two successive times *t* and *s*
L_i	Failure threshold of component *i*
α	Scale parameter of the gamma process
β	Shape parameter of the gamma process
$\Gamma(.)$	Gamma function
$\Phi(.)$	Mathematical expression of cumulative distribution function of the standard normal distribution
C_i^p	Preventive maintenance cost of component *i*
C_i^c	Corrective maintenance cost of component *i*
c^s	Maintenance setup cost
c_i^p	Specific preventive maintenance cost of component *i*
c_i^d	Downtime cost of component *i*
c^d	Downtime cost rate
τ_i	Maintenance duration of component *i*
τ_i^r	Replacement duration of component *i*
τ_i^d	Cumulative disassembly duration of component *i*

τ_i^{pd}	Disassembly duration of component i without considering disassembly of other components
c_i^c	Specific corrective maintenance cost of component i
c^{lost}	Loss cost due to the performance loss caused by the system failure
G^z	Group of components to be maintained at the z^{th} inspection
$\lvert G^z \rvert$	The number of components in group G^z
$G_{CM/PM}^z$	Group of components needs CM and/or PM at the z^{th} inspection
G_{eOM}^z	Group of components are selected for eOM
G_{sOM}^z	Group of components are selected for sOM
C_{G^z}	Total maintenance cost of a group of components G^z
Ω_D	Subset of components
$\Delta\tau_{G^z}$	the total maintenance duration saving when group components G^z are maintained together
D	Disassembly matrix
H_i	Amount of damage on component i due to disassembly operations impact
k_i	Component property coefficient of component i
θ_i	Adjustment factor taking into account the impact of degree of expertise of maintenance technician and the suitability of methods/tools used to perform the disassembly operations of the component i
z	Occurrence of periodic inspection
T_z	Time at the z^{th} inspection
τ	Inspection interval
R_p	Preventive maintenance threshold
eR_o	Economic dependence-based opportunistic maintenance threshold
sR_o	Structural dependence-based opportunistic maintenance threshold
$\Delta R\ (T_{z+1} \lvert i)$	System's reliability at time T_{z+1} when component i is maintained at time T_z
t_{down}	Cumulative maintenance downtime of the system
$C_\infty(\tau, R_p, eR_o, sR_o)$	Long run maintenance cost rate
$C_\infty^*(\tau^*, R_p^*, eR_o^*, sR_o^*)$	Optimal long run maintenance cost rate
$C^t(\tau, R_p, eR_o, sR_o)$	Cumulative maintenance cost of the system within the period $(0, t]$

Résumé de la thèse

La maintenance peut être définie comme un «ensemble de toutes les actions techniques, administratives et de management durant le cycle de vie d'un bien, destinées à le maintenir ou à le rétablir dans un état dans lequel il peut accomplir sa fonction requise » (BS-EN-13306-2010 Maintenance terminology). A travers cet objectif, la maintenance joue un rôle important pour garantir le bon fonctionnement d'un bien et plus précisément d'un système comme c'est le cas pour les systèmes industriels de production de biens ou de services (Maintenir en condition opérationnelle – MCO). Cependant, le coût de la maintenance peut prendre une part importante (15 à 60%) du coût global d'exploitation des systèmes production qui varie en fonction du domaine applicatif considéré (D. S. Thomas, 2018). Par conséquent, la minimisation du coût de maintenance est un challenge important qui doit permettre d'augmenter la compétitivité ainsi que la productivité des entreprises industrielles. À cette fin, plusieurs politiques de maintenance ont été développées au cours des dernières décennies, allant de politiques simples telles que la maintenance corrective (FBM-Failure-Based Maintenance) ou la maintenance préventive basée sur le temps / maintenance systématique (TBM-Time-Based Maintenance) à des politiques plus avancées telles que la maintenance conditionnelle (CBM-Condition-Based Maintenance) et plus récemment la maintenance prédictive (PdM-Predictive Maintenance) (Horenbeek, 2013).

Parmi ces politiques de maintenance, la PdM est la politique la plus « sophistiquée », par l'intégration des résultats d'un pronostic de défaillance (ex., à quel moment et avec quelle probabilité une panne se produira !) dans le processus de prise de décision en maintenance (Ran et al., 2019; Schmidt & Wang, 2015). Dans cette optique, la PdM peut aider à planifier plus efficacement (en tirant profit des opportunités offertes par l'anticipation) les actions de maintenance au bon moment, juste avant la panne, réduisant ainsi les coûts de maintenance et les temps d'arrêt du système. Cependant, cette maintenance n'est pas simple à mettre en œuvre surtout sur des systèmes de plus en plus complexes comme les nouveaux systèmes de production de type Cyber-Physiques où à la partie Physique du composant est associée une vision digitale supportée par les technologies de l'Industrie 4.0. Ces systèmes sont donc structurés autour de plusieurs composants interdépendants amenant à considérer ces exigences de dépendances dans le développement des politiques de maintenance avancées.

Généralement, les dépendances entre composants peuvent être classées en trois catégories principales : les dépendances économiques, stochastiques et/ou structurelles (Keizer et al., 2017; Nicolai & Dekker, 2008):

- La dépendance économique implique que l'exécution simultanée de la maintenance sur plusieurs composants peut être moins chère (dépendance positive) ou plus chère (dépendance négative) que de les maintenir séparément ;
- La dépendance stochastique se produit dans une situation lorsque l'état (discret ou correspondant à un niveau de dégradation) d'un composant peut influencer l'état ou la distribution de durée de vie d'autres composants ;
- La dépendance structurelle implique que des composants du système sont interconnectés (ex. selon une structure mécanique donnée pour supporter une ou plusieurs fonctions) de telle sorte que la maintenance d'un ou de plusieurs composants nécessite le démontage des autres composants.

Au global, les dépendances entre composants influencent de manière significative le processus de dégradation des composants ainsi que le processus de prise de décision en maintenance (Bian & Gebraeel, 2014; Do, Scarf, et al., 2015; Keizer et al., 2017). En ce sens, la non prise en compte des dépendances entre composants dans la modélisation de la maintenance pourrait entraîner des surcoûts de maintenance et un planning de maintenance sous-optimal (Keizer et al., 2017; Nicolai & Dekker, 2008). En lien avec ces considération de nombreux travaux en maintenance prédictive de systèmes multi-composants avec des dépendances entre composants ont été récemment faits (Dekker et al., 1997; Keizer et al., 2017; Nicolai & Dekker, 2008).

Cependant, la plupart des modèles de maintenance prédictive existants ne permettent de prendre en compte qu'un seul type de dépendances, car la considération de plusieurs dépendances entraîne une complexité plus importante lors de la modélisation de la dégradation mais aussi la formalisation des processus de décision et d'optimisation de la maintenance (Nicolai & Dekker, 2008; Van Horenbeek & Pintelon, 2013). Cependant, dans les cas réels de systèmes industriels, plusieurs types de dépendances peuvent exister ensemble, notamment les dépendances économiques et structurelles. Par exemple, la plupart des systèmes mécaniques sont construits sur une structure hiérarchique impliquant que la maintenance d'un composant nécessite le démontage d'autres composants (Dao & Zuo, 2017).

Ce défi de considérer simultanément différents types de dépendances dans la modélisation de la maintenance, est la genèse de cette thèse. L'objectif qui s'y réfère est donc l'intégration à la fois des dépendances économiques et structurelles dans le processus de modélisation de la dégradation et le processus de décision en maintenance d'un système à composants multiples dans le cadre de la maintenance prédictive. Plus précisément, cet objectif repose sur deux axes scientifiques majeurs. Le premier consiste à étudier l'impact des dépendances structurelles et économiques sur le processus de dégradation des composants et sur la structure des coûts de maintenance. Cet axe de recherche se structure autour de deux verrous scientifiques: *(1)-Comment modéliser les dépendances économique et structurelle entre composants ? (2)-Quels sont leurs impacts sur le processus de dégradation des composants ?* Le deuxième axe de recherche a pour objet d'intégrer les impacts des dépendances économiques et structurelles dans les processus de décision et d'optimisation de la maintenance. Cela conduit à un autre verrou scientifique important : *Quelle est la politique de maintenance prédictive la plus adéquate permettant de considérer à la fois les dépendances économiques et structurelles ?*

Ces verrous scientifiques identifiés conduisent dans le cadre de la thèse à proposer 3 contributions principales: *(1)-Formalisation et proposition de modèles mathématiques permettant de modéliser les dépendances structurelles et économiques entre composants; (2)-Développement d'un modèle de dégradation considérant les impacts de la dépendance structurelle entre composants ; (3)-Développement d'une politique de maintenance prédictive opportuniste adaptée permettant de prendre en considération les impacts des dépendances économiques et structurelles dans les processus de prise de décision et d'optimisation de la maintenance.*

Ces 3 contributions sont définies et défendues dans la thèse sur la base de cinq chapitres :

Le chapitre 1 présente un aperçu de la maintenance prédictive (PdM) pour un système à composants multiples avec dépendances. D'un point de vue méthodologique, la PdM se compose de trois phases: (1)-Surveillance de l'état des composants/système, (2)-Modélisation et prédiction de l'évolution de la dégradation et (3)-Prise de décision et optimisation de la maintenance (Ran et al., 2019; Schmidt & Wang, 2015). Étant donné que les dépendances entre composants peuvent avoir un impact important sur la modélisation et l'optimisation de la maintenance (Do, Scarf, et al., 2015; Keizer et al., 2017; Nicolai & Dekker, 2008), deux défis majeurs dans la modélisation et l'optimisation de la maintenance sont identifiés pour un système à composants multiples avec les dépendances structurelles et économiques. Le premier défi est la définition et la modélisation d'impacts des dépendances structurelles et économiques sur le processus de dégradation des composants et sur la structure des coûts de maintenance. Le second défi est relatif au développement d'une politique de maintenance prédictive adéquate permettant de prendre en compte ces impacts dans les processus de décision et d'optimisation de la maintenance.

Le chapitre 2 présente un état de l'art sur les deux défis identifiés au chapitre 1 dans la modélisation et l'optimisation de la maintenance pour un système à composants multiples avec des dépendances économiques et structurelles. Cette étude bibliographique permet d'identifier les verrous scientifiques à attaquer dans le cadre de la thèse. Ainsi, le chapitre 2 s'attache dans un premier temps à identifier et à formuler les impacts des dépendances structurelle et économique sur la modélisation de la maintenance. Ceci conduit à un verrou scientifique important qui est : « *comment modéliser la dépendance économique et structurelle entre composants ?* » (Verrou scientifique n°1). La dépendance structurelle signifie que la maintenance d'un composant implique le démontage d'autres composants. Dans le cadre de cette interaction entre composants, il est important de comprendre que les opérations de démontage peuvent affecter les composants démontés ce qui entraînera un impact sur le processus de dégradation de ces composants démontés (par exemple, le démontage peut conduire à un choc non prévu sur un composant démonté). Cela aboutit à une autre question scientifique importante : « *quels sont les impacts de la dépendance structurelle sur le processus de dégradation des composants ?* » (Verrou scientifique n°2). De plus, dans le cadre de l'optimisation de la maintenance, les impacts des dépendances structurelle et économique doivent être intégrés dans le processus de décision et optimisation de la maintenance. Cela conduit à un autre verrou scientifique à résoudre: « *Quelle est la politique de maintenance prédictive la plus adéquate permettant de considérer à la fois les dépendances économiques et structurelles ?*» (Verrou scientifique n°3).

Le chapitre 3 a pour objet de traiter les contributions liées aux deux premiers verrous scientifiques. Dans ce sens, le chapitre 3 introduit la modélisation des dépendances structurelles et économiques entre composants et leurs influences sur les coûts de maintenance, la durée de maintenance et le processus de dégradation des composants. Pour modéliser la dépendance économique entre composants, un modèle de coût de maintenance est développé. En effet, la dépendance économique entre composants est représentée par le gain de coût de mise en œuvre de la maintenance (c'est-à-dire le coût lié à la préparation de l'intervention pour pouvoir effectuer une action de maintenance) lorsque quelques composants sont maintenus ensemble. Pour la modélisation de la dépendance structurelle, un graphe orienté et une matrice de désassemblage sont proposés pour présenter les séquences de désassemblage entre composants. A partir du schéma de démontage, la durée de démontage d'un composant et d'un groupe de plusieurs composants est calculée. Ce calcul permet de quantifier le gain lié à la durée de démontage lorsque plusieurs composants sont maintenus ensemble. Ensuite, quelques facteurs influençant l'impact des opérations de démontage sur le processus de dégradation des composants sont identifiés et modélisés comme par exemple, les propriétés des composants, le degré d'expertise du technicien de maintenance réalisant l'intervention, l'adéquation des outils utilisés lors de l'intervention et le niveau de dépendance structurelle entre composants. Sur la base de cette modélisation, une formulation mathématique de l'impact des opérations de démontage sur le processus de dégradation des composants démontés est proposée. Ensuite, un modèle de dégradation sur la base du process de gamma est développé pour intégrer l'impact des opérations de démontage dans le processus de dégradation des composants.

Le chapitre 4 détaille la contribution scientifique élaborée pour répondre au troisième verrou scientifique. Il présente une politique de maintenance prédictive que nous avons développée pour permettre de prendre en compte les impacts des dépendances structurelle et économique dans la prise de décision et l'optimisation de la maintenance. En effet, la considération de deux types de dépendances économique et structurelle dans la prise de décision et l'optimisation de la maintenance s'est traduit par la proposition de règles de décision adaptées et le développement d'un algorithme d'optimisation adéquate. Dans ce sens, dans un premier temps, deux groupes différents de composants soumis à différents types de dépendances lors d'une maintenance, appelés composants démontés et non démontés, sont identifiés. Les composants démontés sont soumis à la fois à des dépendances économique et structurelle, tandis que les composants non démontés ne sont soumis qu'à la dépendance économique. Par conséquent, les gains en termes de coûts de maintenance liés à une maintenance opportuniste sur ces deux groupes de composants sont différents. Dans cette optique, une politique de maintenance prédictive opportuniste à plusieurs niveaux est proposée pour considérer les deux types de gains. Cette politique de maintenance est caractérisée par un seuil préventif et deux seuils de maintenance opportuniste différents. Ces derniers permettent de considérer les différents niveaux de dépendance pour les composants démontés et non démontés. La politique proposée semble être plus adéquate pour prendre en compte à la fois les dépendances économique et structurelle entre composants.

Pour le processus d'optimisation de la maintenance, l'algorithme d'optimisation sur la base de l'algorithme PSO (Particle Swarm Optimization) est développé pour la recherche des variables de décision optimales.

Le chapitre 5 en fin de thèse à pour objet de montrer l'applicabilité et les avantages de la politique de maintenance prédictive proposée au chapitre 4. De ce sens, la politique de maintenance opportuniste multi-niveaux élaborée au chapitre 4 est appliquée à un convoyeur industriel.

Une comparaison des performances entre la politique de maintenance prédictive proposée et une politique de maintenance opportuniste conventionnelle, qui consiste en un seul seuil de maintenance opportuniste pour tous les composants, est également menée pour montrer les avantages de la politique de maintenance proposée.

Ainsi, plusieurs d'autre analyses de sensibilité sont également menées pour analyser les impacts de différents facteurs sur la performance de la politique de maintenance proposée.

Enfin, des conclusions et perspectives sont présenté dans la conclusion générale de cette thèse.

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General introduction

Maintenance can be defined as the combination of all technical and associated administrative actions intended to retain an item or system in, or restore it to, a state in which it can perform its intended functions (BS-EN 13306:2010 Maintenance-Maintenance terminology, 2010). In that way, maintenance plays an important role in guaranteeing the system (and mainly the industrial ones such as manufacturing systems) operates efficiently. However, the cost of maintenance takes a significant proportion (15-60%) in the overall operation cost of the manufacturing systems, depending on the specific industry (Thomas, 2018). Therefore, minimizing the maintenance cost could increase the competitiveness as well as the productivity of the industrial companies. For this purpose, several maintenance policies have been developed in the last decades, from simple policies such as failure-based maintenance (FBM) and naïve time-based preventive maintenance (TBM), to more advanced policies such as condition-based maintenance (CBM) and predictive maintenance (PdM) (Van Horenbeek, 2013). Among them, PdM is the most prominent maintenance policies, which incorporate fault prognostics into maintenance decision-making process to predict how soon and how likely a fault will occur (Ran et al., 2019; Schmidt & Wang, 2015). In that way, PdM can help to schedule efficiently maintenance actions at right time, just before failure, consequently, reduce the maintenance cost and downtime. However, with development of the industrial technologies, manufacturing system has become more and more complex, i.e., it consists of multi-interdependent components. This leads to a concern on the development of new maintenance policies allowing to consider the dependences between components.

Generally, the dependences between components can be classified into three main categories: *Economic, stochastic, and structural dependences* (Keizer et al., 2017; Nicolai & Dekker, 2008).

- *Economic dependence* implies that simultaneous maintenance on several components may be cheaper (positive dependence) or more expensive (negative dependence) than maintenance them separately;
- *Stochastic dependence* occurs in situation whereas the state of a component can influence the lifetime distribution of other components;

- *Structural dependence* implies that components in the system are structured in a connected set and maintenance of one or several components requires disassembly of other components.

The dependences between components significantly influence the degradation process of the components as well as the maintenance decision-making process (Bian & Gebraeel, 2014; Do, Scarf, et al., 2015; Keizer et al., 2017). Omitting the dependences between the components in maintenance modeling could result in high maintenance cost and suboptimal maintenance plan (Keizer et al., 2017; Nicolai & Dekker, 2008). Therefore, maintenance for multi-component system considering the dependences between components has been extensively studied in the literature (Dekker et al., 1997; Keizer et al., 2017; Nicolai & Dekker, 2008).

Most of the existing maintenance models only consider one type of dependences since combining more than one makes the models too complicated to analyze and solve (Nicolai & Dekker, 2008; Van Horenbeek & Pintelon, 2013). However, in practice, several types of dependences, especially, the economic and structural dependences, may exist simultaneously in manufacturing systems. For example, most of the mechanical systems are built in hierarchical structure whereas maintenance of a component requires disassembly of other components Dao & Zuo, 2017). To face the challenge of simultaneously considering different types of dependence in maintenance modeling, the objective of this thesis is to **consider both economic and structural dependences into maintenance modeling and optimization of a multi-component system in the framework of predictive maintenance.** More precisely, this objective is based on two major scientific directions. The first one is to investigate the impact of structural and economic dependences on maintenance cost and the degradation process of components. To support this research direction, two scientific issues are identified: (1)-*how to model the economic and structural dependence between components?* (2)-*what are the impacts of structural dependence on the degradation process of the components?* The second research direction is to take into account the impacts of economic and structural dependences in maintenance decision-making and optimization process. This leads to another important scientific issue: *What is an adequate predictive maintenance policy allowing to consider both economic and structural dependences?* These two research directions are supporting the novelty of the works developed.

These scientific issues have been attacked during the Ph.D. work to provide 3 main contributions: (1)-*Proposal of mathematical developments for modeling the structural and* *economic dependences between components based on directed graph and disassembly matrix*; (2)-*Development of a degradation model considering the impacts of structural dependence between components;* (3)-*Development of an opportunistic predictive maintenance policy to fully take into account the impacts of both economic and structural dependences in maintenance decision-making and optimization process.*

In regard to these main contributions, the thesis is structured into six chapters as follow:

Chapter 1 presents an overview about the predictive maintenance (PdM) for multi-component with dependences. Basically, PdM consists of three phases: (1)-Condition monitoring, (2)-degradation modeling and prediction, and (3)-maintenance decision-making and optimization (Ran et al., 2019; Schmidt & Wang, 2015). As the dependences between components may have an important impact on maintenance modelling and optimization (Do, Scarf, et al., 2015; Keizer et al., 2017; Nicolai & Dekker, 2008), two challenges in maintenance modeling and optimization are identified for multi-component system with structural and economic dependences. The first challenge is defining and modeling the impacts of structural and economic dependences on maintenance cost and the degradation process of components. The second one is relating to the development of an adequate predictive maintenance policy that allows considering these impacts in maintenance decision-making and optimization processes.

Chapter 2 presents a literature review focusing on the two previous challenges in maintenance modeling and optimization for multi-component system with economic and structural dependences. This review helps to identify the scientific issues to be attacked. In that way, the chapter 2 is firstly focusing on identifying and formulating the impacts of structural and economic dependence on maintenance modeling. This leads to underline the issue related to "*how to model the economic and structural dependence between components?*" (Scientific issue n°1). The structural dependence means that some components are required to be disassembled in order to reach the maintained components. The disassembly operations play a role like a shock to the disassembled components, leading to an impact on the degradation process of the disassembled components. Therefore, another scientific issue is identified, which is related to "*what are the impacts of structural dependence on the degradation process of the components?*" (Scientific issue n°2). The impacts of structural and economic dependences in degradation process and maintenance modeling lead to another scientific issue to be attacked: "*what is an adequate predictive* *maintenance policy allowing considering both economic and structural dependences?"* (Scientific issue n°3).

Chapter 3 aims at describing the contributions related to the two first scientific issues. In that ways, chapter 3 is devoted to model the structural and economic dependences between components and their influences in maintenance cost, maintenance duration and degradation process of the components. To model the economic dependence between components, a maintenance cost model is established. The economic dependence between components is represented by the saving of maintenance setup cost when several components are maintained together. For structural dependence modeling, the directed graph and disassembly matrix are proposed to present the disassembly sequences between components. Based on the disassembly path model, the disassembly duration of a component and a group of several components are quantified. This model allows formalizing the sharing of disassembly duration when several components are maintained together. Then, it is investigated the factors influencing the impact of disassembly operations on the degradation process of components including properties of the components, degree of expertise of technician, tools suitability and the structural dependence between components. Based on this investigation, a mathematical formulation for the disassembly operations impact on the degradation process of the disassembled components is proposed. A degradation model using gamma process is then developed to integrate the impact of disassembly operations into the degradation process of the components.

Chapter 4 aims at tackling the scientific issue 3 related to a predictive maintenance policy allowing to take into account the impacts of both structural and economic dependence in maintenance decision-making and optimization. The existence of both economic and structural dependence results in two different groups of components subjected to different types of dependences when maintenance occurs, called as disassembled and non-disassembled components. The disassembled components are subjected to both structural and economic dependences, while the non-disassembled components are subjected to only economic dependence. Therefore, the maintenance cost savings due to opportunistic maintenance on the two groups of components are different. In that way, a multi-level opportunistic predictive maintenance policy is proposed to consider both kinds of maintenance cost savings. This maintenance policy leads to a preventive threshold and two different opportunistic maintenance thresholds that allow considering the different dependence levels for disassembled and non-disassembled components.

The proposed policy seems to be more adequate to take into account both economic and structural dependences between components. For maintenance optimization process, the particle swarm optimization algorithm (PSO) is implemented to find the optimal maintenance decision variables.

Chapter 5 aims at showing the use and the advantages of the proposed predictive maintenance policy. In that way, the proposed multi-level opportunistic maintenance policy is applied to an industrial conveyor system. A performance comparison between the proposed predictive maintenance policy and a conventional opportunistic maintenance policy, which consists of only one opportunistic maintenance threshold for all components, is also conducted to show the advantages of the proposed maintenance policy. Several sensitivity analyses are then studied to analyze the impacts of different factors on the performance of the proposed maintenance policy.

Finally, to end this thesis, conclusions and perspectives are drawn in chapter 6.

Chapter 1 - Overview about predictive maintenance policies for multi-component systems

1.1. Introduction

Maintenance policies has evolved from simple policies such as naïve failure-based maintenance and time-based preventive maintenance to more advanced policies such as condition based and predictive maintenance (Van Horenbeek, 2013). Among them, PdM is the most prominent maintenance policies, which incorporate fault prognostics into maintenance decision-making process to predict how soon and how likely a fault will occur (Ran et al., 2019; Schmidt & Wang, 2015). In that way, PdM can increase the probability that maintenance actions are placed at right time, just before failure, consequently, reduce the maintenance cost and downtime. Therefore, PdM has been extensively studied in literature (Bousdekis et al., 2019). However, with development of the technologies, the industrial systems and mainly the manufacturing ones have become more and more complex, i.e., it consists of multi-interdependent components. The dependences between components significantly influence the degradation process of the components as well as maintenance decision-making and optimization process (Do et al., 2015; Keizer et al., 2017; Nicolai & Dekker, 2008). These influences lead to a concern in developing new maintenance policies taking into account the dependences between components. With regard to the PdM context, this chapter aims at presenting an overview about the predictive maintenance policies for multi-component system with dependences and an identification of their challenge.

Before presenting the predictive maintenance, the definitions of maintenance and evolution of the maintenance over time are firstly introduced in section 1.2. The definition and general implementation process of the predictive maintenance are then presented in section 1.3. Section 1.4 is devoted the maintenance modeling for multi-component system with dependences. In this section, the challenges for maintenance modeling of multi-component system are identified. Finally, conclusions of the chapter are drawn in section 1.5.

1.2. Maintenance definitions, concepts and policies

Maintenance can be defined as the combination of all technical and associated administrative actions intended to retain an item or system in, or restore it to, a state in which it can perform its intended functions (BS-EN-13306-2010 Maintenance terminology). In that way, maintenance plays an important role in guaranteeing the system (and mainly the industrial ones such as manufacturing system) operates efficiently. However, the cost of maintenance accounts for a significant proportion (15-60%) in the overall operation cost of the manufacturing systems (D. S. Thomas, 2018). Indeed, the maintenance costs can be divided into two major classes: direct and indirect maintenance costs. The direct maintenance costs are the costs paid directly for maintenance actions, such as spare part cost, labor cost, setup scaffolding, buying/renting tools for conducting maintenance, etc. The indirect maintenance costs are the costs associated with stopping the system for maintenance, such as production loss cost, downtime cost, lost sales due to delays/quality issues, rework and defects cost (D. S. Thomas, 2018). The proportion of maintenance cost in overall operation cost can be varied depending on the specific industries. For example, in food-related industries, average maintenance cost represents about 15% of the cost of goods produced, whereas maintenance cost for iron and steel, pulp and paper, and other heavy industries represent up to 60% of the total production cost (Mobley, 2002). A survey conducted in the United State indicates that the American companies spent well over $300 billion on plant maintenance and operations (Latino, 1996). An estimated 80% of these costs are expended to correct chronic failure of machinery. Eliminating these failures can reduce maintenance cost by 40% up to 60%. From these figures, it can be reasoned that maintenance represents a major cost in equipment-intensive industrial operations. Therefore, minimizing the maintenance cost could increase the competitiveness as well as the productivity of the industrial companies.

For this purpose, over the last decades, companies and scholars have been seeking for advanced maintenance concepts, policies and strategies with possible lowest cost and/or downtime (K.-A. Nguyen et al., 2015). A maintenance concept is a set of maintenance management policies, strategies, actions and the general decision support structure, in which these are planned and supported. The well-known maintenance concepts are total productive maintenance (TPM) (Nakajima & Bodek, 1988) and reliability-centered maintenance (RCM) (J. Moubray, 1997). Maintenance management policy is all activities of management that determine the maintenance objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics. Maintenance strategy is the management method used in order to achieve the maintenance objective (e.g., outsourcing of maintenance, allocation of resources) (BS-EN-13306-

2010 Maintenance terminology). Different maintenance actions such as corrective replacement and preventive replacement, etc., can be applied in different situations. Several maintenance supporting activities can be associated with conducting maintenance, such as ordering spare part, setting up scaffolding, disassembly of the obstructing components, etc. The implementation and allocation of these all concepts, policies, strategies and activities significantly influence the performance of maintenance management system (Van Horenbeek, 2013). The focus of this dissertation is on maintenance policies, which aims to trigger the right maintenance actions at their optimal time with considering the execution and allocation of maintenance activities.

The earliest maintenance policy is naïve failure-based maintenance (FBM), which triggers maintenance whenever the failure occurs or fixes the machine when it failed. Since the failure of the system is stochastic, the maintenance activities cannot be planned. The failure of the system can lead to catastrophic consequences, e.g. significant economic losses, physical damages or threats to human life (e.g., the chemical plant, nuclear power plant). To overcome this drawback, preventive maintenance (PM) (time-based or use-based) was developed and became popular in 1960's. For PM policy, component's replacements are regularly scheduled to avoid any possible unscheduled failure. Classical preventive maintenance usually consists of two steps: (1)-Estimating the lifetime distribution based on historical failure data and (2)-planning and conducting maintenance activities (Nakagawa, 1986). However, the question on implementation PM policy is whether preventive maintenance is over doing by e.g., replacing components with potentially interesting remaining lifetime. Moreover, the lifetime data are difficult to collect for many systems. Therefore, condition based maintenance (CBM) was emerged. CBM recommends maintenance actions based on the condition monitoring information available from the past up until the decision time (Ahmad & Kamaruddin, 2012; Alaswad & Xiang, 2017). In that way, CBM attempts to avoid unnecessary maintenance activities by triggering maintenance activities only when there is evidence of deteriorations or abnormal behaviors. Recently, predictive maintenance (PdM) was developed by incorporating fault prognostics into maintenance decision-making process. Based on the monitoring condition and degradation behavior of the components, PdM predicts how soon and how likely a fault will occur (Ran et al., 2019; Schmidt & Wang, 2015). It means that different from CBM, PdM incorporates more information into the maintenance decision process as information on future of the components degradation is taken into account. Therefore, PdM can increase the probability that maintenance actions are placed at right time, just before failure, consequently, reduce the maintenance cost and downtime. The evolution over time of maintenance is illustrated in Figure 1.1.

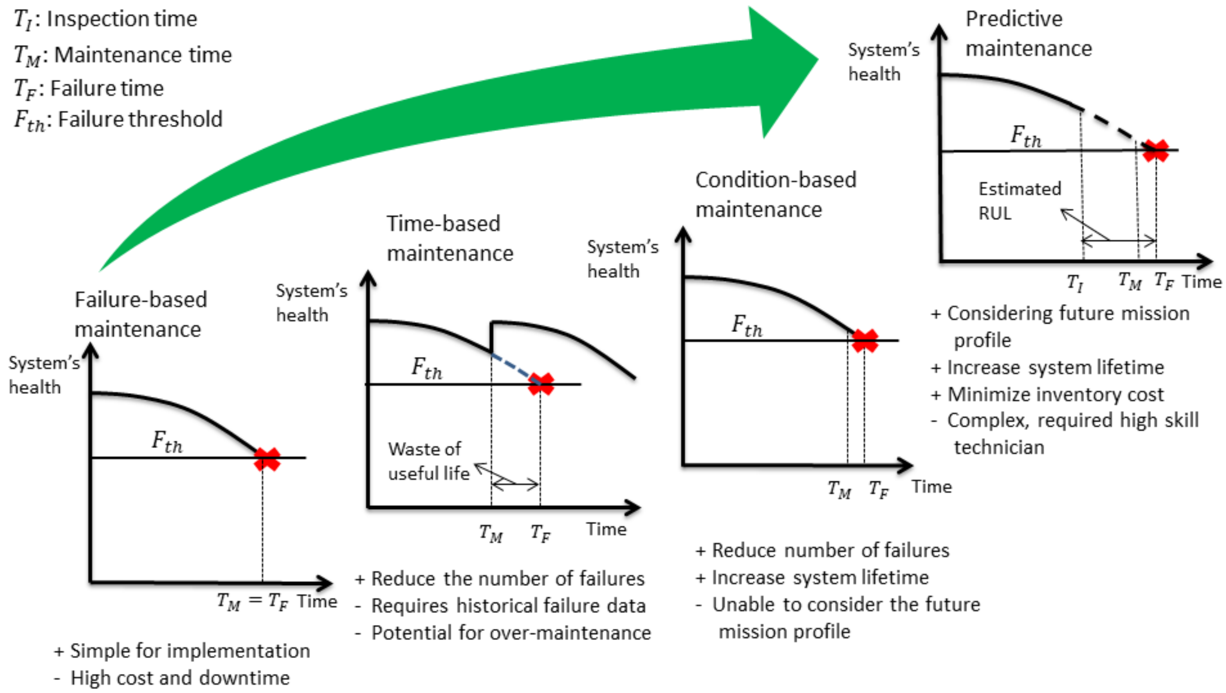

Figure 1.1 The evolution of maintenance policies (Adapted from Van Horenbeek, 2013)

1.3. Predictive maintenance and its implementation process

Predictive maintenance is a condition-driven preventive maintenance approach. Instead of relying on industrial or in-plant average-life statistic (i.e., historical failure time data) to schedule maintenance activities, PdM uses direct monitoring of mechanical system, system efficiency, and other indicators, incorporating with fault prognostics to predict how soon and how likely a fault will occur (Mobley, 2002; Schmidt & Wang, 2015). Basically, PdM consists of three phases: (1)-*Condition monitoring*, (2)-*degradation modeling and prediction* and (3)-*maintenance modeling and optimization* (Figure 1.2).

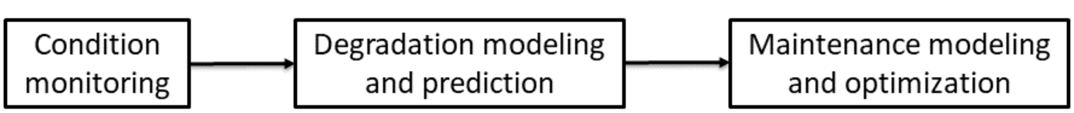

Figure 1.2 General PdM process (Adapted from Ran et al., 2019)

- *Condition monitoring*: The degradation signal of the components can be reveals through the physical health indicators, such as accumulative wear, crack growth, corrosion, vibration, etc., or synthetized health ones which are built from different measurements (K. T. Nguyen et al., 2018). These health indicators can be monitored through inspection activities, which can be conducted continuously or discretely (Alaswad & Xiang, 2017). The continuous monitoring provides real time information about the system states. However, integrating sensors into the system may be expensive. Moreover, with continuous data gathering, the amount of noise increases, possibly resulting in inaccurate diagnostic (Jardine et al., 2006). For discrete condition monitoring approach, the health condition of the component/system is measured periodically or non-periodically. For non-periodic inspection policy, the condition of the component/system is monitored irregularly. The common approach is that the inspection interval decreases as the system deteriorates, which means more inspections should be conducted when the system is in poor state (Castanier et al., 2005; X. Zhao et al., 2010). This approach can lead to potential cost saving by reducing non-necessary inspections at early state of the system. However, non-periodic inspection requires more documentation and rescheduling works, and the risk of human errors significantly increases with additional scheduling work. Moreover, it is very difficult to apply non-periodic inspection policy for multi-component system since the components in the system are heterogeneous, i.e., the lifetime and degradation speed of different components are different. In the framework of periodic condition monitoring maintenance, the condition of the component/system is periodically inspected at the fixed intervals. The inspection interval is a crucial factor influencing the performance of discrete condition monitoring policy. If the inspection interval is too long, the probability that the system failed between inspections is high, leading to high maintenance cost since the cost of corrective maintenance is pretty much higher than preventive maintenance cost. On the other hand, if the inspection interval is too short, considering that inspection may be costly, the overall maintenance cost can be significantly increased. In that way, finding the optimal inspection interval is one of the main issues for periodic monitoring policy.

- *Degradation modeling and prediction:* Degradation modeling in the presence of health monitoring data is extremely important for lifetime prognosis and maintenance planning (K. T. Nguyen et al., 2018). The degradation considered as a random phenomenon often has a gradual time continuous trajectory. Regarding to the system under consideration, the degradation can take values in a discrete or continuous space. For example, the volume of wear can take infinite value as soon as it begins to occur. Similarly, a deteriorating production process can have several quality states, which will impact the production and result of gains and losses. Based on the monitoring condition and historical degradation data acquired in the first phase, the second phase of PdM aims at providing a mathematical model to describe the degradation behavior of the system. This mathematical model also provides tools for prognosis the future evolution of the system's condition. The prognosis information could be the remaining useful life (RUL) or the conditional reliability of the components/system (Bérenguer, 2015). RUL is the time left before a failure occurs, given the current state and past operation profile (and the associated uncertainty quantification, e.g., the probability density function of this time). Reliability of the system at a given future time is the probability that the system operates without failure up to that time, given the current system state and past operation, e.g., the probability that the RUL of the system is greater than the given future time.

- *Maintenance modeling and optimization:* The prognosis information of system future condition plays an important role in maintenance decision-making and optimization process since it is used as the indicator for maintenance decision-making and optimization (Ahmad & Kamaruddin, 2012). Most of the studies in literature assume that the component is preventively maintained immediately at the inspection time if its condition approaches the preventive maintenance (PM) threshold, i.e., the probability that component will be failed before the next inspection is too high (K-A. Nguyen et al., 2015; X. Zhao et al., 2010). It means that PdM can lead to make preventive maintenance actions in order to guarantee that the component is not failed between the inspection intervals because the cost of maintenance for the failed components is much higher than preventive maintenance cost. The preventive maintenance threshold can be the degradation level of the component or the predicted conditional reliability of the component at the next inspection time. The former is usually applied for single component system, while the latter is applied for multi-component system. The reason is that the difference of the failure thresholds of different components in multi-component system makes it too difficult for maintenance optimization (too many variables need to be optimized). The reliability is the ability of the component to perform a required function under given condition for a given time. The reliability can be considered as the normalized index of the health condition of the component. It can be estimated through the component's conditions such as age, failure rate, predicted degradation signal (Blischke & Murthy, 2011). The reliability of the system can be synchronized with the estimated reliability of the component based on the reliability block diagram (RBD). It means that the maintenance decision-making is based not only on the individual condition but also on the synchronized system condition. In that way, the predicted reliability is usually used as the indicator for maintenance decision-making in the framework of predictive maintenance (Bousdekis et al., 2019; Huynh et al., 2014). However, maintenance decision-making relies on not only system prognostic health information but also other characteristics of the system (e.g., cost of maintenance actions, production context, dependences between components, etc.) (De Jonge & Scarf, 2019). Therefore, the last phases of PdM aims to take into account both the system health prognostic information and other characteristics of the system into maintenance decision-making. The maintenance optimization process is conducted to find the optimal maintenance plan with optimal maintenance variables (e.g., inspection interval, preventive maintenance threshold, spare part ordering, etc.) according to the maintenance objectives (e.g., minimizing maintenance cost or system's downtime; maximizing availability and/or reliability of the system, etc.).

1.4. Maintenance policies for multi-component systems with dependences

1.4.1. Multi-component systems

In the early state of the maintenance modeling research, the manufacturing system was usually considered as single-component system to facilitate the mathematical models for maintenance modeling. The maintenance modeling for the single unit-system can be more efficient by taking into account different competing failure modes. However, with the development of technologies, manufacturing system has become more and more complex i.e., it consists of multi-interdependent components. The multi-component system can be defined as the system that consists of a certain number of components, considered as a whole, to support an intended function (De Jonge & Scarf, 2019; Savolainen & Urbani, 2021). For example, a machine tools can be considered as a complex multi-component system. It consists of several sub-systems and components such as motor, gearbox systems, spindle unit, etc. These sub-systems and components synchronically operate to support an intended function, such as machining a part. The components in the system may be dependent on each other in different aspects, such as functionality, technical structure, maintenance cost, etc. Therefore, studying the system like a black box in maintenance is no more realistic.

1.4.2. The dependencies between components

The dependences between components significantly influence the degradation process of the components as well as the maintenance decision-making process. Generally, these dependences can be classified into three main categories: *economic, stochastic, and structural dependences* (Keizer et al., 2017; Nicolai & Dekker, 2008).

In general, economic dependence implies that the cost of simultaneous maintenance on several components is not equal to the summation of maintenance cost of individual components in this group (Huitian Lu et al., 2001; Keizer et al., 2017; Nicolai & Dekker, 2008). The economic dependence can be further classified into *positive* and *negative economic dependences* based on their direction of impact on the total maintenance cost (Dekker et al., 1997; Nicolai & Dekker, 2008).

- *Positive economic dependence* influences the total maintenance cost in a positive way. It implies that jointly maintenance on several components is cheaper than maintenance components separately. The positive economic dependence is usually represented by maintenance setup cost, e.g. the cost associated with different actions for preparation of the maintenance executions such as sending maintenance team to the site, setup scaffolding, ordering spare part, shutting down the system for maintenance, etc. (Dekker et al., 1997). This cost is assumed to be cost-independent of the maintenance operations nature and can be shared when several components are maintained together.
- *Negative economic dependence* influences the total maintenance cost in a negative way. It occurs when combining maintenance on several components leads to higher costs than maintaining them separately. The reasons can be due to the manpower restrictions, safety requirements, or production losses (Nicolai & Dekker, 2008). For example, a company may need to (temporarily) hire additional staff or rent additional tools to simultaneously maintain multiple components. Therefore, the maintenance cost increases with the increase of the number of components needing maintenance. Another example of negative economic dependence occurs in practice is when multiple workers need to operate in a limited space. They will start blocking and irritating each other, hence increases the probability that human errors occur (Keizer et al., 2017).

Stochastic dependence occurs when the state of a component influences lifetime distribution of other components (Bian & Gebraeel, 2014; Do, Scarf, et al., 2015; Nicolai & Dekker, 2008). This type of dependence occurs in two different ways. The first case is called as **failure-induced damage**, whereas the failure of a component can cause a major, one-time damage to other components, leading to an immediate increase of the degradation level or even an immediate failure of these components. For example, a propeller can come off of an airplane and pierce the fuselage, causing tremendous additional damage and safety risk. The second case is called as **failure rate interaction**, whereas degradation state of the components can increase the degradation rate of other components (Bian & Gebraeel, 2014). For example, as the degradation level of the bearing increases, the vibration of the shaft is increased, which in results, increases the degradation rate of the gear mounted on the shaft.

Finally, structural dependence applies in situation where components structurally form a connected set, and the repair or replacement of a component requires disassembly of other components. It means that to reach a component for maintenance, other obstructing components, which block the disassembly path of the maintained components, must be disassembled (Dao & Zuo, 2017; Zhou et al., 2015). For example, a machine tool can be seen as a multi-component system with structural dependence since if one need to take a maintenance action on the bearings of the spindle, then one needs to take a part the spindle unit from the machine, and disassembly other component of the spindle unit such as spindle house, spindle shaft, etc. Therefore, the disassembly operations, including disassembly of the target components for maintenance and the obstructing components, are the maintenance activities associated with the maintenance strategies. The disassembly operations require man-hour and time, results in labor cost and production lost cost due to downtime, both of these costs depend on the disassembly duration. Therefore, maintenance of two or several components together, which are shared the disassembly path, can save disassembly duration (Dao & Zuo, 2017; Zhou et al., 2015). In addition, the disassembly operations could result in damage on the disassembled components (Keizer et al., 2017). The damage could be due to the interactions between disassembled components and tools, or the human errors. The disassembly operations play a role like a shock to disassembled components, affects the degradation of the disassembled components, i.e., disassembly operations could result in an amount of damage on the degradation level of the disassembled components. **The failure risk of the components and the system will be underestimated if the impact of the disassembly**

operations on the components' degradation processes is ignored. This could lead to the inaccuracy health prognostic information and suboptimal maintenance plan. However, most of the existing studies in maintenance for multi-component system with structural dependence ignore the impact of disassembly operations on the degradation of the disassembled components and assume that the degradation state of the components is unchanged during maintenance of the other components. Thus, one important challenge in maintenance modeling for multi-component systems with structural dependence is "*modeling the impact of structural dependence on degradation process of the components and on the maintenance decision-making and optimization process*" (Challenge n°1).

1.4.3. Maintenance policies for multi-component systems

As previously mentioned, the dependences between components significantly influence the maintenance decision-making and optimization process. Omitting the dependences between components usually results in suboptimal maintenance plan, with possible higher cost and/or downtime (Keizer et al., 2017; Nicolai & Dekker, 2008). Therefore, maintenance policies for multi-component system should take into account these dependences in order to find the optimal maintenance plan (Van Horenbeek & Pintelon, 2013).

In literature, the positive economic dependence has been extensively studied due to its widely appearance and direct impacts on maintenance cost. The positive economic dependence implies that simultaneous maintenance on several components at the same time can save maintenance setup cost (Dekker et al., 1997; Keizer et al., 2017). Therefore, several maintenance policies have been proposed for combining the maintenance activities to take the advantages of economic dependence, such as *grouping maintenance* and *opportunistic maintenance policies*.

- *Grouping maintenance policies* are based on joint maintenance of several components to save maintenance preparation/setup cost and/or time (Vu et al., 2014; Wildeman et al., 1997). It is usually assumed that the maintenance setup cost is incurred once the maintenance occurs, independent on the number of components receiving maintenance (Dekker et al., 1997; Keizer et al., 2017; Vu et al., 2014). In that way, if *n* components are simultaneously maintained at the same time, the amount of maintenance setup cost saving is $(n-1).c_s$, with c_s denotes amount of maintenance setup cost.
- *Opportunistic maintenance policies* are the extensions of the grouping maintenance policies, whereas the maintenance actions are grouped under the support of the

maintenance opportunities, since grouping maintenance can save maintenance setup cost. For manufacturing system, during operation, there may be maintenance opportunities (e.g. unscheduled downtime, scheduled maintenance activities, planned shutdown of the system, shortage of material, etc.), which provides advantages (e.g. lower maintenance costs, free downtime cost) for conducting preventive maintenance (Ab-Samat & Kamaruddin, 2014). It means that conducting maintenance at the maintenance opportunities can help saving maintenance downtime cost.

In case of structural dependence, maintenance of a component requires disassembly of other components. It means that to reach a component for maintenance, other obstructing components, which block the disassembly path of the maintained component, must be disassembled. In that way, maintenance of a component offers a great opportunity to consider other components for preventive maintenance, especially for the disassembled components since the disassembly duration, i.e., downtime cost, can be saved. Therefore, opportunistic maintenance approach has been considered for maintenance optimization of multi-component system with structural dependence (Geng et al., 2015; Iung et al., 2016; Zhou et al., 2015).

Most of the maintenance models only consider one type of dependences since combining more than one makes the models too complicated to analyze and solve (Nicolai & Dekker, 2008; Van Horenbeek & Pintelon, 2013). However, in practice, several types of dependences may exist simultaneously in the system. Especially, the economic and structural dependences usually exist simultaneously in the system. For example, most of the mechanical systems are built in hierarchical structure whereas maintenance of a component requires disassembly of other components. Economic dependence results in saving maintenance setup cost when several components are simultaneously maintained at the same time. Structural dependence requires disassembly other components for maintenance of a component. Moreover, for series system, maintenance of a component results in a stoppage of the system. Therefore, the existence of both economic and structural dependences provides a great opportunity for considering other components for preventive maintenance when maintenance is required for a component. In that way, for multi-component system subjected to both economic and structural dependences, joint maintenance several components can save maintenance setup cost (economic dependence) and maintenance duration (structural dependence). Although the structural dependence requires disassembly of other components for maintenance of a component, there only few components are required to be disassembled, while other components are still remaining in the system. So that for maintenance of a component, the rest of the components can be categorized into two different groups: *Disassembled* and *non-disassembled components*. While opportunistic maintenance on the *non-disassembled components* can only save maintenance setup cost (economic dependence), opportunistic maintenance on the *disassembled components* can save not only setup cost (economic dependence) but also disassembly durations, i.e., downtime cost (structural dependence). It means that the maintenance cost saving factors of opportunistic maintenance on the disassembled and non-disassembled components are different. Moreover, the existence of the impact of disassembly operations on degradation process of the disassembled components also results in different levels of interest for opportunistic maintenance on disassembled and non-disassembled components. However, most of the existing studies in literature equally consider disassembled and non-disassembled components for opportunistic maintenance (Geng et al., 2015; Huynh et al., 2014; Iung et al., 2016; Zhou et al., 2015). Therefore, it does not fully take into account the characteristic of both economic and structural dependences. Hence, the second important challenge with regards to maintenance optimization for system with structural and economic dependence is "*Maintenance modeling and optimization taking into account both structural and economic dependences*" (Challenge n° 2).

1.5. Conclusions

From a general overview of maintenance, this chapter identified PdM as the advanced maintenance policy that could lead to several potential benefits (e.g., reducing downtime, reducing consequences of sudden failure, etc.). In that way, it is isolating PdM as the maintenance policy focus for this Ph.D. However, with the development of technologies, manufacturing system has become more and more complex i.e., it consists of multi-interdependent components. The dependences between components include economic, stochastic and structural dependences, whereas, the economic and structural dependences often exist simultaneously in the system. These dependences may significantly influence the degradation process of the components as well as the maintenance decision-making process. In that way, it is necessary to investigate and model the impact of the dependences on the degradation process of the components and maintenance decision-making process. These impacts also lead to another concern in developing the maintenance policy taking into account the dependences between components. In that way, two main challenges in predictive maintenance policy for multi-component with structural and economic dependences are highlighted:

- *Modeling the impact of structural dependence on degradation process of the components as well as on the maintenance decision-making and optimization process.*
- *Maintenance modeling and optimization taking into account both structural and economic dependences.*

Chapter 2 will review the state of the art focusing on these two challenges to define the scientific issues to be attacked.

Chapter 2 - State of the art on Predictive Maintenance for multi-component systems with dependences

2.1. Introduction

In chapter 1, the two challenges related to predictive maintenance policies for multi-component system with structural and economic dependences have been identified. So, the target of chapter 2 is to identify the scientific issues in link to these research challenges. In relation to the first one, chapter 2 begins with presenting the state of the art on degradation modeling of the components. The focus is on the gradual degradation modeling with continuous state space modeled by stochastic processes and the competing degradation processes with shock impacts. Then, it is investigating also the impact of structural dependences in degradation process of the components. With regards to the second challenge, an investigation is done about the maintenance modeling for multi-component system with structural and economic dependences. This investigation is based on maintenance models taking into account the structural and economic dependences between components.

More precisely, chapter 2 is organized as follow. In link to the first challenge, section 2.2 presents the state of the art on degradation modeling and prediction. Several models for degradation modeling of the components are presented and analyzed. The criteria for degradation model selection are then presented. The impact of structural dependence on the degradation process of the components is also investigated. In link to the second challenge, section 2.3 is devoted to present the state of the art on maintenance decision-making and optimization. In this section, several models for maintenance optimization of system with different types of dependence are presented and analyzed. The scientific issues of maintenance modeling for multi-component system with both structural and economic dependences are then identified. Finally, the conclusions are drawn in section 2.4. Economic

Degradation modeling in the presence of health monitoring data is extremely important for lifetime prognosis and maintenance planning. Section 2.2 will introduce the tools and methods for modeling and predicting the evolution of the degradation process of the components.

2.2. Degradation modeling and reliability prediction

Predictive maintenance is based upon the philosophy that "if it is not broken, don't fix it" and it can be considered as the extension of the condition-based maintenance with the prognostic consideration, whereas the maintenance decisions are based on the forecast of the future evolution of the system's health condition (Jimenez et al., 2020). In that way, degradation modeling plays an important role in an efficient implementation of predictive maintenance. There are several models proposed for modeling the degradation process of the components. The important issue is to select which is the best way to describe the degradation behavior of the component with different degradation dataset (K. T. Nguyen et al., 2018). This section is devoted to present the mathematical models for modeling the degradation process of the system and the criteria for selection of the degradation models when the degradation dataset is available. In degradation modeling, one important issue is to predict the future condition of the system and one important indicator of the system's health condition is the reliability.

2.2.1. Reliability prediction

As mentioned in the section 1.3, in the context of predictive maintenance for multi-component system, the reliability of the components is one of the health prognostic information and usually used as the indicator to trigger maintenance activities. Generally, the reliability of a component at time t, denoted as $R(t)$, is defined as the probability that the component is in functioning state between time 0 and t (Rausand & Høyland, 2004) and can be expressed as:

$$R(t) = P(T_f > t) \tag{2.1}$$

Where, T_f is the failure time of the component.

For a gradually deteriorating component, reliability of a component at time t is defined as the probability that its degradation level at time t, denoted as X_t, is still below a given failure threshold (Huitian Lu et al., 2001). Supposed that the failure threshold of the component is denoted as L, i.e., component is considered as failed if the degradation level exceeds the level L. Let T_{ps} be the first passage time of the degradation process to level L, then:

$$T_{ps} = inf\{t \in \mathbb{R}^+, X_t \geq L\} \tag{2.2}$$

In that way, the failure time of the component is defined as the first passage time of its degradation signal to the failure threshold. The reliability of the component at time t then can be expressed as:

$$R(t) = P\left[T_{ps} > t\right] = P[X_t < L] \tag{2.3}$$

Equation (2.3) implies that if the degradation signal of the component can be modeled and predicted, the reliability of the component also can be predicted.

In practice, component/system gradually degrades due to physical phenomena such as wear, fatigue, creep, corrosion, etc. The degradation process caused by these internal factors is called as inherent degradation process. Meanwhile the component may also experience sudden damage caused by external factors, such as hidden manufacturing defects, excessive loads, shocks, and the dependences between components. So, the modeling of inherent degradation process of the components is first introduced in section 2.2.2. Based on these models, the impacts of external factors on the degradation process of the component are investigated in section 2.2.3.

2.2.2. Modeling of the inherent degradation process

Gradual inherent degradation models are based on the measurement of intermediate states between perfect functioning and total failure. There are two approaches for modeling the degradation process of the components: discrete space degradation and continuous space degradation models. The discrete space degradation can be addressed by Markov or semi-Markov model and the maintenance decision is made under the support of dynamic programming tools (Kang et al., 2020). However, this approach usually faces with two main problems: (1)-It is very difficult and burdensome to formalize and solve the decision problems for a general maintenance policy; and (2)-the maintenance structure of the optimal maintenance policy can be complicated and hard to implement on practice. Implementation of the continuous degradation models can avoid the above problems. Since the maintenance decision is based on parametric structure-based decision making rules, and the goal is to determine the set of parameters that tunes the maintenance policy in its optimal configuration. Of course, problem of using this approach is the risk that the imposed maintenance structure does not correspond to the absolutely optimal policy (Huynh et al., 2019). However, its feasibility from both theoretical and practical viewpoint leads us to favor with continuous degradation models in this thesis. The three most popular models for modeling the inherent gradual degradation process of the components, gamma process, inverse Gaussian process and Wiener process, are investigated in this section. The degradation model selection criteria are also presented to evaluate the suitability of each model with different degradation datasets.

2.2.2.1. Gamma process

A stochastic process $(X_t)_{t\geq 0}$ is called Gamma process if it has the following properties:

- $X_0 = 0$;
- $(X_t)_{t \geq 0}$ has independent increments.
- For $t > 0$ and $s > 0$, $X_{t+s} - X_t$ follows a Gamma distribution with shape parameter $\alpha(t+s) - \alpha(s)$ and scale parameter β, and the probability density function of the increment $X_{t+s} - X_t$ is given by:

$$f_{\alpha(t+s)-\alpha(s),\beta}(x) = \frac{\beta^{\alpha(t+s)-\alpha(s)}.x^{\alpha(t+s)-\alpha(s)-1}\exp(-\beta x)}{\Gamma[\alpha_i(t-s)-\alpha(s)]} \quad (2.4)$$

Where, $\Gamma(.)$ is Gamma function and

$$\Gamma[\alpha_i(t-s) - \alpha(s)] = \int_0^\infty u^{\alpha(t+s)-\alpha(s)-1}.e^{-u}du, \alpha > 0 \quad (2.5)$$

and $\alpha(t)$ is an increasing, right-continuous real valued function of time t, with $\alpha(0) = 0$. When $\alpha(t)$ is a linear function of time t, the Gamma process is stationary, otherwise, it is non-stationary.

From the definition, some interesting properties of Gamma process are noted as follows:

- If component fails when the degradation signal, which is modeled by Gamma process with shape parameter $\alpha(t)$ and scale parameter β, exceeds a predefined threshold L, then the reliability of component at time t can be expressed as:

$$R(t) = P(X_t < L) = \int_0^L f_{\alpha(t),\beta}(u)\,du \quad (2.6)$$

- For $t > s > 0$ and the degradation level of the component at time s is known as x_s then the reliability of the component at time t can be predicted as:

$$R(t|\, X_s = x_s) = P(X_t < L|X_s = x_s) = \int_0^{L-x_s} f_{\alpha(t)-\alpha(s),\beta}(u)\,du \quad (2.7)$$

- Mean and variance of X_t are $\frac{\alpha(t)}{\beta}$ and $\frac{\alpha(t)}{\beta^2}t$, respectively. For stationary Gamma process, the mean and variance are all linear functions of time t which means that homogeneous Gamma process can model degradation process with linear tendency over time.

Gamma process is time-homogeneous with independent and positive increment, so it is sensible to use this process to describe a gradual deterioration, especially the gradual damage monotonically accumulating over time in a sequence of tiny increments, such as wear, fatigue, corrosion, crack growth, erosion, creep, degrading health index, etc., Chen-Mao Liao & Sheng-Tsaing Tseng, 2006). Another advantage of Gamma process is that it has an explicit probability distribution function which permits both the mathematical developments and simulation. It has been extensively used to model single-component systems as well as variants such as non-linear shape function and/or parameters depending on covariates (Dieulle et al., 2003; Grall et al., 2006; Lawless & Crowder, 2004; Tian et al., 2011; van Noortwijk, 2009; W. Wang et al., 2000). Figure 2.1 presents a typical degradation process modeled by Gamma process.

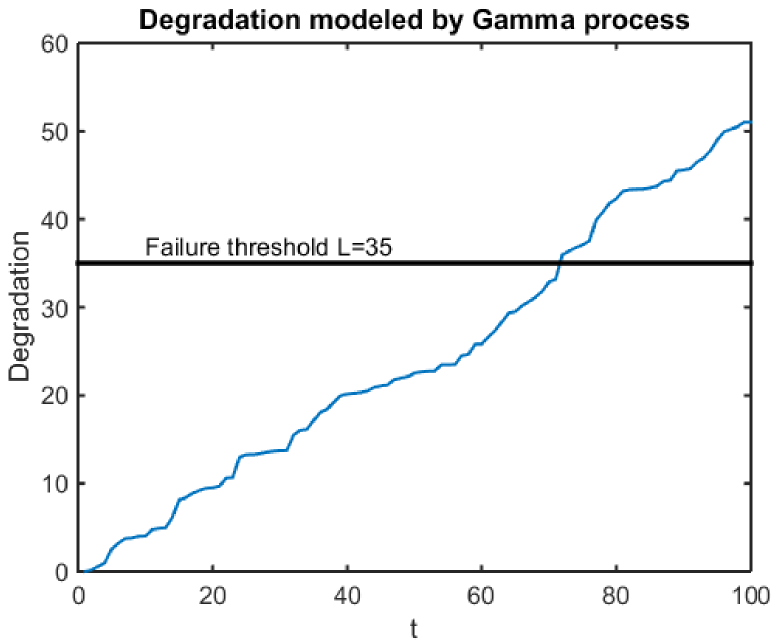

Figure 2.1 A typical degradation process modeled by Gamma process

Although gamma process has been widely used for modeling the monotone gradual degradation processes, it is not capable for considering unit-to-unit variability or random effect in degradation process (Ye & Chen, 2014). In that way, Inverse Gaussian process is proposed to depict unit-to-unit variability or random effect in modeling the degradation process.

2.2.2.2. Inverse Gaussian process

A stochastic process $(X_t)_{t\geq 0}$ is called as Inverse Gaussian (IG) process if it has the following properties:

- $X_0 = 0$;
- $(X_t)_{t\geq 0}$ has independent increments.
- For $t > 0$ and $s > 0$, $X_{t+s} - X_t$ follows a IG distribution with shape parameter $\Lambda(t+s) - \Lambda(s)$ and scale parameter $\eta[\Lambda(t+s) - \Lambda(s)]^2$ and probability density function of IG distribution of IG distribution with parameter (a, b) is given by:

$$f_{IG}(x) = \sqrt{\frac{b}{2\pi x^3}} \exp\left(-\frac{b(x-a)^2}{2a^2 x}\right), x > 0 \tag{2.8}$$

Where, $\Lambda(t)$ is a monotone increasing function. $\Lambda(t)$ is a linear function of time t, i.e., $\Lambda(t) = \zeta . t$, the IG process is a stationary process.

From the definition, some interesting properties of IG process are noted as follows:

- If the degradation process of the component is modeled by IG process, the reliability of the component at time t can be expressed as:

$$R_t = P(X_t < L) = \phi\left[\sqrt{\frac{\eta}{L}}\left(\frac{L}{\zeta} - t\right)\right] + exp\frac{2\eta t}{\zeta}\phi\left[-\sqrt{\frac{\eta}{L}}\left(\frac{L}{\zeta} + t\right)\right] \quad (2.9)$$

where, $\Phi(.)$ is the mathematical expression of cumulative distribution function of the standard normal distribution.

- For $t > s > 0$ and the degradation level of the component at time s is known as x_s then the conditional reliability of the component at time t when the degradation level of the component at time s is x_s can be expressed as:

$$R_t = P(X_t < L | X_s = x_s)$$

$$= \phi\left[\sqrt{\frac{\eta}{L}}\left(\frac{L-x_s}{\zeta} - (t+s)\right)\right] + exp\frac{2\eta t}{\zeta}\phi\left[-\sqrt{\frac{\eta}{L-x_s}}\left(\frac{L}{\zeta} + (t-s)\right)\right] \quad (2.10)$$

- Mean and variance of X_t are ζt and $\frac{\zeta^3}{\eta}t$, respectively. If $\Lambda(t)$ is a linear function of time t, i.e., $\Lambda(t) = \zeta . t$, the degradation process of the component increases linearly over time.

The Inverse Gaussian process has been used to model monotone degradation data when other processes do not fit the data very well, such as the degradation data of GaAs laser (X. Wang & Xu, 2010) and energy pipeline corrosion data (Qin et al., 2013). The IG process also has some advantages over the Gamma process. For example, IG process is used to fit the degradation data in (Ye & Chen, 2014) which has shown that IG process is more flexible than Gamma process in considering unit-to-unit variability. IG process also can be applied to investigate the random effects. For example, two random effect models are proposed into consideration as the first passage of Brownian motion. It has been demonstrated in (Ye & Chen, 2014) that the IG process can be approximated as compound Poisson process. A general Bayesian method is proposed for degradation analysis with inverse Gaussian process model in (W. Peng et al., 2014). A condition based maintenance approach is proposed in (Chen et al., 2015) based on the inverse Gaussian degradation modeling and remaining useful life estimation is investigated with respect to random effect in (Pan et al., 2016).

Figure 2.2 presents a typical degradation process of a component, which is modeled by Inverse Gaussian process.

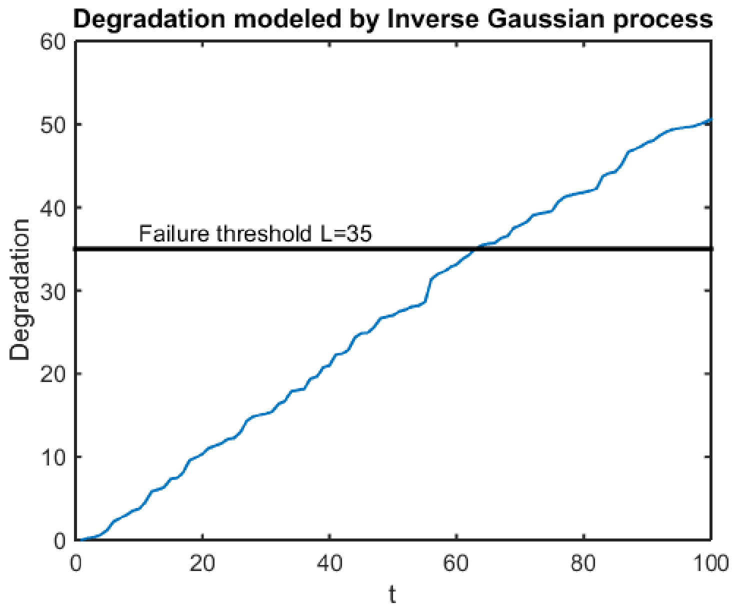

Figure 2.2 A typical degradation process modeled by Inverse Gaussian process

Gamma and Inverse Gaussian processes are used to model the monotone degradation process such as wear out, creep, fatigue, etc. However, the degradation process of some industrial components cannot be explained by monotone degradation models due to internal mechanisms such as self-repair ability in short term or external impact such as measurement errors. Therefore, non-monotone degradation models should be proposed in order to depict the non-increasing increment in short term. In that way, Wiener process is proposed to model the non-monotone degradation process.

2.2.2.3. Wiener process

The Wiener process is also called as Gaussian process of Brownian motion with drift. Generally, a stochastic process $(B_t)_{t\geq 0}$ is called as Wiener process if it has the following properties:

- $B_0 = 0$
- $(B_t)_{t\geq 0}$ has independent and stationary increments.

- For $t > 0$ and $s > 0$, $B_{t+s} - B_t$ follows a normal distribution with zero means and variance s, denoted as $B_{t+s} - B_t \sim N(0, s)$. The probability density function of Normal distribution $N(0, s)$ is given by:

$$f(x|0,t) = \frac{1}{\sqrt{2\pi t}} exp\left(-\frac{x^2}{2t}\right), x > 0 \quad (2.11)$$

Then the degradation process of the component at time t can be expressed as:

$$X_t = \mu t + \sigma B_t, \mu > 0, \sigma > 0 \quad (2.12)$$

Where, μ and σ are two parameters characterizing the degradation process of the component so that the increment between two successive times s and $t + s$, ($t > 0$ and $s > 0$), of the degradation level of the components, $X_{t+s} - X_s$, is normally distributed with mean μt and variance $\sigma^2 t$. Some interesting properties of the Wiener process are noted as follows:

- The component is failed once its degradation, modeled by Wiener process with parameters (μ, σ) exceeds a predefined failure threshold L, then the reliability of the component at time *t* can be expressed as:

$$R_t = P(X_t < L) = \phi\left(\frac{L-\mu t}{\sigma\sqrt{t}}\right) - exp\frac{2\mu L}{\sigma^2}\phi\left(-\frac{L+\mu t}{\sigma\sqrt{t}}\right) \quad (2.13)$$

  Where, $\Phi(.)$ is the mathematical expression of cumulative distribution function of the standard normal distribution.

  In effect, the first passage time of the Wiener process is distributed according to an Inverse Gaussian distribution with parameters $\left(\frac{L}{\mu}, \frac{L^2}{\mu^2}\right)$.

- For $t > s > 0$ and the degradation of the component at time *s* is known as x_s, the predicted reliability of the component at time *t* can be expressed as:

$$\begin{aligned} R_t &= P(X_t < L|X_t = x_s) \\ &= \phi\left(\frac{L-x_s-\mu(t-s)}{\sigma\sqrt{(t-s)}}\right) - exp\frac{2\mu(L-x_s)}{\sigma^2}\phi\left(-\frac{L+\mu(t-s)}{\sigma\sqrt{(t-s)}}\right) \end{aligned} \quad (2.14)$$

- Mean and variance of X_t are μt and $\sigma^2 t$, respectively. It means that the degradation level of the component increases linearly over time in long term. However, the degradation process modeled by Wiener process is not always increasing, the degradation signals sometime decrease without maintenance due to self-repair mechanism.

Due to its useful mathematical properties and physical interpretations, the Wiener process has been widely used for modeling the degradation process. For example, Whitmore (1995) modeled the degradation process subjected to measurement errors by a Wiener diffusion process. A model for modeling the accelerated degradation data using Weiner diffusion process with a time scale transformation is proposed in Whitmore & Schenkelberg (1997). Chiming Guo et al. (2013) proposed a maintenance optimization model for mission-oriented system based on Wiener degradation process. More studies in degradation modeling using Wiener process can be preferred to (J. Huang et al., 2015; X. Wang, 2010). Figure 2.3 presents a typical degradation process of a components, which is modeled by Wiener process.

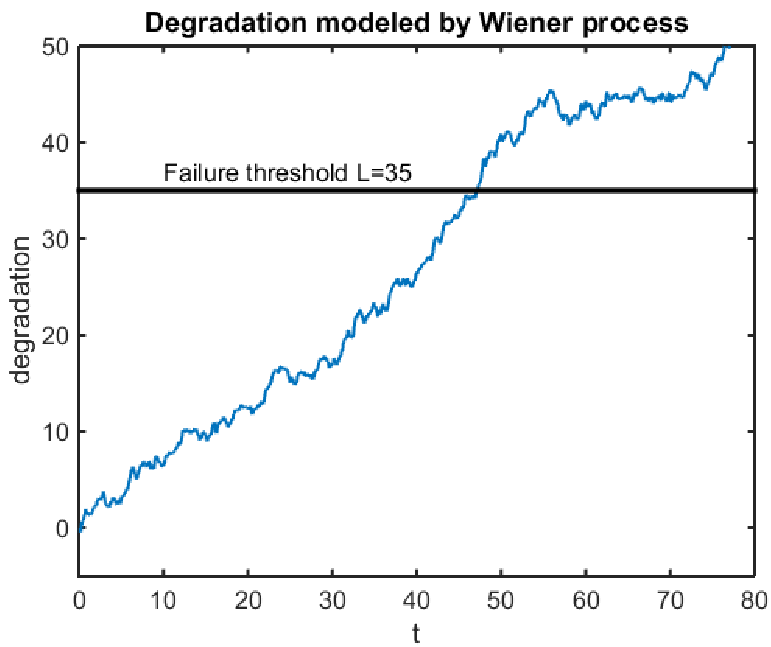

Figure 2.3 A typical degradation process modeled by Wiener process

2.2.2.4. Degradation model selection criteria

In the previous sections, the existing models for modeling the degradation process of the component have been introduced. The important issue is to select the model which describes the underlying degradation phenomenon of the component in the best possible way when the degradation data is available. Nguyen et al. (2018) presents the criteria for degradation model selection. The purpose is to select the best model among a class of competing models given a dataset according to different objectives. The primary objective of degradation model selection is to select the model that best fit with observed degradation data, so called goodness-of-fit criteria. The goodness-of-fit criteria characterizes the ability of the model to match the observation data. They describe the discrepancy between the observed data and the expected values under the considered models. Pearson's Chi-square test and Kolmogorov-Smirnov test are widely used to evaluate the goodness of fit criteria of the models (K. T. Nguyen et al., 2018).

In reliability and maintenance engineering, one of primary purposes of degradation modeling is to predict the future condition of the system. Therefore, another criterion for degradation model selection is the ability to predict the future degradation behavior. In that way, the degradation models can be selected based on lifetime prognostic performance criteria. Prognostic horizon (PH) and prognostic accuracy (PA) are the measures used for evaluating the prognostic performance of the degradation models (Saxena et al., 2010). PH is a measure that considers which degradation model gives an acceptable estimation of RUL in the best time. PA is a measure that evaluates the precision of RUL estimation corresponding to an amount of accumulated observation data with a fixed observation period.

In that way, when the degradation data is available, the above mentioned criteria can be applied to find the model that can describe the degradation behavior of the components in the best way.

So far, the modeling of the inherent degradation process of the components has been introduced. However, in practice, the component may also experience sudden damage caused by external factors, such as hidden manufacturing defects, excessive loads, shocks, and the dependences between components. The degradation modeling considering the impact of these external factors is introduced in the next section.

2.2.3. Degradation modeling considering external impacts

2.2.3.1. Degradation modeling with shock impacts

The early studies considering the impact of shocks and degradation are based on the hypothesis of independence between degradation and shocks, i.e., component failure is either caused by degradation process or fatal shock, whichever arrives first. For example, the degradation process of the component is modeled by a general path model, and random shocks are modeled by nonhomogeneous Poisson process in Fan et al. (2017). Component is considered as failed when the degradation process exceeds the failure threshold or fatal shock arrives, whichever occurs first. W. Li & Pham (2005) considered the existence of a variety of degradation process and shock process in the system itself.

However, in practice, the coupling relationship between inherent degradation process and shocks often exists. Current models describing their correlation can be divided into two research directions. In the first direction, it is assumed that random shocks cause a jump in the degradation level of the component, either leading to failure if the magnitude of this jump is sufficiently large to cross the failure threshold or to incremental damage otherwise. For example, reliability models and maintenance policies for systems subject to multiple dependence competing failure processes are developed in (H. Peng et al., 2010). In addition to the continuous degradation process, random shocks can cause a jump in degradation level or direct failure depending on their magnitude. Song et al. (2014) extent this research to parallel systems with components experiencing dependent degradation processes and categorized shocks. Further research in this direction can also be seen in (Caballé et al., 2015; T. Huang et al., 2021). The second research direction assumes that random shocks impacts on the degradation rate of the component. For example, a dependent competing risk model for system subjects to multiple degradation processes and random shocks are proposed in (Y. Wang & Pham, 2011). In this study, a nonfatal random shock can cause both a sudden jump in degradation level and acceleration the degradation rate. Rafiee et al. (2014) proposed reliability models for system subject to dependent failure processes with changing degradation rate according to particular random shock patterns.

While the above mentioned models can be effectively applied for single-component system, they might not be sufficient in the case of multi-component system. For multi-component system, a shock rarely influences all components but only one or few components. In addition, the system may also experience several types of shocks, and the impacts of different types of shock on the components are different. Moreover, the impacts of a type of shock on different components are also different. A type of shock may result in a jump on degradation level of this component but cause a change in degradation rate of other components. Shen et al. (2018) presents a reliability model for multi-component system with degradation interaction and different types of shocks. The influences of different types of shocks are different, i.e., a type of shock can result in a jump in its degradation level, but other types of shocks can cause a change in its degradation rate. The impact of a type of shock on different components is different, i.e., a type of shock can cause a jump in degradation level of a component, but results in a change in degradation rate of other components. Figure 2.4 presents different impacts of shocks on the degradation process of the components.

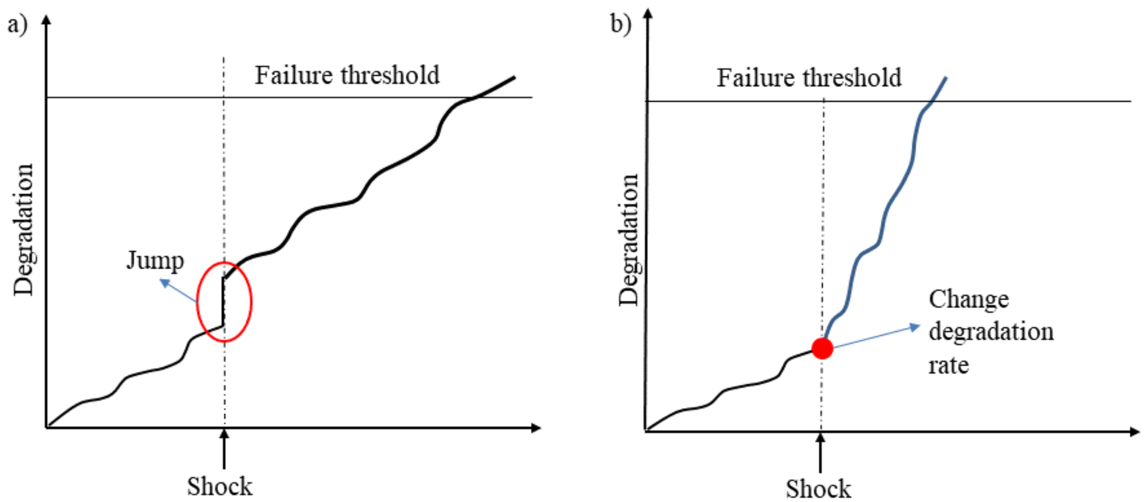

Figure 2.4 Impacts of shocks on the degradation process of the components (a)-increase the degradation level and (b)-accelerate the degradation rate

Besides shock impacts, another external factor that influences the degradation process of the components is state of the components or maintenance actions taken on other components due to the dependences between components.

2.2.3.2. Degradation modeling considering the dependences between components

As mentioned in section 1.4.2, the dependences between components are usually classified into three main types: Economic, stochastic and structural dependences. Another way to classify the dependences between components is related to the influence of the dependences on the degradation process of the dependent components: Degradation influencing dependences and non-degradation influencing dependences. The degradation influencing dependence is the dependence between components so that the degradation process of the components is influenced by the state of other components. The well-known degradation influencing dependence is stochastic dependence. By contrast, the non-degradation influencing dependence is the dependence between component so that the degradation process of the component is not influenced by the state of other components. Economic and structural dependences are usually considered as non-degradation influencing dependences (Nicolai & Dekker, 2008).

Indeed, stochastic dependence implies that the degradation state of a component may influence the degradation state of other components (Bian & Gebraeel, 2014; Do, Scarf, et al., 2015; Keizer et al., 2017). This kind of dependence also called as degradation interaction. Degradation interactions occur in many mechanical systems. For example, the degradation of the hydrodynamic bearings of wind turbines may increase the looseness of primary transimission shafts, then results in increase the vibration signal of the gearbox (Bian & Gebraeel, 2014). A degradation rate interaction model for a system with n components is proposed in (Bian & Gebraeel, 2014). Components in the system are continuously degraded but their degradation states can be divided into discrete degradation states according to their degradation level. When component i shifts to a more severe degradation state, it increases the degradation rate of other component j by an amount of $\delta_{ij}(\forall j \# i)$. In that way, the degradation rate of the components consists of two parts: inherent degradation rate and the increments of the degradation rate due to the degradation rate interactions. Assaf et al. (2018) study the wear rate-state interaction for multi-component system through a gearbox accelerated life testing platform. Later, Do et al. (2015) proposed an opportunistic maintenance policy to take into account the degradation interactions between components.

Most of the studies in maintenance for system with structural dependence only consider the impact of structural dependence on maintenance duration and assume that structural dependence does not influence the degradation process of the components, see (Dao & Zuo, 2017; Geng et al., 2015; Iung et al., 2016; Zhou et al., 2015) for instance. This assumption may not be true. Since structural dependence means maintenance of a component requires disassembly of other components, disassembly operations may have impacts on the degradation state of the disassembled components (Keizer et al., 2017). Indeed, disassembly operations are categorized into three types: Non-destructive, semi-destructive and destructive disassembly (Vongbunyong & Chen, 2015). Destructive disassembly deals with the partial or complete destruction of the obstructing components. The semi-destructive approach aims to destroy only connective components leaving the main components with little or no damage. For non-destructive disassembly methods, the components are claimed for remaining undamaged, this is desirable for maintenance. This technique requires that all fasteners between the components of the system must be reversible or semi-reversible. However, few systems nowadays are actually designed according to design for disassembly guidelines (Vongbunyong & Chen, 2015). Even though the fasteners are reversible or semi-reversible, the disassembly process also can cause some undesired damages. In this case, the interactions between the faying surfaces of the components or between the components and the devices used to perform the disassembly operations may cause some damages such as scratches, dents, blows, wearing down, deformation, etc. These damages can lead to the decrease of the operating performance of the components (Estrada et al., 2007). The damage during disassembly operations may be caused due to the poor skill of maintenance technician, lack of design for serviceability and maintenance, or certain parts of the components cannot be easily removed without being broken (Dhillon & Liu, 2006; Pyy, 2001; Scarf & Cavalcante, 2012). An example of the impact of disassembly operations for maintenance on component's degradation process could be the disassembly of the bearings of the gearbox system. The gearbox system consists of several bearings and gears, which are tightly mounted on the shafts. To disassemble the bearings, force is applied to pull the bearings out of the shaft and these operations could cause scratches, surface degradation, or dent, etc. on the shaft and the bearings as shown in Figure 2.5 (AG, F. K, 2003).

Figure 2.5 Damages of bearings due to disassembly operations: (a)-Brinell marks appear as indentations in the raceways, increasing bearing vibration, (b)-supporting lip is partly or completely broken off or crack and (c)-metal cage with dents (Ag & Kg, 2004)

From the above analysis, regardless to whether non-destructive, semi-destructive or destructive disassembly methods are applied, the disassembly operations may impact on the degradation process of the surviving components. The disassembly operations play a role like a shock to the disassembled components, influencing the degradation of the disassembled components. It means that the structural dependence between components influences not only maintenance downtime but also degradation process of the components. In that way, one scientific issue in maintenance modeling for multi-component system with structural dependence is "*what are the impacts of structural dependence on the degradation process of the components?*".

So far, the degradation models presented in this section consider the case that component failed when its degradation level reaches a critical (failure) threshold. However, in practice, the failure threshold is difficult to determine and usually is a random variable depending on the environment condition and product's characteristic. Moreover, the degradation does not directly lead to the system failure but it increases the likelihood of failure of the system, i.e. system failure due to aging effect and cumulative degradation (Hu & Chen, 2020). A convenient and prevalent way to integrate the aging and degradation effects into system failure is using proportional hazard model (PHM) (Lin & Wei, 1989).

2.2.4. Proportional hazard model

Proportional hazard model incorporates a baseline hazard function, which accounts for the aging effect, with a link function, that takes the degradation signal into account to improve the failure time prediction (Tran et al., 2012). The most popular proportional hazard model is Weibull based line proportional hazard model, which is defined as follow:

$$h\big(t, Z(t)\big) = h^o(t).\,\varphi\big(Z(t)\big) \qquad (2.15)$$

Where:

- $h^o(t)$ is the Weibull baseline hazard rate with shape β and scale λ, which can be defined as:

$$h^o(t) = \frac{\beta t^{\beta-1}}{(\lambda)^{\beta}} \qquad (2.16)$$

$\varphi\big(Z(t)\big)$ is the function of degradation signal, which takes into account the influence of cumulative degradation into the failure behavior of the system. The common useful forms of $\varphi\big(Z(t)\big)$ is linear model, i.e. $\varphi\big(Z(t)\big) = \alpha.Z(t)$ or log linear model i.e. $\varphi\big(Z(t)\big) = log\big(\alpha.Z(t)\big)$. Where, α is the regression coefficient quantifying the impact of degradation on the failure rate of component.

The reliability of the component at time t when the failure of the component is characterized by a Weibull baseline hazard model can be expressed as:

$$R(t) = P(T_f > t) = exp\left[\int_0^t h(s, Z(s))ds\right] \quad (2.17)$$

Where T_f is the failure time of the component.

In literature, several studies applied proportional hazard model in condition based maintenance. Wu & Ryan (2010) investigated the value of condition monitoring in the proportional hazard model setting, where a continuous time Markov chain was used to describe the system condition. Tian & Liao (2011) proposed a CBM policy for multi-component system using proportional hazard model. A Weibull baseline proportional hazard model is used in (B. Liu et al., 2020) to integrate the effect of aging and cumulative damage. Similarly, Hu & Chen (2020) proposed a predictive maintenance for system subject to hard failure based on proportion hazard model.

In that way, proportional hazard model is used to model the failure process of the component subjected to hard failure. For these components, the degradation does not directly lead to the system failure but it increases the likelihood of failure of the system, i.e. system failure due to aging effect and cumulative degradation.

In summary, the properties of the degradation models are presented in table 2.1.

Table 2.1 Summary of degradation models

Model type	**Model name**	**Properties**	**Most relevent references**
Inherent degradation process	Gamma process	- Monotone degradation process - Time-homogeneous with independent and positive increment	Do et al., 2015
	Inverse Gaussian process	- Monotone degradation process - Ability to consider unit-to-unit variability - Ability to consider the random effects	Ye & Chen, 2014
	Wiener process	- Non-monotone degradation process - Considering the measurement errors	Wang, 2010
Degradation with external impacts	Stochastic dependence	- Degradation rate interactions	Bian & Gebraeel, 2014
	Degradation with external shock	- Shock influences the degradation level and/or degradation rate	Shen et al., 2018
Proportional hazard model	Proportional hazard model	- Incorporating the degradation process and aging effects	Hu & Chen, 2020

2.3. Maintenance modeling and optimization

Regarding to the second challenge in "*Maintenance modeling and optimization taking into account both structural and economic dependences*", this section presents a literature review on the maintenance modeling and optimization for both single-component and multi-component systems. Although the maintenance models for single-component system cannot be directly applied for multi-component systems, they provide the basic foundations to support maintenance modeling for multi-component system (H. Wang, 2002). Given historical data and/or degradation modeling, maintenance modeling and optimization phase aims at allocating of the maintenance resources and scheduling the maintenance actions according to the objectives of maintenance management policy. The objectives of maintenance management policy could be, e.g., minimizing the maintenance cost and/or downtime, maximizing the availability and/or the reliability of the system, etc. According to the number of components within the system, they can be classified as maintenance policies for single-component systems and maintenance policies for multi-component systems (H. Wang, 2002).

Before discussing the maintenance modeling, the impacts of different kinds of maintenance actions on the state of the components are discussed in the next section.

2.3.1. Maintenance actions

Maintenance actions can be classified into different classes depending on the state of the component before maintenance or the quality of the maintenance actions. Based on the state of the components before maintenance, maintenance actions are classified into two major classes: corrective maintenance (CM) and preventive maintenance (PM) actions. Corrective maintenance is the maintenance actions applied when a component is failed, i.e., CM action restores the failed component to the operation state. While preventive maintenance applied to the surviving components but considered to be degraded enough to need maintenance. PM action is designed to avoid or mitigate the sudden failure of the components through planned maintenance. Since the sudden failure of the component could lead to huge economic losses or damage to the system, the planned preventive maintenance is often more economic benefit than unplanned corrective maintenance. Therefore, maintenance optimization should encourage the planned preventive maintenance actions while mitigate the unplanned corrective maintenance.

Depending on the efficiency of the maintenance actions on the maintained components, maintenance actions can also be classified into perfect maintenance, imperfect maintenance and minimal repair (H. Wang, 2002). Perfect maintenance restores the component to as good as new state (AGAN), and is usually referred to replacement action for non-reparable system (Do et al., 2015). The assumption of perfect maintenance is simple and can facilitate for maintenance modeling and optimization. Therefore, most of the studies in maintenance consider perfect maintenance in their model (H. Wang, 2002). Minimal repair restores the failed components to the operation state, but its characteristics are the same as just before maintenance, that is as bad as old state (ABAO) (Block et al., 1985). Imperfect maintenance restores the maintained component to intermediate state between ABAO and AGAN state (Do et al., 2015). Figure 2.6 presents the impact of perfect, imperfect and minimal maintenance on the degradation of the system.

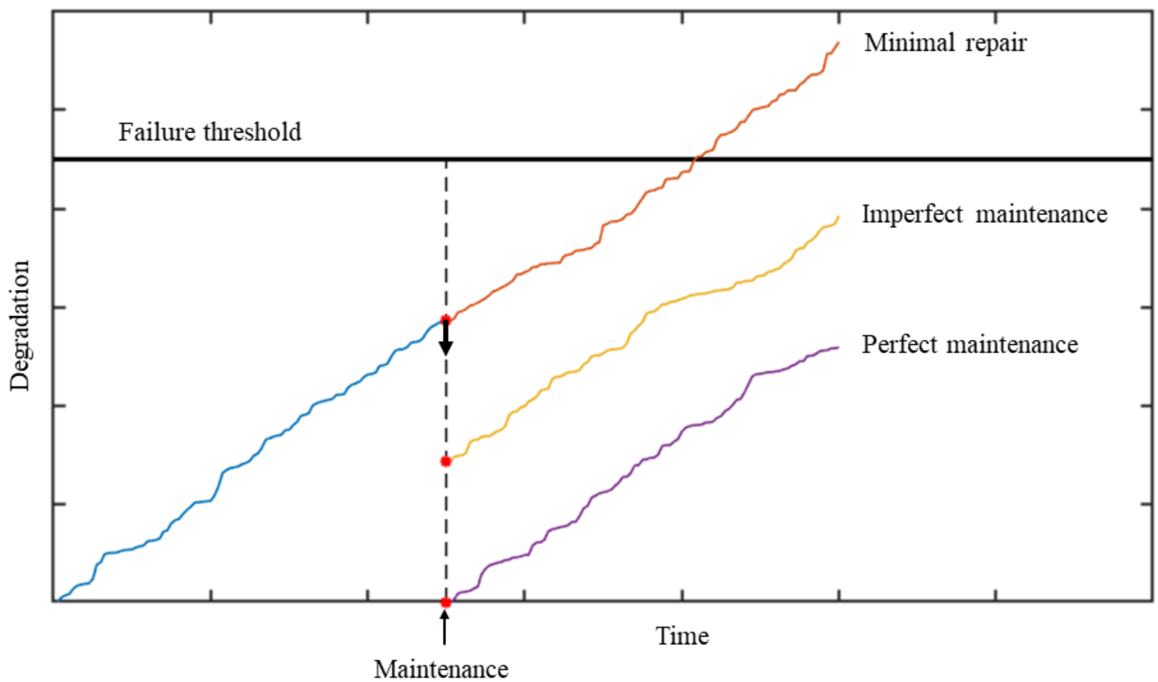

Figure 2.6 Impact of minimal repair, imperfect and perfect maintenance on the degradation of the system (Adapted from Do et al., 2015)

Maintenance modeling and optimization aims at combining and allocating the maintenance strategies, maintenance actions, maintenance supporting activities and other resources to achieve the objectives of the maintenance management policy. The maintenance modeling for single unit system is firstly introduced in the next section. Based on the maintenance modeling for single unit system, the maintenance modeling for multi-component system is established by considering the dependences between components.

2.3.2. Maintenance modeling for single-component systems

In the framework of predictive maintenance, two following features of maintenance modeling are considered: (1)-*Condition monitoring scheme* and (2)-*Maintenance decision-making rule* (Huynh et al., 2019).

For the *condition monitoring scheme,* the degradation of the component can be revealed through inspection. It means that the state of the component can be known at inspection and therefore, the maintenance decision is made at inspection time (Dieulle et al., 2003; Shin & Jun, 2015; W. Wang et al., 2000). The inspection can be carried out continuously (Liao et al., 2006) or discretely (Huynh et al., 2011). For continuously inspection policy, the system is continuously monitored so that it can provides the real-time information about the system state and a warning alarm is triggered whenever something wrong is detected. However, continuous inspection policy may be costly, and even cannot be implemented in practical applications. In this context, it is more suitable to implement the discrete inspection policy. Of course, one of the disadvantages of the discrete inspection policy is the risk of missing some failure events occurring between successive inspections. The inspections can be performed at fixed interval over the whole lifetime (periodic inspection) or dynamically at variable inspection intervals (non-periodic inspection). In that way, finding the optimal inspection intervals, which balance between the risk of missing some failure events occurring between successive inspections and inspection cost is one of the main issues for discrete monitoring policy. By non-periodic inspection policy, the unequal inspection intervals can adapt to either the system age, to the system deterioration rate, to the system deteriorate level, to the system remaining useful life, and to the working environment, or just be simply random value. The common approach is that the inspection interval decreases as the system deteriorates, which means more inspections should be conducted when the system is in degraded state. From the economic point of view, the periodic inspection policy is normally less profitable than the non-periodic inspection policy. However, its implementation in an industrial context is obviously much easier (Huynh et al., 2019).

The maintenance decision-making rule in the context of predictive maintenance is usually based on the control-limit maintenance decision-making rule. By this kind of decision-making rule, maintenance actions are performed on the system whenever the considered condition index, which characterizes the system health condition, exceeds a critical threshold (H. Wang, 2002). The most used condition indices are the system degradation level, predicted remaining useful life

(RUL), means residual life (MRL) (the expectation of remaining useful life), and predicted conditional reliability. For example, a periodic inspection and replacement policy is proposed in (Huynh et al., 2011), whole replacement operations are performed when the degradation level exceeds a given threshold.

In Ponchet et al. (2010), by the same way, the degradation level is used to make maintenance decision for non-periodic inspection. The replacement decisions are made at inspection time according to the system condition reliability and the system conditional MRL in (Khac Tuan Huynh et al., 2014a) and (Khac Tuan Huynh et al., 2014b), respectively. Nguyen & Medjaher (2019) incorporates spare part provisioning in the framework of predictive maintenance using the system conditional reliability as the maintenance decision indicator. Khoury et al. (2013) proposed two predictive maintenance policies based on maintenance cost and reliability criteria for a gradually deteriorating system operating under uncertain environment. A performance comparison between the proposed maintenance policies and a benchmark deterioration-based maintenance policy was conducted, which shows that the proposed maintenance policies is more profitable. Do Van et al. (2012) proposed a maintenance decision-making model based on the system's RUL. The system is discretely inspected at time T_i $(i = 1,2, \dots)$, with inspection interval ΔT, i.e., $T_i = T_{i-1} + \Delta T$. At inspection, the system's RUL is predicted and maintenance decision is made. If the predicted RUL of the system at inspection T_i is less than the inspection interval, $RUL(T_i) < \Delta T$, i.e., system is likely to be failed before the next inspection, component is preventively maintained.

Although the maintenance models for single-component system have been extensively studied in literature, maintenance models for single-component system cannot be directly extended for multi-component system due to the interdependences between components.

2.3.3. Maintenance modeling for multi-component systems with dependences

The dependencies between components significantly influence the degradation process of the components and maintenance decision-making process. Omitting the dependences between components in maintenance modeling could result in higher maintenance cost and suboptimal maintenance plan (Keizer et al., 2017; Nicolai & Dekker, 2008). Then, maintenance policies for multi-component systems should take into account the dependencies between components. In this section, we discuss the extensions of maintenance policies for multi-component system with economic and structural dependences.

2.3.3.1. Maintenance modeling with economic dependence

Economic dependence means that combining maintenance on several components is either cheaper (positive economic dependence) or more expensive (negative economic dependence) than maintaining these components separately (Keizer et al., 2017). A system is subjected to negative economic dependence if combining maintenance on several components leads to higher costs than maintaining them separately. The reasons can be due to the manpower restrictions, safety requirements, or production losses (Nicolai & Dekker, 2008). For example, a company may need to (temporarily) hire additional staff or rent additional tools to simultaneously maintain multiple components. So, the maintenance cost can be increased with the increase of the number of components need maintenance. Another example of negative economic dependence occurs in practice is when multiple workers need to operate in a limited space. They will start blocking and irritating each other, hence increase the probability that human errors occur (Keizer et al., 2017). Positive economic dependence occurs when high costs are involved in preparation for maintenance execution, e.g., ordering spare parts, traveling to the maintenance site (such as offshore wind farm, offshore oil platform) or shutting down and restarting an oil refinery to perform maintenance. In literature, this dependence is usually modeled as maintenance setup cost, which is paid once if maintenance is perform on the system, independent on the number of components that receive maintenance (Keizer et al., 2017; Nicolai & Dekker, 2008). Generally, the maintenance setup cost is independent on the system structure, types of maintenance actions that performed and maintenance duration. However, when the system consists of several subsystems or component types, the maintenance setup cost may be different for different types of components or subsystems. In this case, the multiple setup costs structure can be applied. For example, the setup costs are divided into system setup cost and setup cost for each component type or subsystem in (Tian & Liao, 2011) and (Wijnmalen & Hontelez, 1997). Similarly, a distinction for maintenance setup cost also can be made for different types of maintenance actions. For example, the setup cost for preventive maintenance and corrective maintenance actions are different. The studies distinguish the maintenance setup costs between maintenance activities can be referred to (Do, Scarf, et al., 2015; Shafiee & Finkelstein, 2015; Tian et al., 2011). Furthermore, maintenance setup cost may also be time-dependent. For example, the maintenance setup cost for a hydro-generating unit in a deregulated power system can be time-dependent due to fluctuations in the monthly electricity price (Qian & Wu, 2014).

Positive economic dependence means that combining maintenance on several components is cheaper than maintenance them separately. In that way, positive economic dependence between components offers an incentive to combine maintenance actions (grouping maintenance). Optimizing the maintenance decisions for each component separately will therefore not result in an optimal maintenance policy at system level. Instead, the maintenance policy for multi-component system should allow combining maintenance on several components to take the advantages of positive economic dependence. Grouping maintenance strategies aim (1) to take advantage of the resources, efforts and time already dedicated to the maintenance of other components of the system and (2) to extend equipment lifetime and reduce the failure occurrence (Samhouri, 2009). In literature, three main types of maintenance grouping strategies have been studied: (a)-Long-term (stationary), (b)-medium-term (dynamic) and (c)-short-term (opportunistic) grouping (Chalabi et al., 2016).

a. Stationary grouping maintenance policy

The most popular maintenance policy for multi-component system with economic dependence is grouping maintenance in which several components are planned to be maintained together. Since the maintenance setup costs are incurred once the maintenance occurs independent on the number of components received maintenance, grouping maintenance can save maintenance setup cost. In stationary grouping policy, a long term stable situation is assumed and mostly these models assume an infinite planning horizon (H. Wang, 2002). They provide statics rules for maintenance which do not change over the planning horizon. Depending on the number of components in the system are grouped, the grouping maintenance policy can be classified into complete grouping and incomplete grouping maintenance.

For complete grouping maintenance policy, complete system replacement is initiated as soon as one component requires maintenance (Shafiee et al., 2015; Shafiee & Finkelstein, 2015). This can be based upon a component failure or scheduled preventive maintenance. The complete grouping maintenance policy is typically applied for the systems subject to very strong economic dependence, i.e., a very high setup cost. For a weaker form of economic dependence, this policy can lead to overdoing preventive maintenance, leading to high overall maintenance cost (Nicolai & Dekker, 2008).

For incomplete grouping maintenance policies, only few components or a part of system are clustered for grouping maintenance. The group of maintenance actions can be only corrective maintenance, preventive maintenance or mixed of preventive and corrective maintenance. The set of components in a group may be prefixed or dynamically determined (Dekker et al., 1997).

The grouping of corrective maintenance actions is usually applied to system with redundancy such as parallel systems or *k*-out-of-*n* systems. The redundancy components allow the system continue to operate even one or several components failed. Therefore, it allows to postpone the corrective maintenance actions to benefit from cost saving achieved by grouping the maintenance actions when subsequent failures occur. For example, a clustering maintenance policy for *k*-out-of-*n* system based on a dynamic programing model is proposed in (Olde Keizer et al., 2016). The optimal result turns out that the failed components should wait and be left in failure state until the sum of degradation level of other components exceeds a certain level. An optimum grouping maintenance policy is proposed to minimize the maintenance cost and production loss due to failure of a system with redundancy in (Okumoto & Elsayed, 1983). Under this policy, all failed components are replaced only at $k.T$ $(k \in \mathbb{N})$. The maintenance setup cost can be shared if several units are replaced at the same time. With the increase of numbers of failed component at time $k.T$, the maintenance cost per unit is reduced. whereas the production loss per unit is increasing. The maintenance policy aims to obtain the optimal replacement interval T so that the maintenance cost and production loss cost is minimal.

For series system or mixed series and parallel system, a failure of a component may cause the system failure. Therefore, postponing the corrective maintenance actions for grouping is not economic. Hence, grouping preventive maintenance policy is proposed. The models in grouping preventive maintenance policy can be further divided into direct and indirect grouping (Dekker et al., 1997). For direct grouping methods, components are set into a fixed group and they are always preventively maintained with other components in the group at an appreciate moment. The components in the groups and preventive maintenance time of each group should be predetermined. For example, in van Dijkhuizen & van Harten (1997), the maintenance date of the group is set to be the shortest individual replacement date of components in the group. However, the number of possible maintenance groups for a system consisting of n components is $2^n - 1$, such that finding the optimal grouping structure is a NP-hard problem (Wildeman et al., 1997). A dynamic programing algorithm is developed to find the optimal grouping structure. For indirect grouping method, a component *i* is preventively maintained at $k_i.T$ $(k \in \mathbb{N})$ such that k_i and T are the variables to be optimized (Dekker et al., 1996; Goyal & Gunasekaran, 1992). As the degradation of the component is heterogeneous, the indirect grouping does not fix the components in a group.

b. Dynamic grouping maintenance policy

The stationary grouping policies provide statics rules for maintenance which do not change over the planning horizon. It means that the short term information such as a varying of degradation of the components or unexpected opportunities are not taken into account. To take into account the short term information into maintenance planning, the dynamic grouping maintenance policies are proposed. Depending on the planning horizon, dynamic grouping maintenance policies can be divided into finite-horizon and rolling horizon dynamic grouping (Wildeman et al., 1997).

Finite-horizon models consider the system in this horizon only and assume that the system is not used afterward. In finite horizon maintenance policies, the replacement decision variables are parameterized with time, and to keep the model simple, the time is usually discretized. For example, in (Moghaddam & Usher, 2011), the planning horizon is segmented into J discrete intervals, and the maintenance decisions are made at the end of each interval, either preventive, corrective or no maintenance action. When the maintenance actions are simultaneously conducted, the downtime cost can be saved.

Rolling horizon policies also use a finite horizon, but they repeat the finite horizons based on a long-term (infinite horizon) plan. Rolling horizon policies aim to fill the gap between finite and infinite horizon policies and combine the advantages of both. Although, the planning horizon is finite, the decisions are made based on a long-term plan and are adapted according to short-term information. That is, once decisions of the finite horizon are implemented or when new information becomes available, a new horizon is considered and a tentative plan based on the long term is adapted according to short term information. This yield more stable solutions than finite horizon policies (Dekker et al., 1997). Generally, the dynamic grouping with rolling horizon consists of four phases as follow (Vu et al., 2014):

- *Individual optimization*: The aim of this phase is to determine the optimal maintenance schedule for each component without considering the dependences between component. The optimal maintenance schedule, denoted as t_i^*, for each component i individually can be obtained by minimizing the expected long-term cost on an infinite horizon.

- *Tentative planning*: From the optimal maintenance schedule of the component individually, the planning horizon is defined as $HP = \left[0, max_{i\in\{1,\dots,n\}}(t_i^*)\right]$, so that all components are maintained at least once on the planning horizon. In the system there may be components degraded with different speeds. The scheduling horizon *HP* may cover several occurrences of maintenance operations of components degraded with fast speed.
- *Grouping maintenance optimization*: This phase aims to find an optimal grouping structure for maintenance actions over the planning horizon *HP*. The grouping structure is the groups of maintenance actions and their optimal maintenance date over the planning horizon. A penalty cost function is established to take account for the shifting (advance or delay) the maintenance date of the components in each group. The optimal maintenance date of each group can be achieved by minimizing the penalty cost function. The optimal grouping structure is the grouping structure that has the maximum cost saving and minimum penalty cost.
- *Updating the maintenance plan:* When new information is available (such as maintenance resource constraints, component's degradation information, failures, etc.), the maintenance planning is updated by repeating the steps of tentative planning and grouping optimization. In this way, the maintenance planning is dynamic and adaptive.

For manufacturing system, during operation, there may be maintenance opportunities (e.g. unscheduled downtime, planned shutdown of the system, shortage of material, etc.), which provide advantages for conducting preventive maintenance (e.g. lower maintenance costs, free downtime cost). In that way, opportunistic maintenance policies are proposed to take the advantages of opportunities in maintenance modeling.

c. Opportunistic maintenance policy

Maintenance opportunity is a break time of the system that may provide advantages for conducting preventive maintenance (e.g. lower maintenance costs, free downtime cost). Based on the original of the factors contributing to the existence of the maintenance opportunities, the maintenance opportunities (MOs) can be classified into two main classes: External and internal MOs (Ab-Samat & Kamaruddin, 2014). The external MOs are the system downtime triggered by external factors such as system scheduled downtime, shortage of materials, hash environment conditions, lack of demands, etc. (Do et al., 2011; Yang et al., 2018a). Note that maintenance does not influence the arrival of the external MOs. Most of the studies working with external MOs usually consider single-component system and focus on modeling of the maintenance opportunities (Vu et al., 2020). The two main characteristics of the external MOs are arrival time and durations of the MOs are taken into modeling. For example, the MOs occurrences are assumed to follow homogeneous Poisson process in (P. Li et al., 2016; Yang et al., 2018a) and non-Homogeneous Poisson process in (Truong Ba et al., 2017; Yang et al., 2018b).

Internal maintenance opportunities occur due to the maintenance actions on the system and usually exist in multi-component systems with dependences. During maintenance of a component, the system may be stopped, consequently, it offers downtime opportunities to conduct maintenance on other components. Moreover, due to the dependences between components, e.g. economic and structural dependences, joint maintenance of several components at the same time can reduce maintenance cost and downtime. According to the types of maintenance actions (preventive and corrective maintenance), the internal maintenance opportunities are further classified into preventive and corrective maintenance based opportunities (Vu et al., 2020). The PM based opportunity is triggered by PM activities of components. Since PM date may be planned, the supports for opportunistic maintenance at a PM based opportunity can be done proactively. The CM based opportunity is triggered by CM activities or failures of the components. Since CM date as well as the failure time of the components is random, the support for the opportunistic maintenance at CM based opportunities is more complicated in comparison to PM based OM.

Opportunistic maintenance policies aim to take into account the arrival of the maintenance opportunities into maintenance decision-making. When maintenance opportunities arrive, maintenance conducting at MOs can help avoiding or reducing future failure, as consequently reducing the induced downtime and cost. However, advancing maintenance actions also results in reduction of the lifetime of the component. Therefore, opportunistic maintenance decision-making aims to balance between the gains by conducting preventive maintenance at maintenance opportunities and cost of reducing the lifetime of the components. This kind of maintenance decision-making is called as control limit policy (Koochaki et al., 2012). Under the control limit maintenance policy, different maintenance thresholds are introduced for different maintenance actions: preventive and opportunistic maintenances. Depending on the criteria used for selecting the components for opportunistic maintenance, several opportunistic maintenance models have been proposed: (1) age-based OM models; (2) failure-rate-tolerance-based OM models; (3)

condition based control limit OM models; and (4) Reliability based control limit models (X. Zhang & Zeng, 2015).

For age-based OM models, the age of the component is used as the criteria for opportunistic maintenance decision-making. The well-known age-based OM is (n_i, N) model, which is firstly introduced by (Radner & Jorgenson, 1963). Under this maintenance model, the component is replaced on its failure or the arrival of its preventive maintenance age *N*, and replaced opportunistically with a failed component *i* if its age reach a critical age n_i, $n_i \leq N$. Later, this model is then extended by several researchers. For instance, Van der Duyn Schouten & Vanneste (1990) studied this model for two-unit systems in series. Hongzhou Wang & Pham (2006) considered imperfect maintenance concepts in this context. (Gertsbakh, 1984) extended this model for a system with *n* identical units with age control limit (t, T). In this model, if a unit fails within time interval $[0, t]$, CM is implemented on this component individually. If the component fails within time interval $(t, T]$, it will be correctively replaced and another component is opportunistically replaced as well. If no failure occurs before time *T*, the whole system is replaced at time *T*. The (t, T) opportunistic maintenance policy is then extended for k-out-of-*n* system in (Pham & Wang, 2000). In their model, minimal repair are carried out if the failure occurs in $[0, \tau]$. For the failure within $[\tau, T]$, the components are lying idle until the m^{th} $(m = n - k + 1)$ component fails. If m components failed in the time interval $[\tau, T]$, CM is performed in combination with preventive maintenance, if less than *m* components failed, PM is carried out at time *T*.

(Zheng & Fard, 1992) used failure rate as the criteria for opportunistic maintenance decision-making, and called as failure-rate-tolerance based opportunistic maintenance policy $(L - u, L)$. Under these policies, a component is replaced at failure or preventively replaced when its failure rate reaches a critical threshold *L*, whichever occurs first. When maintenance occurs (preventive or corrective), other components are opportunistically replaced if their failure rate fall in $[L - u, L)$.

With the development of CBM, several opportunistic maintenance policies in framework of CBM have been proposed (Koochaki et al., 2012). The opportunistic maintenance policies in framework of CBM use degradation level of the components as the criteria for maintenance decision-making. For example, Wijnmalen & Hontelez (1997) adopted a complex scheme of actual degree of degradation control limits of the equipment to allow taking discounts from coordinating repair actions. In the model presented in this paper, two preventive maintenance thresholds are proposed, the upper threshold is considered to induce a mandatory preventive repair action independent of other equipment. A lower threshold is introduced for each equipment allowing a repair on this equipment to be made earlier if it can be combined with a mandatory repair of one or more other equipment if the combinations of repair actions offer a cost reduction larger than the cost of advancing the repair. A condition based maintenance model with multi-maintenance thresholds for a two-component system is proposed in (Castanier et al., 2005). In this model, a critical level and sequential decision threshold values for the preventive maintenance of component *i* is denoted as $L^{(i)}$ and $\xi_k^{(i)}$, $(k = 1,2, \dots n)$, respectively. Another threshold ζ_i is added for each component i which defines a zone of opportunistic maintenance. The maintenance decision-making on component *i* at inspection time t_k is based on its degradation level, denoted as $x_k^{(i)}$. If $x_k^{(i)}$ belongs to inspection zone $[0, \xi_k^{(i)})$, the component is left as it is, no maintenance action is required. The component is preventively replaced if $x_k^{(i)} \in [\xi_k^{(i)}, L^{(i)})$ and correctively replaced if $x_k^{(i)} \in [L^{(i)}, \infty)$. If a replacement is scheduled for component *i*, component *j* $(j \neq i)$ is simultaneously replaced with component *i* if the degradation of the component *j* belong to the opportunistic maintenance zone, i.e., $x_k^{(j)} \in [\zeta_i, \xi_k^{(i)})$. This maintenance policy is then extended in (Do et al., 2019) for two component system with considering stochastic dependence.

Although the above mentioned opportunistic maintenance policies take advantage of the maintenance opportunities to promote economic dependence between components, they are inefficient to apply for multi-component system with large number of components. The reason is that the criteria used for maintenance decision-making of the above models (age, failure rate, degradation level) are the individual index of each component and not synchronized with other components and the whole system. Therefore, with the increase of the number of components in the system, the maintenance decision variables, which need to be optimized, increase significantly, consequently increase the computing time dramatically. It is therefore, most of the above mentioned opportunistic maintenance models only consider two-unit systems. For multi-component system, the reliability of the components is used as the maintenance decision-making variable. Reliability of the component can be considered as the normalized index of the condition of the component. The reliability of the components can be estimated through the components' conditions, such as age, failure rate, degradation level (Blischke & Murthy, 2011). The reliability of the system can be synchronized with the estimated reliability of the components based on the reliability block diagram. It means that the maintenance decision-making is based on not only the individual condition but also the synchronized system condition. For example, Huynh et al. (2014) proposed an opportunistic maintenance model for multi-component system in framework of predictive maintenance using reliability as the criteria for maintenance decision-making. In this model, the system's components are assumed to be inspected regularly at time $T_k = k.\Delta T$ $(k = 1,2,\ldots,n)$. At inspection, failed components are correctively replaced and the surviving components are preventively replaced if their conditional reliability at the next inspection time given the actual detected degradation level is less than a preventive maintenance threshold R_p. If one or several components is scheduled to correctively or/and preventively replaced at inspection T_k, other components also can be opportunistically replaced if their conditional reliability at the next inspection time is less than the opportunistic maintenance threshold R_u $(R_u < R_p)$. An opportunistic preventive maintenance model for multi-component system based on dynamic programming is proposed in (Zhou et al., 2009). In this model, a component i is preventively maintained if its reliability reach is preventive maintenance threshold R_i. Whenever a PM is scheduled for a component i, other components can be considered for opportunistic maintenance based on the cost saving of opportunistic maintenance. The opportunistic maintenance cost saving consists of two parts, the positive parts includes downtime cost saving and maintenance setup cost saving, and negative part is the penalty cost of advancing the maintenance.

The reliability based opportunistic maintenance models are very popular for maintenance of the wind farms. Due to the high maintenance setup cost, i.e., strongly economic dependence between components, joint maintenance of several components can significantly reduce the overall maintenance cost of the system. For example, C. Zhang et al. (2017) proposed an opportunistic maintenance model for wind farms considering imperfect, reliability based maintenance. In this model, corrective and preventive maintenance are implemented if the component is failed or its reliability reaches the preventive maintenance threshold $\mathrm{R_p}$. Whenever maintenance required (corrective or preventive maintenance), other components are opportunistically maintained if their reliability reaches the opportunistic maintenance threshold R_o $(R_o > R_p)$. This model is then extended in C. Zhang et al. (2019) by considering weather condition and spare parts inventory management. More studies in opportunistic maintenance for wind farms can be referred to (Ding & Tian, 2012; Lu et al., 2017).

2.3.3.2. *Maintenance modeling with structural dependence*

Structural dependence means that components structurally form a connected set and maintenance of a component requires disassembly of other components. There exists a disassembly sequence between components in the system, so disassembling all preceding components in a disassembly sequence is required in order to reach a certain component for maintenance. So that there are a few researches on disassembly sequence planning which are oriented to system maintenance (Behdad & Thurston, 2012; X. Liu et al., 2012). However, the main concern of these studies is how to optimize the disassembly sequence to obtain the lowest disassembly cost. They paid little attention on the maintenance modeling for multi-component system under the constraint of disassembly sequence. Early studies on maintenance for multi-component systems with structural dependence focus on replacement policy (L. C. Thomas, 1986). In these studies, it is suggested that the system is built in a vertical structural of modules, and replacing a component at a higher level requires replacing all the components at its lower level. The problem is whether to replace the whole system or replace a sub-assembly or just a single component when that single component failed. Zhou et al. (2015) considered a more realistic model given the relationships of components in a hierarchical structure, where the components can have relationships with others at both higher and lower levels and at the same level. An opportunistic maintenance policy is proposed to take advantages of economic and structural dependences. Under this policy, minimal repair is applied when component is failed and preventive maintenance is applied if the reliability of the component reaches the preventive maintenance threshold. A time window T_w is proposed to consider other components for opportunistic maintenance. If a maintenance occurs (corrective or preventive) at time t_k, other components that have the optimal maintenance time within the period $[t_k, t_k + T_w]$ is also opportunistically replaced. The hierarchical structural model is then extent to the selective maintenance framework for multi-state system with structural dependence in Dao & Zuo (2017). Jia (2010) divided a multi-component system into m modules and assumed that replacing a component requires dismantling all components in the same module. So the structural dependence results in the shared disassembly and re-assembly components. The shared disassembly and re-assembly cost can be considered as maintenance setup cost. Therefore, the structural dependence is usually considered as a part of economic dependence. Van Horenbeek & Pintelon (2013) added another cost element to setup cost to represent the structural dependence. The limitation of these studies is to simplify the concept of structural dependence so that it can be treated using a single parameter. However, the manufacturing systems (our system of interest) become more and more complex and it may be decomposed into sub-system, sub-assemblies, parts and components. Therefore, modeling the structural dependence between components is an issue in maintenance modeling for multi-component system with structural dependences.

So far, maintenance modeling for multi-component system considering economic dependence or structural dependence separately has been introduced. However, in practice, several types of dependences may exist simultaneously in the system. Especially, the economic and structural dependences usually exist simultaneously in the system. Maintenance modeling for multi-component system considering both economic and structural dependences are presented in the next section.

2.3.3.3. Maintenance modeling with both structural and economic dependences

When a system is subjected to more than one type of dependence, the effects of these dependences on the optimal maintenance policy can be heavily intertwined (Keizer et al., 2017). However, most of the existing maintenance models only consider one type of dependences since combining more than one makes the models too complicated to analyze and solve (Nicolai & Dekker, 2008; Van Horenbeek & Pintelon, 2013). In section 2.3.3.1 we defined that positive economic dependence offers an incentive to group several components for simultaneous maintenance. Whereas, section 2.3.3.2 revealed that for system subjected to structural dependence, maintenance of a component offers a great opportunity for maintenance of other components, especially for disassembled components since the disassembly duration can be saved. In that way, for multi-component system with both economic and structural dependences, joint maintenance on several components can save maintenance setup cost (economic dependence) and maintenance duration (structural dependence). However, the structural dependence means some components are required to be disassembled for maintenance of a component, but there are still other components remaining in the system. So that when maintenance occurs, the rest of the components can be categorized into two different groups: Disassembled and non-disassembled components. The disassembled components are the ones need to be disassembled in order to reach the target components for maintenance. The non-disassembled components are the ones that do not need to be disassembled due to the maintenance of other components. While opportunistic maintenance on the non-disassembled components can save only maintenance setup cost, opportunistic maintenance on the disassembled components can save not only setup cost but also disassembly durations, i.e., downtime cost. It means that the savings of opportunistic maintenance on the disassembled and non-disassembled components are different. Moreover, the existence of the impact of disassembly operations on degradation process of the disassembled components also requires different treatment for disassembled and non-disassembled components for opportunistic maintenance. However, most of the existing studies in literature equally consider disassembled and non-disassembled components for opportunistic maintenance (Huynh, Barros, et al., 2014; Lu et al., 2017; Zheng & Fard, 1992; Zhou et al., 2009). Indeed, in the literature, the conventional approach for opportunistic maintenance is usually based on two different maintenance thresholds for preventive and opportunistic maintenance (Khac Tuan Huynh, et al., 2014; Koochaki et al., 2012; X. Zhang & Zeng, 2015). The first threshold is to identify components which preventive maintenance can be applied. If a preventive maintenance (PM) or corrective maintenance (CM) occurs, the second threshold is used to select component for opportunistic maintenance (OM). A component is correctively or preventively maintained when it fails or when its reliability reaches the preventive maintenance threshold (R_p) respectively. When PM or CM occurs, other components are considered for opportunistic maintenance if their reliability reaches the opportunistic maintenance threshold $R_u (R_u > R_p)$. These approaches equally consider all components for opportunistic maintenance with only one opportunistic maintenance threshold. Therefore, it does not allow considering the advantages of both structural and economic dependences. This lead to a scientific issue "*What is an adequate predictive maintenance policy allowing to consider both economic and structural dependences?*".

To develop a maintenance policy that can take into account both economic and structural dependences in maintenance decision-making and optimization process, it is firstly necessary to propose mathematical model that can couple both economic and structural dependences between components. The models for formalizing the economic and structural dependences separately have been extensively studied as presented in section 2.3.3.1 and section 2.3.3.2, respectively. However, there is still lack of study that can couple both economic and structural dependences between components (Keizer et al., 2017). Therefore, another scientific issue related to maintenance modeling for multi-component system with both structural and economic dependences is "*how to model the economic and structural dependence between components?*".

In summary, the characteristics of the maintenance policies for multi-component system are presented in table 2.2.

Table 2.2. Summary of maintenance policies for multi-component system

Maintenance policy	Characteristics	Type of dependences	Most relevent references
Stationary grouping maintenance	- The components in group are fixed over the planning horizon - Planning horizon is infinite - The whole group is maintained as soon as one component in the group requires maintenance - Applicable for the system with very high maintenance setup cost	Economic dependence	H. Wang, 2002 Olde Keizer et al., 2016
Dynamic grouping maintenance	- The components in group are flexible and can be changed - Short term information is taken into maintenance planning - Planning horizon could be finite or in-finite (rolling horizon) - Saving maintenance setup cost	Economic dependence	Wildeman et al., 1997 Vu et al., 2014
Opportunistic maintenance	- Maintenance are conducted at maintenance opportunities (system downtime, lack of demand, shortage of materials) - Saving maintenance setup cost and downtime cost	Economic and structural dependences	Do et al., 2011 Huynh et al., 2014

2.3.4. Maintenance optimization

Maintenance optimization process aims at finding the optimal maintenance decision variables according to the objectives of maintenance management policy. The objectives of maintenance management policy may be to minimize the maintenance cost or to maximize the availability and/or reliability of the system. According to the maintenance optimization models, the optimization method is applied to find the optimal maintenance decision variables. Since this study focuses on predictive maintenance for multi-component system with continuous degradation state space, the literature review on the state of the art of maintenance optimization is only focus on the models applicable for multi-component system with continuous degradation state space.

2.3.4.1. Maintenance optimization models

Maintenance cost is usually used as the criteria for maintenance optimization. Several maintenance cost models have been proposed to find the optimal maintenance policy, leading to the minimum maintenance cost. The maintenance cost includes all the costs associated with maintenance actions, such as preventive maintenance cost, corrective maintenance cost, downtime cost rate, and inspection cost. Inspection intervals and preventive maintenance thresholds are two main maintenance decision variables that influence the maintenance cost. Dieulle et al. (2001) proposed a maintenance model aims at finding the optimal inspection interval and predictive maintenance threshold with the minimal maintenance cost rate. At inspection, two decisions need to be made: (1)-Whether the system needs to be preventively or correctively maintained or left as it is; (2)-determine the time of the next inspection. Several models adapt the same maintenance decision rules aiming at minimizing the long run maintenance cost rate. For example, Fouladirad et al. (2008) adapted the same maintenance decision rules for the system subjected to different deterioration modes. Castanier et al. (2005) proposed a maintenance cost model to find the optimal preventive maintenance threshold and inspection interval in order to minimize the long run maintenance cost rate.

While cost is important in maintenance optimization, cost parameters are sometimes difficult to obtain. Maintenance durations, and the uptime/downtime of the system can often be measured and obtained more accurate and easier (Alaswad & Xiang, 2017). Therefore, system's availability could be used as a practical performance measure for evaluating the effectiveness of the maintenance policy. Klutke & Yang (2002) proposed an expression for limiting average availability taking into account the ratio of the system expected uptime to the expected time to the first replacement of the system. An opportunistic inspection policy is then suggested based on the proposed availability model. Liao et al. (2006) proposed an availability limit model to maximize the average short-run availability of the system by monitoring its degradation state and setting preventive maintenance threshold. More studies on predictive maintenance using availability as the criteria for maintenance optimization could be referred to (Biswas et al., 2003; Xu & Hu, 2008; Zhu et al., 2010).

2.3.4.2. Optimization methods

Optimization methods are seen as the tools to find the optimal value of the maintenance decision variables leading to the optimal maintenance policy. With an identical mathematical model, there may be different methods that can be implemented to find the optimal solutions. Renewal theory are usually used to find the optimal maintenance decision variables for single unit system (Dieulle et al., 2003; Grall et al., 2002). However, the long run maintenance cost rate of the multi-component system subjected to stochastic degradation is often mathematically complex. Therefore, the heuristic optimization algorithms are usually applied to find the optimal maintenance decision variables for multi-component system. For example, Marseguerra et al. (2002) applied genetic algorithm combined with Monte Carlo simulation to find the optimal preventive maintenance threshold. The genetic algorithm considers a population of chromosomes, each one encoding a threshold degradation value for each component type. For a given chromosome, the Monte Carlo simulation estimates the objective functions. Siddiqui et al. (2017) adapt the similar approach for maintenance optimization with multiple optimization objectives. However, genetic algorithm are usually applied for discrete variables (McCall, 2005).

For PdM context, the maintenance decision variables (inspection interval and preventive maintenance thresholds) are the continuous variables. In that way, finding these maintenance decision variables is a main problems of maintenance optimization in the framework of PdM. Particle swarm optimization (PSO) algorithm is a prominent method that can be applied to solve the problem of predictive maintenance optimization. PSO algorithm is an efficient optimization method to reduce the computing time of the optimization problem. PSO has been widely applied to solve optimization problems due to its advantages of simple operations, rapid searching, and promise to approach the global optimum (D. Wang et al., 2018). PSO has shown its feasibility in maintenance optimization in several studies. For example, Chalabi et al. (2016) proposed an adaption of PSO algorithm opportunistic maintenance with the consideration of imperfect maintenance. Low et al. (2010) presented a modified particle swarm optimization algorithm to solve the single-machine scheduling problem with periodic maintenance activities. Tiwary (2019) applied particle swarm optimization algorithm to find the optimal inspection interval for predictive maintenance policy. C.-H. Wang & Lin (2011) proposed an improved particle swarm optimization algorithm to minimize the periodic preventive maintenance cost for series-parallel system.

PSO is inspired by social and cooperative behavior displayed by various species to fill their needs in the searching space. Each individual in the species population is a particle moving within a multidimensional searching space and striving for the optimal solution. Thus, each particle corresponds to a candidate solution of the optimized problem in D-dimensional searching space ($D \in \mathbb{N}$), and it can memorize the optimal position of the swarm and that of its own as well as the moving velocity. Particles can adjust their position toward their best position according their experience and that of their neighboring particles. In each generation, the particles information is combined together to adjust the velocity of each dimension, which is used to compute the new position of the particles. By continuous adjusting their direction and position, all particles are expected to gradually approach the global optimum. Unique connection among different dimensions of the problem space is introduced via the objective functions. The flowchart of the PSO algorithm is shown in Figure 2.7 (D. Wang et al., 2018).

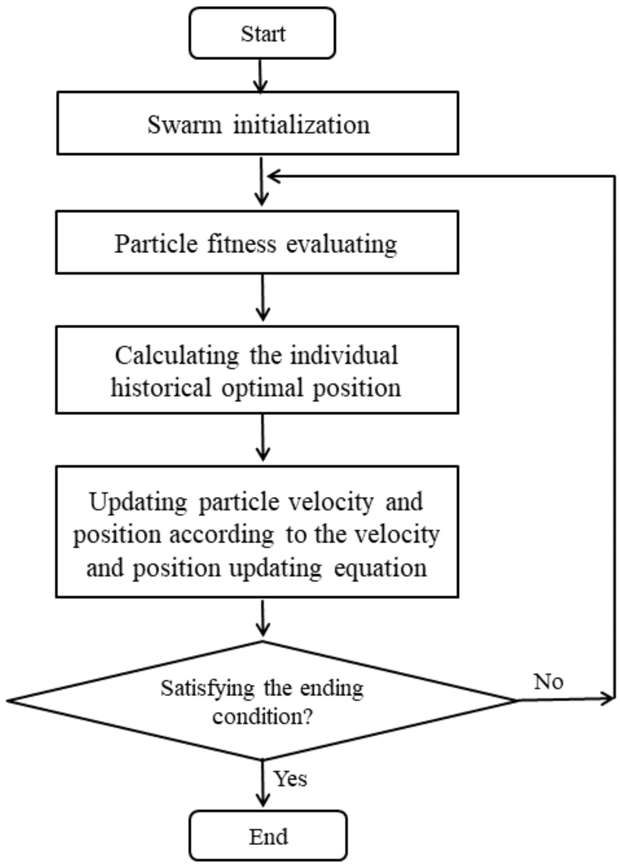

Figure 2.7 Flowchart of particle swarm optimization algorithm

In a continuous space coordinate system, mathematically, the PSO for solving the optimization problems with the objective function $f = f(X)$ in a D-dimensional space can be described as follow. Assume that the swarm size N ($N \in \mathbb{R}^{+}$), each particle's position vector in D-dimensional space is $Y_i = (y_{i,1}, y_{i,2}, \dots, y_{i,d}, \dots, \ y_{i,D})$, velocity vector is $V_i = (v_{i,1}, v_{i,2}, \dots, v_{i,d}, \dots, \ v_{i,D})$, individual's optimal position (i.e., the optimal position that particle i has experienced) is $P_i = (p_{i,1}, p_{i,2}, \dots, \ p_{i,D})$, swarm's optimal position (i.e., the best position that all individuals in this swarm has experienced) is represented by $P_g = (p_{g,1}, p_{g,2}, \dots, \ p_{g,D})$. The individual optimal position is updated in case of minimizing problems and maximizing problems are presented in Eq. (2.18) and Eq. (2.19), respectively.

$$p_{i,t+1}^{d} = \begin{cases} y_{i,t+1}^{d}, if\ f(Y_{i,t+1} < f(P_{i,t}) \\ p_{i,t}^{d}, \qquad\qquad otherwise \end{cases} \tag{2.18}$$

$$p_{i,t+1}^{d} = \begin{cases} y_{i,t+1}^{d}, if\ f(Y_{i,t+1} > f(P_{i,t}) \\ p_{i,t}^{d}, \qquad\qquad otherwise \end{cases} \tag{2.19}$$

The velocity and position of each particle are updated by Eq. (2.17) and Eq. (2.18) respectively.

$$v_{i,t+1}^{d} = \omega * v_{i,t}^{d} + c_1 * rand * \left(p_{i,t}^{d} - x_{i,t}^{d}\right) + c_2 * rand * \left(p_{g,t}^{d} - x_{i,t}^{d}\right) \tag{2.20}$$

$$y_{i,t+1}^{d} = y_{i,t}^{d} + v_{i,t+1}^{d} \tag{2.21}$$

Figure 2.8 illustrate the scheme of updating the velocity and position of each particle.

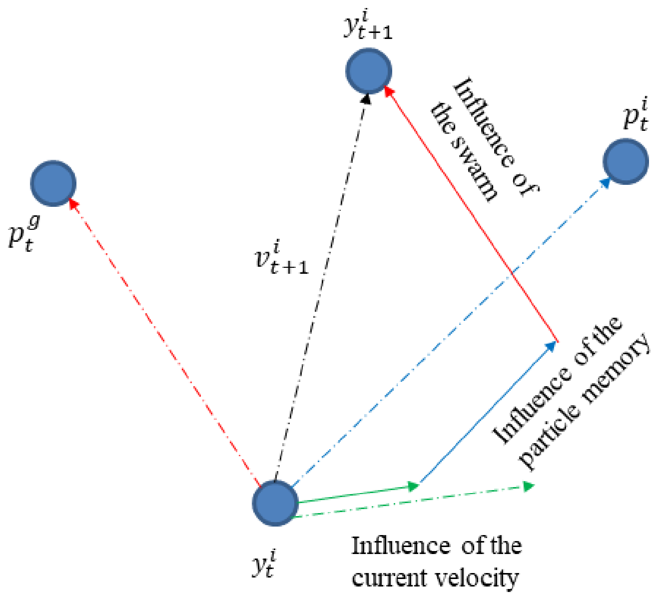

Figure 2.8 Iteration scheme of the particles (D. Wang et al., 2018)

There are three factors influencing the moving velocity of each particle. The first factor is the particle’s previous velocity. It means that the particle has confidence on its current moving state and conducts inertial moving according to its own velocity, so parameter ω is call inertia weight. The inertia weight is used to balance the global search and the local search, and the bigger inertia weight is tended to global search, while the smaller inertia weight is tended to local search, so the value of inertia weight should gradually reduce with the number of iterations. Shi & Eberhart (1998) suggested that inertia weight should be set to [0.9, 1.2], and a linearly time decreasing inertia weight could significantly enhance the PSO performance. The second factor depends on the distance between the particle's current position and its own optimal position, called the 'cognitive' item. Its means particle own thinking, i.e., particle's move resulting from its own experience. Therefore, the parameter c_1 is called as cognitive learning factor. The third factor relies on the distance between the current position of the particle and the current global optimal position of the swarm, called as social factor. It means the information share and cooperation among the particle, namely particle's moving coming from other particles' experience in the swarm. It simulates the move of good particle through the cognition, so the parameter c_2 is called as social learning factor. In most cases, the two learning factors c_1 and c_2 have the same value, so that the social and cognitive searches have the same weight. In many cases, c_1 and c_2 are set to 2.0 which make the search to cover the region centered in the best position of the particle and that of the warm (D. Wang et al., 2018).

2.4. Conclusions

This chapter is devoted to present the literature review in relation to the identified research challenges in predictive maintenance for multi-component system with economic and structural dependences. So the chapter 2 is focusing on identifying the impact of structural and economic dependence on maintenance modeling. This leads to underline the issue related to "*how to model the economic and structural dependence between components?*" (Scientific issue n^{0}1). The structural dependence means some components are required to be disassembled in order to reach the maintained components. The disassembly operations play a role like a shock to the disassembled components, leading to an impact on the degradation process of the disassembled components. Therefore, one of scientific issues related to maintenance modeling for multi-component system with structural dependence is "*what are the impacts of structural dependence on the degradation process of the components?" (Scientific issue n^{0}2).* The impacts of structural and economic dependence in degradation process and maintenance modeling lead to identify another issue related to the "*what is an adequate predictive maintenance policy allowing to consider both economic and structural dependences?*" (Scientific issue n^{0}3).

These scientific issues have been attacked during PhD period to provide 3 main contributions:

- *Proposal of mathematical developments for modeling the structural and economic dependences between components based on directed graph and disassembly matrix* (Contribution n°1)

- *Development of a degradation model considering the impacts of structural dependence between components* (Contribution nº2)
- *Development of an opportunistic predictive maintenance policy to fully take into account the impacts of both economic and structural dependences in maintenance decision-making and optimization process* (Contribution nº3)

Chapter 3 is devoted to address the two first contributions. Firstly, a maintenance cost model is established integrating both economic and structural dependences between components. Secondly, a degradation model that takes into account the impact of disassembly operation on the degradation process of the components is proposed. Chapter 4 addresses the third contribution by proposing an opportunistic predictive maintenance policy which takes into account both structural and economic dependences between components. The case study is conducted in chapter 5 to validate the performance of the proposed maintenance policy.

Chapter 3 – Structural and economic dependences modeling

3.1. Introduction

This chapter aims at tackling the first two scientific issues related to investigating and modeling the impact of structural and economic dependences on maintenance cost, duration and degradation process of the components.

For modeling the economic impacts of the economic and structural dependences, a maintenance cost model is established. The economic dependence is represented by the sharing maintenance setup cost when several components are maintained together. The economic impact of structural dependence depends on the disassembly duration for the components. Since maintenance of a component requires disassembly of other components, a disassembly sequence model is proposed to model the disassembly sequence of the components. The proposed model allows defining the maintenance duration saving when several components are maintained simultaneously.

Structural dependence between components influences not only maintenance cost (maintenance duration) but also degradation process of the disassembled components. To cover this issue, in this chapter, we first analyze the factors influencing the impact of disassembly operations on the degradation process of the component. Then, the formulation to quantify the impact of disassembly operations on the degradation state of the component is established. A model integrating the impact of disassembly operation on the degradation process of the component is then developed.

More precisely, the chapter 3 is organized as follows. Section 3.2 develops the model to present the economic dependence between components. Section 3.3 is devoted to model the structural dependence between components. In this section, the impacts of structural dependence on maintenance cost and degradation process of the components are both modeled. The reliability prediction for the components considering the impact of disassembly operations are presented in section 3.4. A numerical example on the impact of structural dependence on reliability of the components is also conducted in section 3.4. Finally, the conclusions are drawn in section 3.5.

3.2. Maintenance cost and economic dependence modeling

The cost of maintenance actions depends on the types of maintenance actions. Performing a PM action on surviving component *i* ($i = 1,2, \dots, n$) incurs a preventive maintenance cost, denoted as C_i^p, which can be divided into three elements:

$$C_i^p = c^s + c_i^p + c_i^d, \tag{3.1}$$

where,

- c^s represents logistic cost or preparation cost, which is associated with different actions such as, sending maintenance team to the site, setup scaffolding, ordering the spare parts, etc., c^s is also called as maintenance setup cost. This cost is considered to be cost-independent of the maintenance operation nature and can be shared when several components are maintained together. The setup cost represents the economic dependence between components. In this study, we consider the case that only one setup cost is required when several components are maintained simultaneously. Note that this is also a common assumption used by a large number of works in the framework of maintenance optimization for multi-component system with economic dependence, see for instance (Chalabi et al., 2016, 2016; K.-A. Nguyen et al., 2015; Olde Keizer et al., 2016). Other setup cost models considering the varying of the setup cost with the number of maintained components can be found in (Shafiee et al., 2015; Tian & Liao, 2011; Wijnmalen & Hontelez, 1997).
- c_i^p is a specific preventive cost including the component spare part cost, delivery cost, specific tools for maintenance of component *i*, etc. This cost depends on only the characteristics of component *i*.
- c_i^d is the downtime cost that incurs due to the loss of production during maintenance of component *i*. This cost depends on both the downtime cost rate, denoted as c^d, due to the stoppage of the system, and the maintenance duration, denoted as τ_i, that can be divided into two parts: Replacement duration (τ_i^r) and cumulative disassembly duration (τ_i^d) . More precisely, c_i^d can be expressed as follows:

$$c_i^d = c^d . \tau_i = c^d . (\tau_i^r + \tau_i^d) \tag{3.2}$$

While the replacement duration τ_i^r depends only on the characteristics of component *i* and cannot be shared if several components are maintained together, the cumulative disassembly duration τ_i^d can also be shared if maintenance on a component j ($j \neq i$) requires a disassembly of component i. This is due to the structural dependence between two components. More details on structural dependence are presented in Section 3.3.

Similarly, if component i is failed, a corrective maintenance is executed and incurs a corrective maintenance cost:

$$C_i^c = c^s + c_i^c + c_i^d \tag{3.3}$$

where, c_i^c is specific corrective cost including spare part cost, delivery cost of component i and also cost related to damage caused by the failure of component i. The failure of the components may cause huge economic losses, damage to other components or threat to the life (in chemical or nuclear plants). Therefore, the specific corrective maintenance cost is likely to be more expensive than the specific preventive maintenance cost ($c_i^c > c_i^p$).

Note that if a component fails between the two successive inspection epochs, an additional cost is incurred due to the performance loss caused by the system failure. It is assumed that downtime cost rate is c^{lost}.

It is now considered the case that a group of several components, denoted as group G^z, which are jointly maintained, the setup cost of the group can be shared due to the economic dependence between components. Consequently, the total maintenance cost of G^z can be expressed as follows:

$$C_{G^z} = \sum_{i \in G^z} [C_i^c . I_i^c + C_i^p . (1 - I_i^c)] - (|G^z| - 1). c^s - \Delta\tau_{G^z} . c^d \tag{3.4}$$

Where,

- I_i^c is the indicator function, $I_i^c = 1$ if corrective maintenance is executed on component i (i.e., $X_i(T_z) > L_i$), $I_i^c = 0$ otherwise.
- $|G^z|$ is the number of components in group G^z and $(|G^z| - 1). c^s$ represents the total setup cost saving when jointly executing the maintenance of group components G^z. This amount of setup cost saving represents the advantage of economic dependence between components.
- $\Delta\tau_{G^z}$ is the total maintenance duration saving when group components G^z are maintained together (see section 3.3.2). $\Delta\tau_{G^z}$ represents the economic advantage of the structural dependence between components. Indeed, $\Delta\tau_{G^z}$ is related to the fact that maintenance on a component may require a disassembly of other components. Therefore, the disassembly

duration may be shared if there are intersections between the disassembly paths of different components in group G^z.

3.3. Structural dependence modeling and disassembly operations impacts

3.3.1. Structural dependence modeling

From the physical structure point of view, the components in the system form a hierarchical structure with multiple levels. Each level may consist of several components or groups of components. There exists a disassembly sequence between components/groups of components. The precedence relations govern the order of disassembly of components, which is graphically represented by directed graph (Dao & Zuo, 2017; Zhou et al., 2015). The directed graph utilizes nodes to represent the components/sub-system, directed and undirected lines to present the disassembly precedence between components. There are three different types of nodes: Root node, denoted as “0”, representing the system; intermediate nodes, denoted by a letter, representing the sub-system; and leaf nodes, denoted by a number, representing the component lowest level. The line connecting the nodes in upper and lower level indicates that disassembly of the node in lower level requires disassembly of the node in upper level. The line connecting the nodes in the same level may be directed (line with arrow) or undirected (straight line without arrow). The directed line represents the disassembly sequence between components. The disassembly sequence begins from the component in the origin of the arrow to the head of the arrow, i.e., to reach the component on the head of the arrow, the component on the origin of the arrow must be disassembled in advance. The undirected line between the two components in the same level means that the components are mutually restricted, and disassembly of a component always means disassembly of the other.

As an example, consider a simple gearbox, which is shown in Figure 3.1. Basically, a simple gearbox consists of input shaft unit and output shaft unit. The input shaft unit (A) includes the input shaft (C2), pinion (C3) and bearings (C1 and C4). Similarly, the output shaft unit (B) consists of output shaft (C6), pinion (C7) and bearings (C5 and C8).

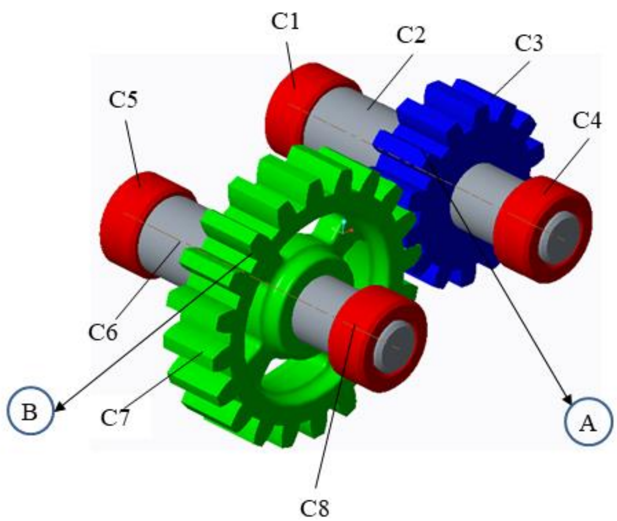

Figure 3.1 Scheme of a gear box

The directed graph of the gearbox is sketched in Figure 3.2.

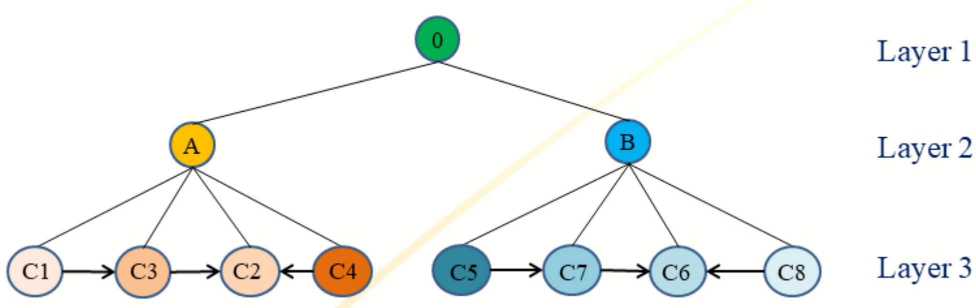

Figure 3.2 Directed graph of the gearbox

From the directed graph, we can define the disassembly path of the components for maintenance, i.e., which components need to be disassembled in order to reach the maintained components. For example, maintenance on component Shaft-C2 requires disassembly of the components Bearing-C1, Gear-C3, Bearing-C4. The disassembly matrix, $D = [D_{ij}]_{n\times n}$, is proposed to mathematically presents the disassembly path of the components. The elements of the disassembly matrix have the value "0" or "1". Where, $D_{ij} = 1$ if component *j* is on the disassembly path of component *i*, i.e., to reach component *i* for maintenance, component *j* is also disassembled; $D_{ij} = 0$ otherwise; $D_{ii} = 1$ implies that for maintenance of component *i*, component *i* itself is also disassembled. In that way, the row i^{th} of the matrix *D* presents the disassembly path of component *i*. Reconsider the above example, the disassembly matrix of the gearbox is shown in Figure 3.3. Disassembly path of component Shaft-C2 is defined by the 2nd row of the matrix *D* in Figure 3.3, where it indicates that components Bearing-C1 ($D_{21} = 1$), Gear-C3 1 ($D_{23} = 1$), Bearing-C4 ($D_{24} = 1$) are on disassembly path of component shaft-C2.

$$D = \begin{array}{c} \\ C1 \\ C2 \\ C3 \\ C4 \\ C5 \\ C6 \\ C7 \\ C8 \end{array} \begin{array}{c} \begin{array}{cccccccc} C1 & C2 & C3 & C4 & C5 & C6 & C7 & C8 \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$

Figure 3.3 Disassembly matrix of the gear box

3.3.2. Impact of disassembly operations on maintenance duration

As mentioned in section 3.3, the maintenance duration includes replacement duration and disassembly duration. While the replacement duration of a component only depends on its characteristics, the disassembly durations depends on other components on its disassembly path. The disassembly path of a components is defined by the components that needs to be disassembled in order to reach that component for maintenance. The cumulative disassembly duration of a component can be calculated through its disassembly path. From the disassembly matrix, the disassembly path of each component can be defined. As a result, the cumulative disassembly duration of a component i, denoted as τ_i^d, is the total disassembly durations of all components on its disassembly path and can be expressed as follow:

$$\tau_i^d = \sum_{j=1}^{n} \tau_j^{dp} . D_{ij} \tag{3.5}$$

Where, τ_j^{dp} is the disassembly duration of component j itself without considering whether other components need to be disassembled or not.

For disassembly of a group of several components, there may be some intersections between the disassembly paths of different components. For example, as shown in the directed graph and disassembly matrix of the gearbox, component C3 is on the disassembly path of component C2. It means that if component C2 and component C3 are maintained simultaneously, the disassembly duration of the component C3 can be saved. Therefore, the total maintenance duration can be reduced when these components are maintained together. Consider that a group of components G^z that is jointly maintained. There may be some intersections between the disassembly path of different components in group G^z, i.e., a component may be on the disassembly path of different components in group G^z. In that way, the disassembly durations of the intersection nodes are counted only one time even its appear on the disassembly paths of several components in group G^z. Therefore, the disassembly duration of the group G^z can be calculated as follow:

$$\tau_{G^z} = \sum_{i\in G^z} \tau_i - \Delta\tau_{G^z}$$

$$= \sum_{i\in G^z} \sum_{j=1}^{n} \tau_j^d \, . D_{ij} - \Delta\tau_{G^z} \quad (3.6)$$

The first part contributing to the disassembly duration of the group G^z is the total disassembly durations of all components in the groups G^z when they are disassembly separately. The second part is the disassembly duration saving due to the intersections among the disassembly paths of different components in group G^z and can be expressed as follow:

$$\Delta\tau_{G^z} = \sum_{j=1}^{n} \tau_j^d . max\left(\sum_{i\in G^z} D_{ij} - 1,\ 0\right) \quad (3.7)$$

Where, $\sum_{i\in G^z} D_{ij}$ is the total number of components in group G^z that have component j on their disassembly path, i.e., total number of times that component j is disassembled if the components in group are maintained separately. Equation (3.7) indicates that if there is no intersection among the disassembly paths of different components in group G^z, $\sum_{i\in G^z} D_{ij} - 1 \leq 0$, leading to $\Delta\tau_{G^z} = 0$, i.e., no disassembly duration saving. On the other hand, if there are intersections between disassembly paths of different components in group G^z, $\sum_{i\in G^z} D_{ij} - 1 \geq 1$, leading to $\Delta\tau_{G^z} > 0$, i.e., grouping maintenance leading to saving disassembly duration.

3.3.3. Impact of disassembly operations on degradation process of the components

Disassembly operations for maintenance may affect not only maintenance duration but also the degradation process of the disassembled components. Disassembly operation plays a role like a shock to the disassembled components. The impacts of shock on the degradation process have been studied widely in literature (T. Huang et al., 2021; Shen et al., 2018; Song et al., 2014). However, the impact of shocks on degradation process of the components presented in the previous studies assumed that shocks impact on all components are independent on the system's structure. In this study, the impact of shocks due to disassembly operations on the degradation process of a component occurs when conducting maintenance on other components and depends on the structural dependence between these components, i.e., a component is impacted if it is on the disassembly path of the maintained components. We assume that the shocks due to disassembly operations results in an increase in the degradation level of the disassembled components. Note that this assumption on shock impacts has been applied in several studies, see for instance Caballé et al., 2015; T. Huang et al., 2021; Song et al., 2014). In that way, it is assumed that when a component i is disassembled for maintenance of other components, its degradation level is increased by an amount of H_i.

The amount of damage H_i depends on the properties of component *i* (e.g., materials properties, manufacturing process, part geometry, surface finishing, etc.). For example, components made of high strength materials will be suffered less damage than the components made of low strength materials, such as the shaft made of high strength steel alloy will suffered less damage than the journal bearing made of copper alloys. This is commonly in machinery design, whereas a component is designed to be a sacrificed component, so that in the interactions between the two components, the sacrificed component will receive more damage, while the main component will receive little or no damage. This is because the main component is more important and the cost of maintenance of the main component is much more expensive than maintenance cost of the sacrificed component.

The amount of damage due to disassembly operations, H_i, also depends on the methods/tools used for conducting the disassembly operations. For disassembly a component, several methods/tools can be applied, and the impact of each method/tool is different from each other. For example, using mechanical method, such as using hammer for dismounting the bearings causes higher impact than hydraulic method (Ag & Kg, 2004) . The degree of expertise of technicians also influences the disassembly operations impact, H_i. The degree of expertise of technician is defined as the ability of the technician to correctly perform the maintenance activity. The maintenance induced damage due to the poor skill of maintenance technicians was reported in (Dhillon & Liu, 2006; Pyy, 2001; Z. Zhao et al., 2019). Some technicians have very good skills and experiences, while others have not. The maintenance technicians with good skill may know the good ways to minimize the impact of disassembly operations, while the poor skill technician can cause higher impact on the degradation process of the component. In that way, the adjustment factor θ_i is used to reflect the degree of expertise of technician and the suitability of methods/tools used to perform the disassembly operation of the component *i*. It should be noted that the methods/tools for disassembling a component may be different from each other.

From above analysis, the impact of disassembly operations, H_i, can be expressed in a form of linear function of the component's property and the adjustment factor taking into account the impact of disassembly tools and technicians. It should be noted that the linear form is inspired by the form to calculate the volume of wear out due to friction in (JM. Thompson & MK. Thompson, 2006) since they have similar physical meaning. However, other forms may be possible but this is not the scope of the present work. In that way, the impact of disassembly operations can be expressed as follows:

$$H_i = k_i.\theta_i \tag{3.8}$$

Where:

- $k_i \geq 0$ is called as the component property coefficient, which is related to the property of component i. The higher strength material, the lower value of k_i is. The coefficient k_i can be estimated from previous data, life testing, engineering judgment, etc.
- θ_i is the adjustment factor that allow considering the impact of degree of expertise of maintenance technician and the suitability of methods/tools used to perform the disassembly operations of the component i. It is clearly that $1 \leq \theta_i$, when $\theta_i = 1$, the disassembly operations are carried out with a perfect maintenance tool and by a technician with perfect skill.

The adjustment factor, θ_i, can be seen as the quality of the disassembly operations. It is very difficult to evaluate precisely the quality of a disassembly operation. It is therefore more realistic to assume that the quality of the disassembly operations is stochastic and therefore could be modeled as a random variable governed by a proper distribution function. The expected value and standard deviation of θ_i are denoted by μ_{θ_i} and σ_{θ_i}, respectively. The expected value μ_{θ_i} of the adjustment factor θ_i reflects the impact of disassembly method/tools used to perform the disassembly of the component i. The uncertainty endowed with the degree of expertise of maintenance technician is characterized by the corresponding standard deviation σ_{θ_i}, which reflects the expertise degree of the maintenance technician to correctly perform a disassembly operation. From above analysis, the half-normal distribution is herein used to model the adjustment factor. This distribution is flexible with two dimensions which can be used to present the impact of the disassembly method and the degree of expertise of the maintenance technician. By this assumption, if $\mu_{\theta_i} = 1$, the disassembly method is perfect and does not have any influence in disassembly impact. On the other hand, if $\sigma_{\theta_i} = 0$, the technician skill is perfect and has no influence in disassembly impact. The probability density function of the half-normal distribution (Cooray & Ananda, 2008) is:

$$f_{\sigma_{\theta_i},\mu_{\theta_i}}(x) = \sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{\theta_i}}e^{-\frac{1}{2}\left(\frac{x-\mu_{\theta_i}}{\sigma_{\theta_i}}\right)^2}.I(x) \tag{3.9}$$

Where, $I(x) = 1$ if $x \geq \mu_{\theta_i}$ and $I(x) = 0$ otherwise.

Therefore, the disassembly operations impact on component i, H_i, also follows a half normal distribution with mean μ and standard deviation σ are shown in equation (3.10) and (3.11), respectively.

$$\mu = \mu_{Hi} + \sigma_{Hi}\sqrt{2/\pi} \tag{3.10}$$

$$\sigma = \sigma_{Hi}\sqrt{1 - 2/\pi} \tag{3.11}$$

Where, $\mu_{H_i} = k_i.\mu_{\theta_i}$ and $\sigma_{H_i}^2 = k_i^2.\sigma_{\theta_i}^2$.

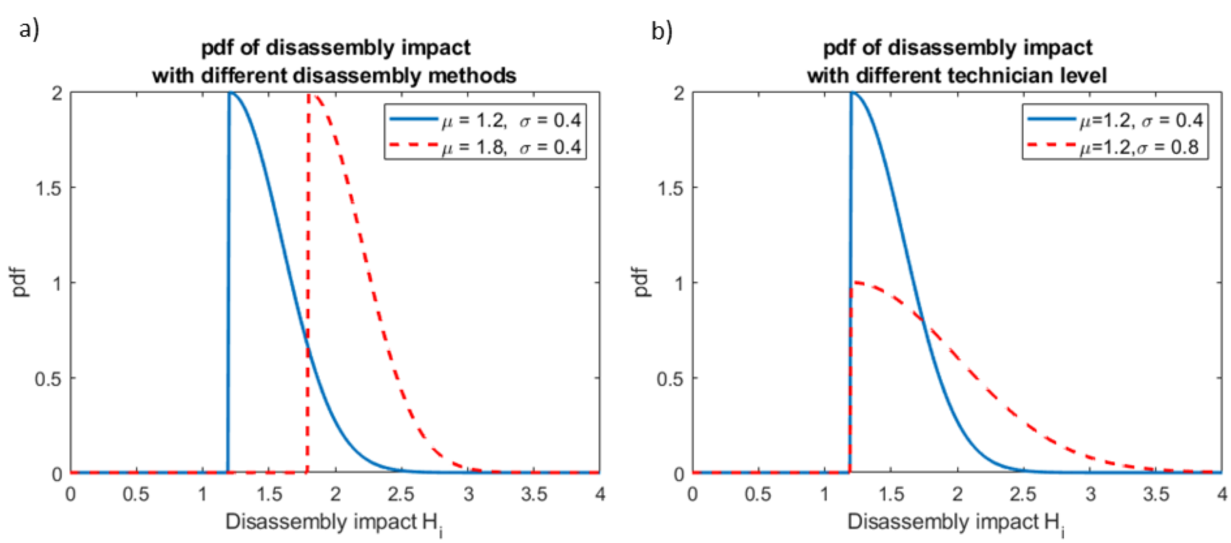

Figure 3.4 Disassembly impact when the disassembly operations are conducted by (a)-different methods and (b)-different technician levels

As an illustration, Figure 3.4 (a) shows the distribution of disassembly operations impact when the disassembly operations are conducted by different methods ($\mu_{\theta_i} = 1.2$ and $\mu_{\theta_i} = 1.8$) with the same technician level ($\sigma_{\theta_i} = 0.4$). While the disassembly operations impact shown in Figure 3(b) is for the case where disassembly operations is conducted by the same method ($\mu_{\theta_i} = 1.2$) and different technician level ($\sigma_{\theta_i} = 0.4$ and $\sigma_{\theta_i} = 0.8$). The components' property coefficient is $k_i = 1$. It shows that the lower value of μ_{θ_i} and σ_{θ_i}, the better disassembly method and maintenance technician skill are, respectively.

Suppose that between the two executive epochs *s* and *t*, a group G^z of several components are maintained separately, the degradation level of component *i* between the two executive epochs *s* and *t* can be expressed as:

$$X_{Hi}(t) = X_i(s) + \Delta X_i(t-s) + \sum_{j \in G^z} D_{ji} \,.\, H_i \tag{3.12}$$

Where,

- $X_i(s)$ is the degradation level of component *i* at time *s*;
- $\Delta X_i(t-s)$ is the increment on the degradation level of component *i* due to the inherent degradation process between two epochs *s* and *t*, which is assumed to follow the gamma distribution with shape parameter and scale parameter $\alpha_i(t-s)$ and β_i, respectively. The degradation model is generalized and other model such as Inverse Gaussian process or Wiener process can also be applied;
- D_{ji} is the element (*j*,*i*) of the disassembly matrix, which indicates whether or not component *i* is on disassembly path of component *j*;
- H_i is the impact of disassembly operations on the degradation process of component *i*.

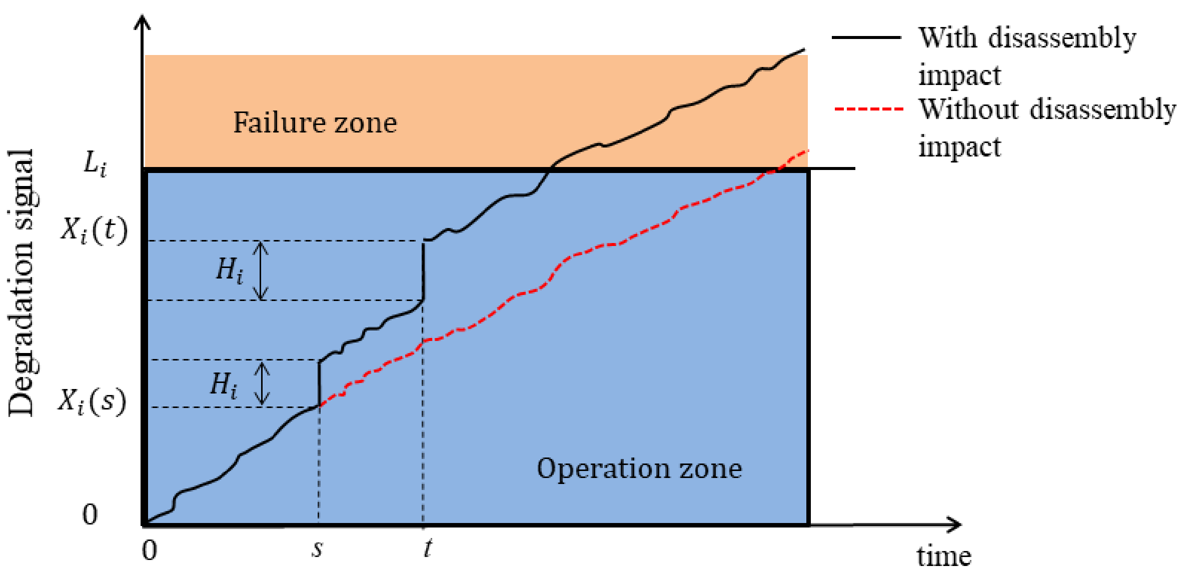

Figure 3.5 Illustration of a degradation process considering disassembly operations impact

The degradation process of components i considering disassembly impact is illustrated in Figure-3.5.

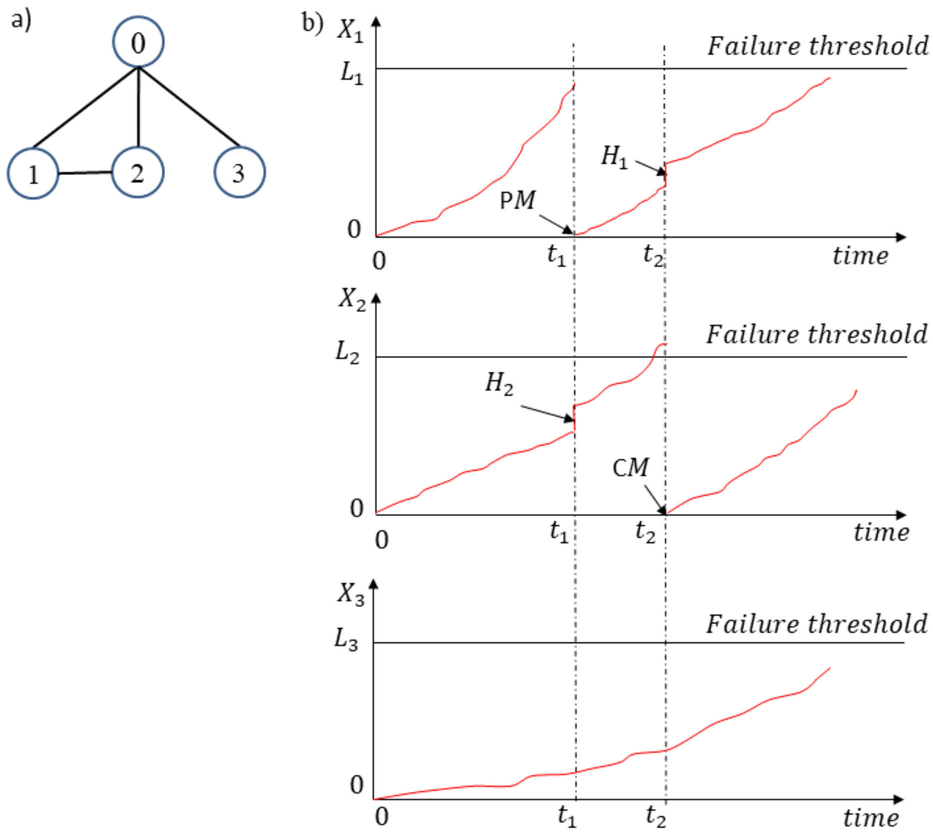

Figure 3.6 (a) - Directed graph of a system composed of three components and (b) - the illustration of the impact of disassembly operations on components degradation process

Figure 3.6 (b) illustrates the impact of the disassembly operations on the degradation process of the components in the case of system composed of three components, knowing that the directed graph of the system is shown in Figure 3.6 (a). The directed graph underlines that component 1 and component 2 are restricted mutually and the disassembly of one component always means the disassembly of the other, while component 3 is structurally independent with the other components. The system starts working at time $t = 0$ with the initial degradation of the components equal to zero. At time t_1, preventive maintenance (PM) is performed on component 1. Due to the impact of disassembly operations, the degradation of component 2 jumps by an amount of H_2. Similarly, at time t_2, component 2 failed and a corrective maintenance (CM) is applied. The disassembly operations impact causes the degradation level of component 1 jumped by an amount of H_1. Since components 3 is structurally independent with component 1 and component 2, the maintenance of these two components does not affect the degradation process of component 3 and vice versa.

When conducting maintenance on a group of several components simultaneously, there may be intersections among the disassembly paths of different components. It implies that component *i* may be on the disassembly path of several components. The shock due to disassembly operations only impacts on the disassembled components, i.e., the components on the disassembly path of the maintained components. Therefore, suppose that between the two executive epochs *s* and *t*, a group G^z of several components are maintained together, i.e., component *i* ($i \notin G^z$) is disassembled one time for maintenance of the whole group, the degradation level of component *i* between the two executive epochs *s* and *t* can be expressed as:

$$X_{Hi}(t) = X_i(s) + \Delta X_i(t-s) + H_i.\max\left(D_{ji}\right),\ j \in G^z \quad (3.13)$$

Equation (3.12) implies that if component i is not on the disassembly path of group G^z $\left(D_{ji} = 0, \forall j \in G^z\right)$, i.e., it is not disassembled for maintenance of group G^z, hence, it is not impacted due to the disassembly operations for maintenance of group G^z. On the contrary, if component i is on disassembly path of one or several components of the group G^z $\left(\exists D_{ji} = 1, j \in G^z\right)$, component *i* is affected due to the disassembly operations for maintenance of group G^z. However, the impact occurs only once even the component *i* is on disassembly path of several components. Equation (3.12) and (3.13) implies that grouping maintenance can reduce disassembly operations impacts on the degradation process of the components. The benefit of grouping maintenance on reducing disassembly impact is illustrated in Figure 3.7. The directed graph shows that the system composed of 3 components, and component 1 is on disassembly path of component 2 and component 3. If component 2 and component 3 are maintained separately at two different times, the component 1 is disassembled two times and resulting in more damage than in case of grouping maintenance on components 2 and 3. It should be noted that L_i ($i = 1,2,3$) denotes the failure threshold of the component *i*.

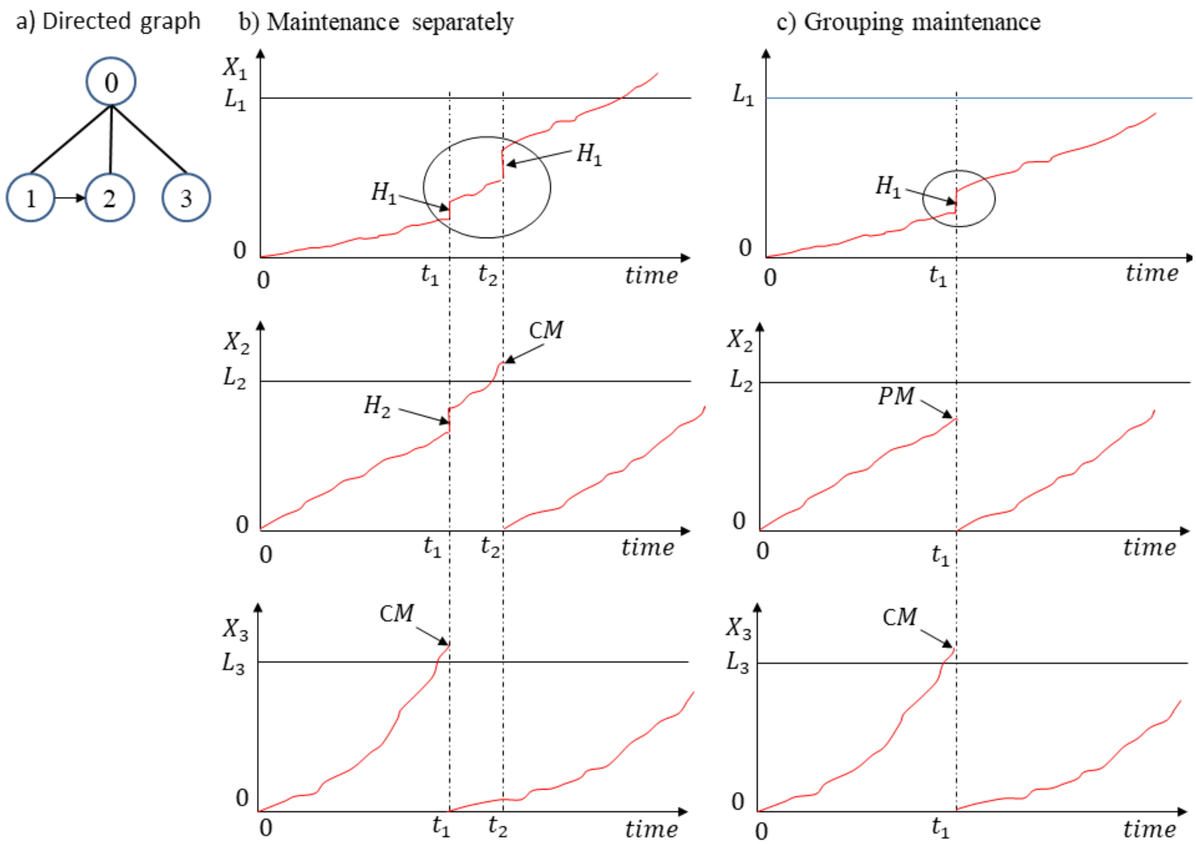

Figure 3.7 (a) Directed graph of the system; disassembly impact when components are (b) maintained separately and (c) simultaneously maintained

3.3.4. Impact of disassembly operation on the failure rate of the components

In section 3.3.3, it is assumed that component is failed once its degradation level reaches its failure threshold. However, in practice, the failure threshold is difficult to determine and usually is a random variable depending on the environment condition and product's characteristic. Moreover, in some cases, the degradation does not directly lead to the system failure but it increases the likelihood of failure of the system, i.e. system failure due to aging effect and cumulative degradation (Hu & Chen, 2020). In that way, it is assumed that the failure rates of component *i* (*i* = 1, 2… *n*) can be described by a Weibull baseline Proportional Hazard Model:

$$h_i\big(t, X_i(t)\big) = h_i^0(t)\varphi\big(X_i(t)\big) \qquad (3.14)$$

Where:

- $h_i^0(t) = \beta_i t^{\beta_i - 1}/(\lambda_i)^{\beta_i}$ is the Weibull baseline hazard rate with shape β_i and scale λ_i;

- $\varphi(X_i(t)) = \varepsilon_i . X_i(t)$, $X_i(t)$ is degradation signal and ε_i is regression coefficient quantifying the impact of degradation on the failure rate of component i.

The degradation process of the components consists of two parts, the inherent degradation process and the impact of disassembly operations. In that way, the failure rate of the component considering the disassembly operations when maintenance on a group of component G^z can be expressed as:

$$h_i(t, Z_{Hi}(t)) = \varepsilon_i . h_i^0(t)\left[Z_i(t) + H_i . \max\left(D_{ji}\right)\right],\ j \in G^z \tag{3.15}$$

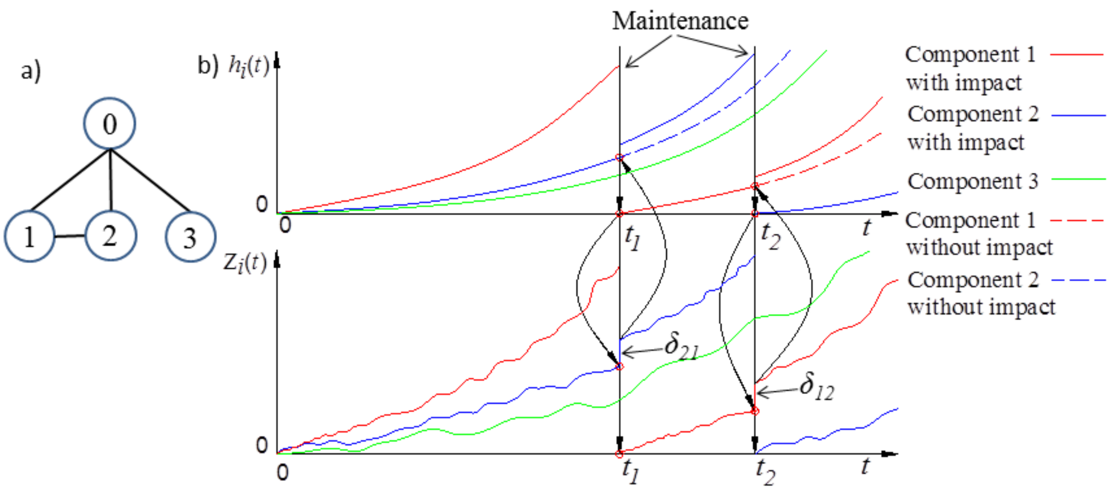

Figure 3.8 (a)-directed graph and (b)-illustration of the evolution of degradation signal and failure rate of the system's components

Figure 3.8 (b) illustrate the impact of disassembly operations on the failure rate of the components in the case of system composed of three components, knowing that the directed graph of the system is shown in Figure 3.8 (a). Assume that component 1 is maintained at time t_1 and the maintenance of component 1 requires disassembly of component 2. It results in an impact of the degradation level of component 2, consequently, increasing the failure rate of component 2. Since component 3 is structurally independent on components 1 and 2, its degradation process and failure rate are not impacted.

3.4. Reliability assessment with consideration of the disassembly impacts

As pointed out in the previous sections, the disassembly operations for maintenance of a component may affect the degradation process of the disassembled components, i.e., influence the failure probability of these components. It is now necessary to analyze the impact of the disassembly operations on the reliability of these components and hence the whole system. Note that the disassembly operations impact only occurs at each maintenance time and maintenance actions can be conducted at inspection time.

3.4.1. Reliability evaluation

Considering that at the z^{th} inspection (time T_z), the degradation level of component i is x_i^z, then the probability that the component i will survive until the next inspection $(z+1)^{th}$ with inspection interval τ is presented by the conditional reliability $R_i(T_{z+1}|x_i^z < L_i)$ as follow:

$$R_i(T_{z+1}|x_i^z \leq L_i) = P[X_i(T_{z+1}) \leq L_i|x_i^z \leq L_i] \tag{3.16}$$

For a series system, the reliability of the system in the next inspection is calculated by:

$$R_s(T_{z+1}) = \prod_{i=1}^{n} R_i(T_{z+1}|x_i^z \leq L_i) \tag{3.17}$$

Consider the case that there is a group of components, G^z, are selected for maintenance at the z^{th} inspection. The reliability of component i ($i \notin G^z$) considering the impact of disassembly operations on group G^z is:

$$R_i(T_{z+1}|x_i^z, G^z) = P\,[X_{H_i}(T_{z+1}) \leq L_i|x_i^z \leq L_i, G^z] \tag{3.18}$$

Where, $X_{H_i}(T_{z+1})$ is the degradation level of component i at time T_{z+1} considering the impact of disassembly operations of group G^z and is calculated by Eq. (3.13).

Therefore, Eq. (3.16) becomes:

$$\begin{aligned} R_i(T_{z+1}|x_i^z, G^z) &= P\left[X_{H_i}(T_{z+1}) \leq L_i|x_i^z, G^z\right] \\ &= 1 - \int_{L_i-(x_i^z+H_i.\max(D_{ji}),j\in G^z)}^{\infty} f_{\alpha_i.\tau,\beta_i}(x)dx \\ &= 1 - \frac{\Gamma[\alpha_i.\tau,\beta_i(L_i-(x_i^z+H_i.\max(D_{ji}),j\in G^z))]}{\Gamma[\alpha_i.\tau]} \end{aligned} \tag{3.19}$$

Where:

- $f_{\alpha_i.\tau,\beta_i}(x)$ is the probability density function of gamma distribution with scale parameter $\alpha_i.\tau$ and shape parameter β_i;
- $\Gamma[\alpha_i.\tau]$ is the gamma function;

- $\Gamma[\alpha,\vartheta] = \int_{\vartheta}^{\infty} x^{\alpha-1} e^{-x} dx$ is the upper incomplete gamma function;

The predicted reliability of the system in the next inspection under consideration of the disassembly operations impact is then rewritten as:

$$R_s(T_{z+1}|G^z) = \prod_{i=1}^{n} R_i(T_{z+1}|x_i^z \leq L_i, G^z) \tag{3.20}$$

The procedure for the modeling and assessment of the reliability of the system considering the impact of disassembly operations is shown in Figure 3.9.

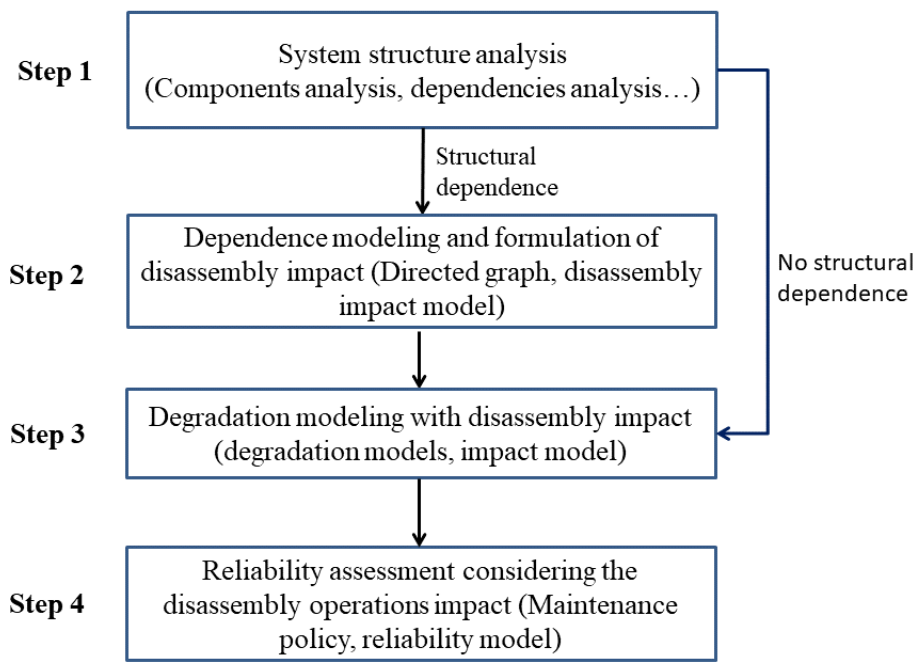

Figure 3.9 Implementation procedure for reliability assessment with disassembly impact

Step 1: System analysis (component analysis, dependencies analysis...)

This step is conducted to analyze and identify the features of the system's components and the dependencies between components. If components in the system are structurally dependent, the process continues to step 2, otherwise, the process goes to step 3.

Step 2: Dependence modeling and formulation of disassembly impacts (Directed graph, disassembly matrix, disassembly impacts models)

In this step, the structural dependence between components is modeled through directed graph and disassembly matrix. Based on the directed graph and disassembly matrix, the impact of disassembly operations is formulated.

Step 3: Degradation modeling with disassembly impacts (degradation models, impacts model)

The degradation process of the components is modeled. The impact of disassembly operations calculated in step 2 is then integrated in the degradation model.

Step 4: Reliability assessment with disassembly impacts (maintenance actions, reliability model)

Based on the executed maintenance activities, the reliability assessment model is established. The degradation process considering the impact of disassembly operations formulated in step 3 is used to predict the reliability and the components.

The reliability analysis of a multi-component system with structural dependence is numerically discussed though a gearbox in the next section.

3.4.2. Numerical example on disassembly operations impact

The purpose of this subsection is to illustrate (i) the impact of disassembly operations on the degradation process of the components and (ii) how the disassembly operations impact on the reliability of the system and maintenance selection.

Reconsider the gearbox shown in Figure 3.1. The system is inspected regularly with inspection interval $\tau = 600$ (hour). Suppose that at the current inspection, $T_z = 600$ (hour), the degradation state and other system's parameters are given in Table 3.1.

Table 3.1 The gear box's parameters

Parameters \ Component		1	2	3	4	5	6	7	8
L_i (Failure threshold)		400	400	400	400	400	400	400	400
x_i^z (Current degradation)		100	150	220	115	110	90	150	150
α_i (shape parameter of gamma process)		0.45	0.2	0.17	0.3	0.4	0.22	0.25	0.2
β_i (scale parameter of gamma process)		1.0	0.8	1.8	1.5	0.75	0.9	1.2	1.5
θ_i (adjustment factor)	μ_{θ_i}	10	10	10	10	10	10	10	10
	σ_{θ_i}	5	5	5	5	5	5	5	5
k_i (component's property coefficient)		2	0.8	1.2	2	2	0.8	1.4	2

3.4.2.1. Reliability assessment

Based on the current degradation level, the reliability of the components and the entire system at the next inspection is evaluated. As shown in Figure 3.10, the reliability of the system at the end of the next inspection ($T_{z+1} = 1200$) in the scenario of no maintenance action occurs (dotted black line) is 0.3237. Suppose that to increase system's reliability in the next inspection, one or several components are selected for maintenance. For the purpose of illustration of the impact of disassembly operations on the reliability of the system, the maintenance optimization is not presented in this section. Suppose that component 3 is selected for maintenance at the z^{th} inspection ($T_z = 600$). In the scenario of omitting the impact of disassembly operations (continuous blue line), the reliability of the system at the end of the next inspection is 0.7459.

However, to reach component 3 for maintenance, component 1 is required to be disassembled as well. The disassembly operations impact on the degradation process of component 1. Therefore, the reliability of component 1 and the system considering the impact of disassembly operations is calculated by Eq. (3.16) and Eq. (3.17), respectively. It shows in Figure 3.10 that the impact of disassembly operations results in decrease of the system reliability. When considering the disassembly impact (dashed blue line), the reliability of the system is 0.6509. It means that omitting the disassembly impact could result in underestimating the failure risk of the system.

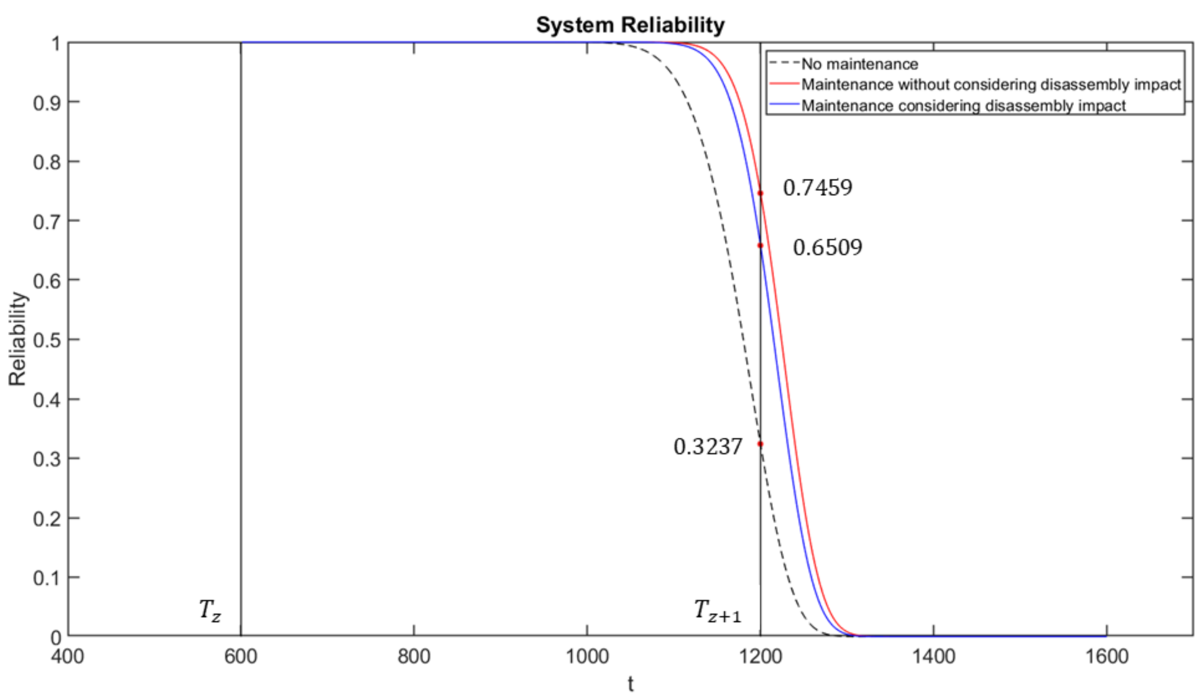

Figure 3.10 The system reliability in the next inspection in the scenarios of no maintenance, maintenance with and without considering the impact of disassembly operations

3.4.2.2. Impact on the component's ranking for individual maintenance

So, the objective now is to analyze the impact of maintenance of each component on the improvement of the system reliability in two scenarios: with and without considering the impact of disassembly operations. The improvement of the system's reliability at time T_{z+1} when component i is maintained at time T_z is defined as:

$$\Delta R\ (T_{z+1}|i) = R_s(T_{z+1}|i) - R_s(T_{z+1}) \quad (3.21)$$

Where, $R_s(T_{z+1}|i)$ is the system's reliability when only component i is maintained; $R_s(T_{z+1})$ is the system reliability when no component is selected for maintenance.

The results on the system's reliability improvement at $T_{z+1} = 1200$, when a given component is replaced at $T_z = 600$, is reported in Table 3.2.

Table 3.2 System's reliability improvement at $T_{z+1} = 1200$ when each component is individually replaced at $T_z = 600$

Selected component for maintenance	System's reliability improvement (ΔR)	
	Without considering disassembly operation impact	Considering disassembly operation impact
1	0.0257	0.0257
2	0	**-0.2627**
3	0.4222	0.3342
4	0.0616	0.0616
5	0.0022	0.0022
6	0	**-0.1363**
7	0.0082	**-0.2029**
8	0.0035	0.0035

Table 3.2 shows that when considering the impact of disassembly operations, the improvement of the system's reliability, when component 2, component 6 or component 7 individually maintained, is negative. This is because the maintenance of these components requires the disassembly of other components and impacts on the degradation as well as the reliability of the disassembled component. In this case, these components should not be individually selected for maintenance. It also shows that, without considering the disassembly impact, component 7 is more important than component 8. However, when considering the disassembly impact, component 8 become more important than component 7.

3.5. Conclusions

In this chapter, with regard to the first two scientific issues, an investigation on the influence of economic and structural dependence on the degradation process of the components and maintenance cost is conducted. A maintenance cost model is first established to model the impact of the economic and structural dependences on maintenance cost. The influence of economic dependence is presented in saving maintenance setup cost when several components are maintained simultaneously. In addition, simultaneous maintenance on several components also leads to saving disassembly duration (saving downtime cost), thanks to the structural dependence between components. For modeling the structural dependence, the directed graph and disassembly matrix are proposed to present the disassembly path of the components. Based on the disassembly path model, the disassembly duration of a component and a group of component can be calculated. This model also allows modeling the sharing disassembly duration when several components are maintained simultaneously.

The structural dependence requires disassembly of other components to maintain a component. The disassembly operations play a role like a shock to the disassembled components and could result in an amount of damage on the degradation level of the disassembled components. This amount of damage depends on the properties of the disassembled components, degree of expertise of technician and tools suitability. A formulation of the impact of structural dependence on the degradation process of the disassembled components taking into account the influencing factors is then proposed. A model is then developed integrating the inherent degradation process of the components and the disassembly impact. Finally, a numerical example is conducted to analyze the impact of structural dependence on the degradation process and reliability of the components and system, respectively. The results of the numerical example show that the structural dependence significantly influences the degradation process of components. Omitting the impact of structural dependence on the degradation process could lead to underestimating the failure risk of the components and the whole system.

To complement the contributions proposed in this chapter, in chapter 4, an opportunistic maintenance policy is proposed in response to the influence of both economic and structural dependence on maintenance cost and degradation process of the components.

Chapter 4 – Multi - level opportunistic predictive maintenance policy

4.1. Introduction

In relation to the influences of economic and structural dependences on maintenance cost, duration and the degradation process of the components, chapter 4 presents the third contribution related to a multi-level opportunistic predictive maintenance policy that allows considering both economic and structural dependences between components.

The existence of both economic and structural dependence results in two different groups of components subjected to different types of dependences when maintenance occurs, called as disassembled and non-disassembled components. The disassembled components are subjected to both structural and economic dependences, while the non-disassembled components are subjected to only economic dependence. The maintenance cost saving factor of opportunistic maintenance on the two groups of components are different. In that way, a multi-level opportunistic predictive maintenance approach is proposed for maintenance optimization of multi-component system with structural and economic dependences. The proposed maintenance policy provides different opportunistic maintenance thresholds to consider disassembled and non-disassembled components for opportunistic maintenance to take into account the different levels of dependence between disassembled and non-disassembled components. It seems to be adequate regarding to existing maintenance policies. For maintenance optimization process, the particle swarm optimization algorithm (PSO) is implemented to find the optimal maintenance policy.

To detail this contribution, the remainder of this chapter is organized as follow. Section 4.2 describes the proposed maintenance policy. The maintenance optimization process is then presented in section 4.3. In this section, a cost model is developed and the optimization algorithm is proposed. Finally, the conclusions are presented in section 4.4.

4.2. Description of the multi-level opportunistic predicted maintenance policy

Since the degradation of the components is hidden, and the failure of the components is self-announcement, inspection is often necessary to reveal the degradation level of the components. It is assumed that periodic inspection policy is applied, i.e., all system’s components are inspected at regular time $T_z = z.\tau, (z = 1,2, \dots), \tau$ is the inspection interval and it is a decision variable that needs to be optimized. Inspection is assumed to be instantaneously and can perfectly reveal the real degradation level of the components. At the z^{th} inspection epoch, degradation levels of the components are measured. The degradation level of component *i* at the z^{th} inspection epoch is denoted as x_i^z. Based on the degradation information, reliability of the component at the next inspection epoch is predicted. The predicted reliability of the component at the next inspection is evaluated following the guidance presented in section 3.4. Based on the predicted reliability of the components at the next inspection epoch, maintenance decision at the z^{th} inspection epoch is made.

4.2.1. Maintenance decision-making process

The main objective of the proposed maintenance policy is to find optimally one or several components to be opportunistically maintained when maintenance (corrective and/or preventive action) on one or several components is needed at each inspection time. To take into account both structural and economic dependences, the maintenance decision process at the z^{th} inspection epoch is divided into 3 steps, (1)-*CM/PM maintenance selection,* (2)-*Economic dependence-based opportunistic selection (eOM decision)* and (3)-*Structural dependence-based opportunistic selection (sOM decision)* as shown in Figure 4.1.

- *Step 1 – CM/PM maintenance selection:* Two cases are herein considered:
  - If a component is failed between T_{z-1} and T_z, i.e., $x_i^z \geq L_i$, the failed component needs to be correctively maintained at time T_z.
  - If no failed component is revealed between T_{z-1} and T_z, the degradation levels of all surviving components are firstly measured. The predictive reliability of each surviving component at the next inspection epoch (T_{z+1}) is then evaluated (see chapter 3, section 3.4). Component i (with *i=1,2,…,n*) is selected to be preventively maintained at T_z if its predicted reliability at T_{z+1} is below the preventive maintenance threshold, R_p $(R_i(T_{z+1}|x_i^z) \leq R_p, 0 \leq R_p < 1)$, ($R_p$ is a decision variable to be optimized).

 The results of this step can be specified into two cases:

  - If no maintenance action (corrective or preventive action) is identified, steps 2 and 3 are unnecessary. This means that no maintenance activity is required at the z^{th}

inspection epoch, the system is left as it is and maintenance decision is postponed until the next inspection epoch.

- If a corrective or preventive maintenance action on one or several components is needed, it may offer an opportunity to maintain other surviving components to take the advantages of the dependences between components. One important issue is that opportunistic maintenance on several components can reduce the maintenance cost and/or duration thanks to the economic and/or structural dependence between these components (see chapter 3).

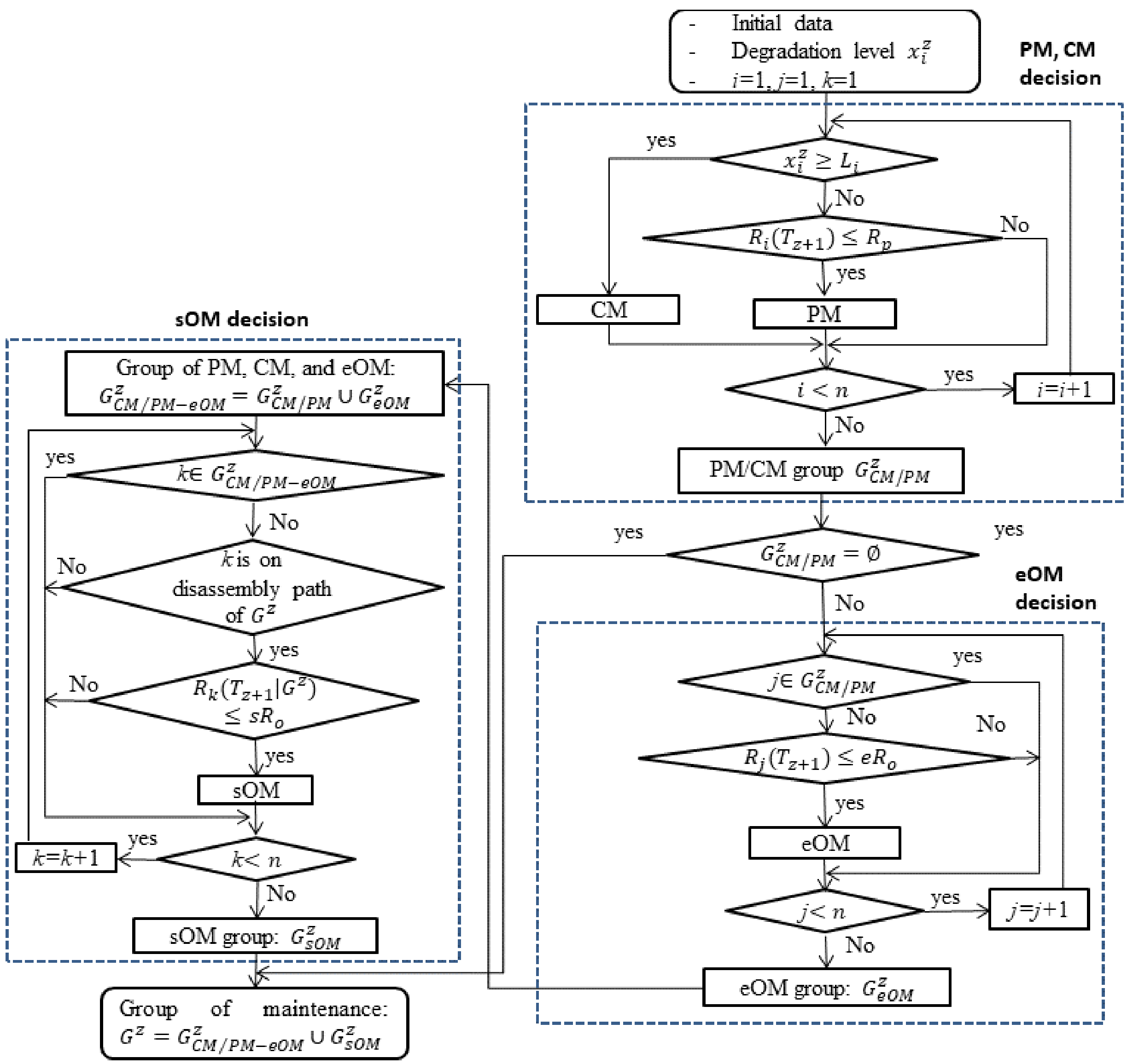

Figure 4.1 Illustration of the maintenance decision process at inspection epochs

In that way, consider the case that there is one or several components after step 1, denoted as group $G_{CM/PM}^{z}$, selected to be maintained preventively and/or correctively maintained at the z^{th} inspection. To find other surviving components to be opportunistically maintained with the maintenance of group $G_{CM/PM}^{z}$ to take the advantages of economic dependence between components, it is necessary to trigger step 2.

- *Step 2-Economic dependence-based opportunistic selection (eOM decision):* A surviving component i ($i \in \{n \backslash G_{CM/PM}^{z}\}$) is selected to be economically opportunistically maintained with group $G_{CM/PM}^{z}$ at time T_z, if its predictive reliability is below a threshold eR_o, called economic dependence-based opportunistic threshold, denoted as $eR_o, i.e., R_i(T_{z+1}|x_i^z) \leq eR_o$ with $R_p \leq eR_o < 1$. eR_o is a decision variable which needs to be optimized. After this step, a component/group of components, denoted group G_{eOM}^{z}, may be selected for opportunistic maintenance together with group $G_{CM/PM}^{z}$. The opportunistic threshold eR_o is approaching R_p when the economic dependence is small.

  Let $G_{CM/PM-eOM}^{z}$ be the set of all selected components from steps 1 and 2, i.e.,

$$G_{CM/PM-eOM}^{z} = G_{CM/PM}^{z} \cup G_{eOM}^{z} \tag{4.1}$$

It is important to note that the maintenance of group $G_{CM/PM-eOM}^{z}$ may require the disassembly of other components which are classified into the subset Ω^D:

$$\Omega^D \cap G_{CM/PM-eOM}^{z} = \emptyset \tag{4.2}$$

To take the advantages of structural dependence between the disassembled components and group of components $G_{CM/PM-eOM}^{z}$, one or several disassembled components in Ω^D should be also opportunistically maintained at time T_z. In that way, step 3 is activated to select the disassembled components for opportunistic maintenance considering the structural dependence between components.

- *Step 3: Structural dependence-based opportunistic selection (sOM decision):* This step aims to find one or several disassembled components (components in Ω^D) to be opportunistically maintained together with group $G_{CM/PM-eOM}^{z}$. Thereby, a second opportunistic threshold sR_o, called structural dependence-based opportunistic threshold, is herein introduced for opportunistic maintenance decision. Indeed, if the predicted reliability of a disassembled component i is below the structural dependence-based opportunistic threshold sR_o, i.e.,

$R_i\left(T_{z+1} \middle| x_i^z, G_{CM/PM-eOM}^z\right) \leq sR_o$, disassembled component i is selected to be opportunistically maintained at time T_z. It is noticeable that the predicted reliability of the disassembled component is evaluated considering the impact of disassembly operations following the instruction presented in section 3.4.1. sR_o is a decision variable which needs to be optimized. It is nature to get that $eR_o \leq sR_o < 1$ since the opportunistic maintenance of the disassembled components can save not only setup cost but also downtime cost, i.e., the saving factors of opportunistic maintenance on the disassembled component is higher than that of non-disassembled components. The threshold sR_o is approaching eR_o when the structural dependence impact is small and can be neglected.

The structural dependence-based opportunistic decision is a major novelty of this work because it allows considering the benefit of structural dependence between components into the maintenance decision-making.

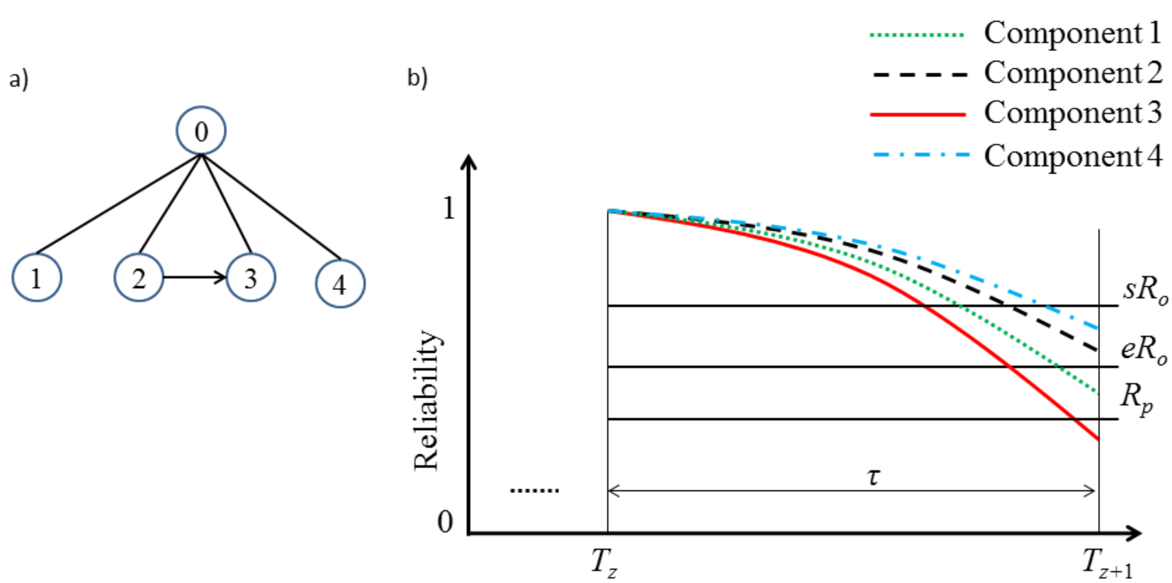

Figure 4.2 (a)-Directed graph of a 4-component system and (b)-illustration of the proposed opportunistic

Figure 4.2 (b) illustrates the multi-level opportunistic maintenance policy for a 4-components system for which the system's directed graph is shown in Figure 4.2 (a). Consider the case that at inspection epoch T_z, 4 components are still working. Their degradation levels are measured and their reliability at the next inspection epoch, T_{z+1}, are predicted as shown in Figure 4.2 (b). In this case, component 3 is selected for preventive maintenance at T_z because its predicted reliability is below the preventive maintenance threshold R_p. The preventive maintenance on component 3 offers an opportunity to consider other components for preventive maintenance in order to take into account the economic and structural dependence between components. Indeed, the predicted reliability of component 1 is below eR_o, therefore, component 1 is selected for opportunistic maintenance due to the economic dependence (saving setup cost). The directed graph implies that maintenance of component 3 requires disassembly of component 2. In addition, the predicted reliability of component 2 is below sR_o, therefore, component 2 is also opportunistically maintained (saving setup cost and downtime cost). It is noticeable that the predicted reliability of component 4 is also below the structural dependence-based opportunistic maintenance threshold, sR_o, but component 4 is not selected for opportunistic maintenance because it is not disassembled, i.e., component 4 is structurally independent with the maintained components.

It should be noted that the proposed multi-level opportunistic maintenance threshold consists of two different opportunistic maintenance thresholds, eR_o and sR_o, to consider the components for opportunistic maintenance according to the types of dependence of those components with the maintained components. In that way, the proposed opportunistic maintenance policy can be considered as the generalized case of the conventional opportunistic maintenance policy, which consists of only one opportunistic maintenance threshold. Generally, the conventional opportunistic maintenance policy is proposed to consider only the economic dependence between components (Ding & Tian, 2012; Huynh, Barros, et al., 2014; Zhou et al., 2009). In that way, if structural dependence does not exist, the structural dependence-based opportunistic maintenance threshold is expected to approach the economic dependence-based opportunistic maintenance threshold, i.e., sR_o approaches eR_o. It means that the proposed multi-level opportunistic maintenance policy is expected to tend to the conventional opportunistic maintenance policy with only one opportunistic maintenance threshold. This conclusion will be clarified with numerical example in chapter 5 by sensitivity analyses on the degree of dependence between components.

4.3. Optimization of the proposed maintenance policy

As mentioned above, the maintenance model consists of four decision variables, including inspection interval, τ, preventive maintenance threshold, R_p, the economic dependence-based and structural dependence-based opportunistic maintenance threshold, eR_o and sR_o, respectively. In order to find an optimal maintenance plan, these decision variables need to be optimized. In the maintenance optimization framework, maintenance cost rate is usually used as the main criterion

(Vu et al., 2014). Therefore, the long run maintenance cost rate is used as the objective function for maintenance optimization in this study.

4.3.1. Long run maintenance cost model

The long run maintenance cost rate is defined as (Grall et al., 2002):

$$C_{\infty}(\tau, R_p, eR_o, sR_o) = \lim_{t\to\infty} \frac{C^t(\tau, R_p, eR_o, sR_o)}{t - t_{down}} \tag{4.3}$$

Where, $C_t(\tau, R_p, eR_o, sR_o)$ and t_{down} are cumulative maintenance cost and downtime of the system within the period $(0, t]$, respectively. Without losses of generality, it is assumed that $t = N.\tau$ with N is the number of inspections within the period $(0, t]$. The maintenance cost at each inspection is calculated by Eq. (3.6). According to the renewal theory, the long-run maintenance cost rate can be rewritten as:

$$C_{\infty}(\tau, R_p, eR_o, sR_o) = \frac{\mathbb{E}[\sum_{z=1}^{N}\left(C_{insp}^{z} + C_{G^z} + C_{lost}^{z}\right)]}{\mathbb{E}[t - t_{down}]} \tag{4.4}$$

Where,

- $\mathbb{E}[.]$ is mathematical expectation;
- c_{insp}^{z} is the inspection cost at the z^{th} inspection;
- C_{G^z} is the maintenance cost of group of components G^z which are jointly maintained at the z^{th} inspection, which is calculated by Eq. (3.6);
- $t_{down} = \sum_{z=1}^{N} \tau_{G^z}$, with τ_{G^z} is the maintenance duration of group G^z;
- C_{lost}^{z} is the cost associated with production loss due to the failure of the component between the $(z\text{-}1)^{th}$ and z^{th} inspection epoch. The production loss could be due to the defective products or the system could work with lower efficiency during the failure. For example, the failure of the bearing of spindle unit in machine tools could cause the wrong dimension of the machined parts. The defective products need to be reworked, and it incurs a cost. This cost can be expressed as:

$$C_{lost}^{z} = \left(\tau - \max\left(T_z - T_i^f\right)\right).c^{lost} \tag{4.5}$$

with T_i^f is the failure time of component *i*.

It is important to note that a closed-form expression for the maintenance cost rate in Eq. (4.4) is very difficult or even impossible to obtain due to the complexity of the proposed maintenance policy. An efficient method based on semi-regenerative processes theory is introduced to obtain a closed-form expression for the maintenance cost rate (Khac Tuan Huynh et al., 2014). However, this analytical method is applicable for single-component deteriorating systems with time-homogeneous degradation behavior. Therefore, in this work, the maintenance cost rate is numerically calculated, given τ, R_p, eR_o, sR_o, by using Monte Carlo simulation. The optimal value of decision variables can be obtained by minimizing the long run maintenance cost rate, i.e.,

$$C_\infty^*\left(\tau^*, R_p^*, eR_o^*, sR_o^*\right) = \min_{(\tau, R_p, eR_o, sR_o)} C_\infty\left(\tau, R_p, eR_o, sR_o\right), (\tau > 0, 0 < R_p < 1, R_p \leq eR_o < 1, eR_o \leq sR_o < 1) \quad (4.5)$$

Where, $\tau^*, R_p^*, eR_o^*, sR_o^*$ are the optimal values of inspection interval, preventive, economic and structural dependences based opportunistic maintenance threshold, respectively. The method for finding the optimal value of these maintenance decision-making variables will be presented in the next section.

4.3.2. Implementation of PSO for maintenance optimization

The maintenance decision variables include inspection interval (τ), preventive, economic and structural dependences based opportunistic maintenance threshold (R_p, eR_o, sR_o), respectively. These variables receive values in continuous space. As introduced in section 2.3.4.2, particle swarm optimization (PSO) algorithm is an efficient optimization method for continuous variables. PSO has been widely applied to solve optimization problems due to its advantages of simple operations, rapid searching, and promise to approach the global optimum (D. Wang et al., 2018). Therefore, to find the optimal values of decision variables, $\left(\tau^*, R_p^*, eR_o^*, sR_o^*\right)$, PSO is applied. The objective of PSO in this maintenance optimization problem is to minimize the long run maintenance cost rate $C_\infty\left(\tau, R_p, eR_o, sR_o\right)$ as shown in Eq. (4.4), subjected to the conditions of $(\tau > 0)$, R_p $(0 < R_p < 1)$, eR_o $(R_p \leq eR_o < 1)$, and sR_o, $(eR_o \leq sR_o < 1)$. The implementation process of the PSO including 6 steps is as follows:

- *Step 1 – PSO parameters realization:* The initial parameters of PSO includes swarm population size (N_p), inertia weight (ω), cognitive learning factor (c_1), social learning factor (c_2) and the maximum number of iterations. For the effective implementation of PSO, N_p should be selected between 50 to 100, ω should be set to [0.9, 1.2] and linearly time decreased (Shi & Eberhart, 1998), c_1 and c_2 are set to 2.0 which make the search to cover the region centered in the best position of the particle and that of the warm (D. Wang et al., 2018). The maximum number of iterations is selected so that the difference of the value of the objective function between two executive iterations is less than a specific value ϑ, this value is called as the error of the optimization problem.

- *Step 2 - Swarm initialization*: This step generates a swarm with N_p particles and initially generates the position of each particle. The initial value of the optimal position of each particle and of the swarm is also generated in this step. Noted that these optimal values will be updated every iteration following step 3 and step 4. The position of each particle is characterized by the value of the maintenance decision variables τ, R_p, eR_o, sR_o. In that way, the value of the initial position of particle i ($i = 1,2, \dots N_p$), $Y_i = (\tau^i, R_p^i, eR_o^i, sR_o^i)$, is randomly generated according to the conditions $\tau^i > 0$, $0 < R_p^i < 1$, $R_p^i \le eR_o^i < 1$ and $eR_o^i \le sR_o^i < 1$. The initial value of the individual optimal position of particle i is set to be very closed to zero, i.e., $P^i = \left(\tau^{i,*}, R_p^{i,*}, eR_o^{i,*}, sR_o^{i,*}\right) = (10^{-5}, 10^{-5}, 10^{-5}, 10^{-5})$. Similarly, the initial value of the global optimal position of the swarm is also set to be very closed to zero, i.e., $P^g = \left(\tau^*, R_p^*, eR_o^*, sR_o^*\right) = (10^{-5}, 10^{-5}, 10^{-5}, 10^{-5})$. The initial value of the optimal maintenance cost rate is set to be infinity, $C_\infty\left(\tau^*, R_p^*, eR_o^*, sR_o^*\right)=\infty$.
- *Step 3 - Particle fitness evaluation*: For the k^{th} iteration, the long run maintenance cost rate of each particle i is evaluated according to the value of its position, $C_\infty\left(\tau^i, R_p^i, eR_o^i, sR_o^i\right)$, by Eq. (4.4).
- *Step 4 - Update the optimal position of each particle*: For the k^{th} iteration, the individual optimal position of each particle is updated using Eq. (2.18). If $C_\infty\left(\tau^{i,k}, R_p^{i,k}, eR_o^{i,k}, sR_o^{i,k}\right) < C_\infty\left(\tau^{i,*}, R_p^{i,*}, eR_o^{i,*}, sR_o^{i,*}\right)$, then $P^i = Y_i^k$, where, $Y_i^k = \left(\tau^{i,k}, R_p^{i,k}, eR_o^{i,k}, sR_o^{i,k}\right)$ is the position of particle i at the k^{th} iteration.
- *Step 5 - Update the optimal position of the swarm*: Suppose that at the k^{th} iteration, particle i has the smallest maintenance cost rate in the swarm, the optimal position of the swarm, denoted as P^g, is updated as follow.

If $C_\infty\left(\tau^{i,k}, R_p^{i,k}, eR_o^{i,k}, sR_o^{i,k}\right) < C_\infty\left(\tau^*, R_p^*, eR_o^*, sR_o^*\right)$ then $P^g = Y_i^k$.

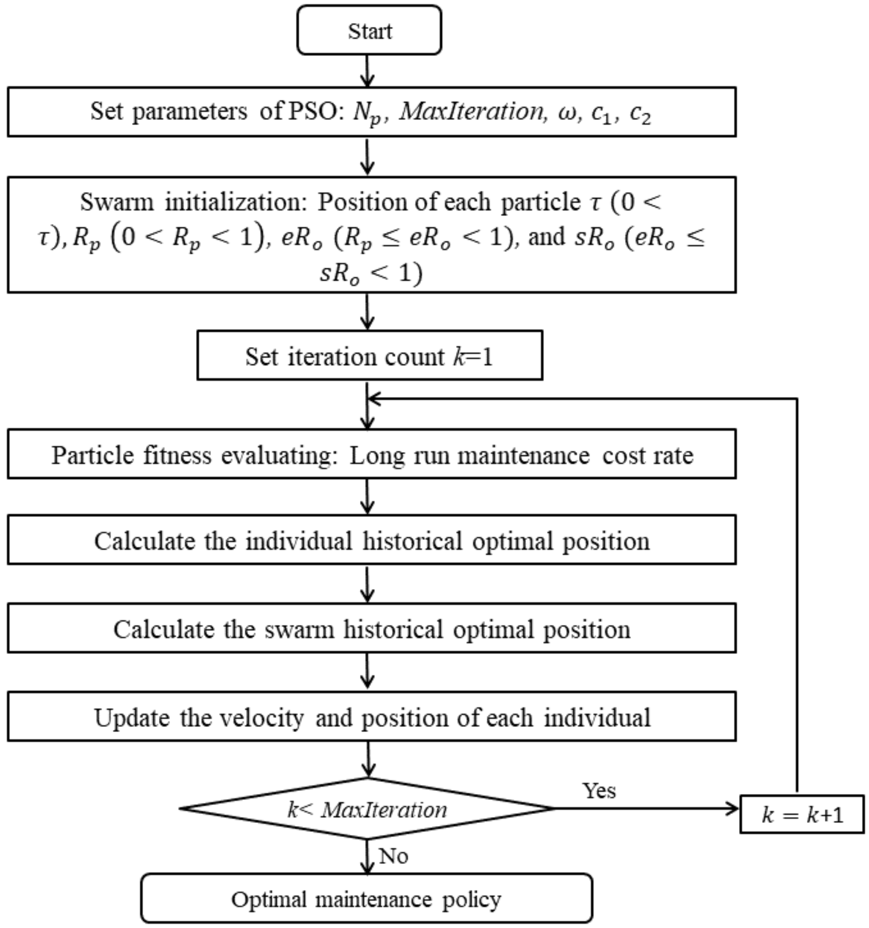

Figure 4.3 Implementation of PSO algorithm for the proposed opportunistic maintenance policy

- *Step 6 - Update the velocity and position of each particle*: For the k^{th} iteration, the velocity and position of each particle is updated considering its current velocity and position, its optimal position and the swarm optimal position according to Eq. (4.10) and Eq. (4.11) respectively.

$$v_{k+1}^{i,d} = \omega . v_k^{i,d} + c_1 . rand . \left(p_k^{i,d} - x_k^{i,d}\right) + c_2 . rand . \left(g_k^d - x_k^{i,d}\right) \tag{4.10}$$

$$x_{k+1}^{i,d} = x_k^{i,d} + v_{k+1}^{i,d} \tag{4.11}$$

Where,

- $v_k^{i,d}$ is the velocity of decision parameters d (d can be τ, R_p, eR_o, or sR_o) at the k iteration;
- $p_k^{i,d}$ is the optimal position of decision parameter d of particle i at the k iteration;

- g_k^d is the optimal position of decision parameter d of the swarm at the k iteration;
- $x_k^{i,d}$ is the value of decision parameters d of the i particle at the k iteration.

If the iteration finishing condition is not met, the algorithm is repeated from step 3, otherwise, the optimal decision parameters are the optimal position of the swarm.

The detail algorithm for implementation of PSO algorithm for optimization of the proposed opportunistic maintenance policy is illustrated in Figure 4.3.

4.4. Conclusions

In this chapter, a novel multi-level opportunistic predictive maintenance policy is developed to consider the impacts of economic and structural dependences on maintenance-decision-making and optimization process. The proposed opportunistic maintenance approach consists of one preventive threshold and two opportunistic thresholds. The preventive threshold, R_p, is used to select the components for preventive maintenance. If corrective/preventive maintenance occurs, the economic dependence-based opportunistic threshold, eR_o, is defined to select components for opportunistic maintenance. This first opportunistic maintenance decision allows considering the economic dependence between components. The maintenance of the selected components may require disassembling other components which could be also good candidates to be opportunistically maintained. The structural dependence-based opportunistic threshold, sR_o ($sR_o \geq eR_o$), is then developed to select disassembled components to be opportunistically maintained. This second opportunistic threshold allows promoting both structural and economic dependences, i.e., the setup cost and downtime cost saving. In that way, the proposed multi-levels opportunistic maintenance approach promises to be more profitable in considering both economic and structural dependences in maintenance optimization.

For maintenance optimization, a long run maintenance cost rate is used as the objective function to be minimized. To find the optimal maintenance decision variables, e.g., inspection interval τ, preventive and opportunistic maintenance thresholds, R_p, eR_o and sR_o, particle swarm optimization algorithm is then implemented for maintenance optimization.

The advantages of the proposed maintenance policy will be demonstrated with numerical example in chapter 5.

Chapter 5 - Illustration of the contributions through maintenance of an industrial conveyor system

5.1. Introduction

To illustrate the use and the advantages of the contributions introduced in chapter 3 and chapter 4, a case study is investigated in this chapter. Indeed, the investigation is brought to an industrial conveyor system, which is widely used in several industries, such as food production, automotive manufacturing, mining, packaging, etc.

Firstly, the structural dependence between components of the conveyor system is modeled through directed graph and disassembly matrix. The multi-level opportunistic maintenance policy proposed in chapter 4 is then applied to find the optimal maintenance policy, considering both structural and economic dependences between components. A performance comparison between the proposed maintenance policy and a conventional opportunistic maintenance approach (which consists of only one opportunistic maintenance threshold to equally consider non-disassembled and disassembled components for opportunistic maintenance) is conducted to show the advantages of the proposed multi-level opportunistic maintenance policy. Several sensitivity analyses are also conducted to analyze the influence of interesting factors (maintenance setup cost, disassembly duration, amount of disassembly operation impact) on the performance of the proposed maintenance policy.

To support more precisely these contributions and the illustration steps, this chapter is organized as follow. Section 5.2 presents the modeling of the conveyor system. Section 5.3 describes the optimal maintenance decision variables for the conveyor system by implementing the proposed opportunistic maintenance policy. Section 5.4 conducts a performance comparison between the proposed multi-level opportunistic maintenance policy and a conventional opportunistic maintenance policy. Several sensitivity analyses are conducted in section 5.5 to analyze the impact of different factors on the performance of the proposed maintenance policy. Finally, conclusions of the chapter are drawn in section 5.6.

5.2. Description of the conveyor system

5.2.1. Structural dependence modeling of the conveyor system

Conveyor system is a durable and reliable equipment in transporting bulk materials. It is widely used in several industries, such as food production, automotive manufacturing, mining, packaging, etc. Maintenance cost accounts for a significant proportion in overall operations cost of the conveyor system, especially for the conveyor used for handling the abrasive materials (Havey, 1979; Zimroz et al., 2015). The focus of this study is to propose a new maintenance policy to search for the optimal maintenance plan for the conveyor system with minimum maintenance cost. The chosen conveyor system is composed of 15 interdependent components, such as belt, drive motor, couplers, pulleys, bearings, as shown in Figure 5.1.

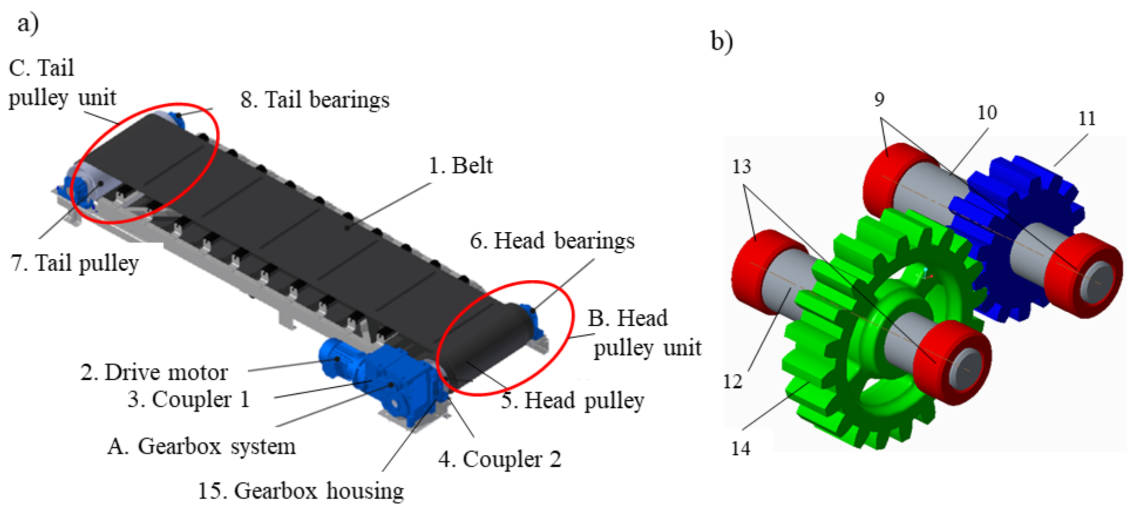

Figure 5.1 (a)-Conveyor system and (b)-its gearbox A

The directed graph of the conveyor system is sketched in Figure 5.2.

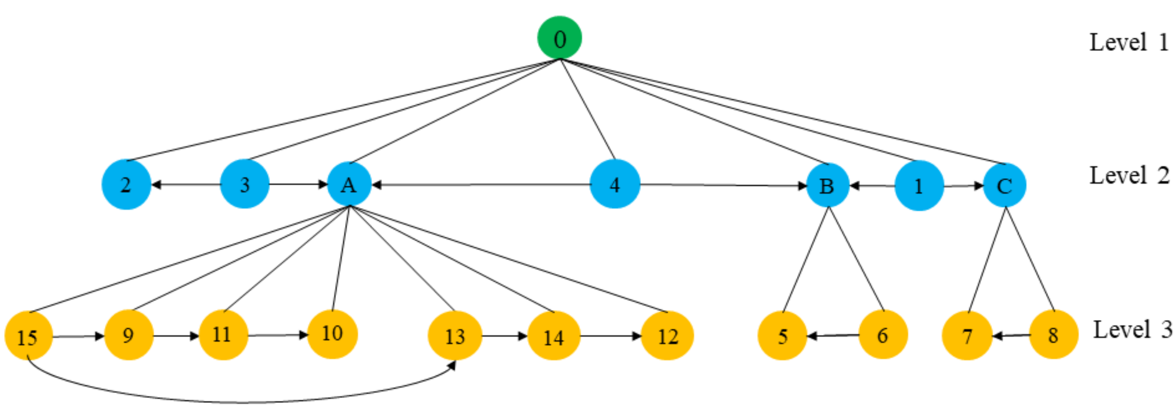

Figure 5.2 Directed graph of the conveyor system

From the directed graph, the disassembly matrix of the conveyor system is established as shown in Figure 5.3.

$$
D= \begin{array}{cc}
 & \begin{matrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \end{matrix} \\
\begin{matrix} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10\\11\\12\\13\\14\\15 \end{matrix} &
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\end{array}
$$

Figure 5.3 Disassembly matrix of the conveyor system

5.2.2. Maintenance parameters of conveyor system

It is assumed that all the parameters of the maintenance model are available. Indeed, these data can be estimated through historical maintenance records of the system. The degradation and maintenance cost parameters of the system's components are given in table 5.1. The maintenance cost parameters can also be collected from historical maintenance records. However, in this study, these parameters are chosen randomly for the illustration purposes only. Noting that lifetime of the components and replacement and disassembly durations are in hour unit, cost parameters are in arbitrary cost unit (acu).

Table 5.1 Data of a conveyor system

Parameters / Component	α_i $(10^2 h)$	β_i	L_i	τ_i^r	τ_i^{pd}	c^s	c^p	c^c	c^{in}	c^d	c^{lost}	H_i	
												μ_{Hi}	σ_{Hi}
1. Belt	4	6	450	0.15	1.6		30	75				10	5
2. Drive motor	1.4	4	600	0.3	2.0		300	750				8	4
3. Coupler 1	3	6	600	0.2	2.4	150	50	125	50	100	250	24	12
4. Coupler 2	3.5	6	600	0.2	2.4		55	130				24	12
5. Head pulley	2	3.2	450	0.3	2.0		250	750				28	14

6. Head bearings	4.6	6	450	0.2	1.6		40	100				40	20
7. Tail pulley	1.8	3.1	450	0.3	2.0		250	750				28	14
8. Tail bearings	4.4	5.6	450	0.2	1.6		40	100				40	20
9. Gearbox bearing 1	4.2	6	600	0.2	1.6		35	80				40	20
10. Shaft 1	3	3	600	0.3	2.0		100	250				24	12
11. Gear 1	3	4	600	0.3	2.0		120	300				24	12
12. Shaft 2	2	3	600	0.3	2.0		120	300				24	12
13. Gear 2	3	3.5	600	0.3	2.0		150	400				24	12
14. Gearbox bearing 2	4	6	600	0.2	1.6		35	80				40	20
15. Gearbox housing	1.2	1.5	600	0.5	2.5		50	120				5	1

5.3. Optimal maintenance policy

To find the optimal maintenance policy, the long-run maintenance cost rate is evaluated with different values of the decision variables (τ, R_p, eR_o, sR_o) by stochastic Monte Carlo simulation. PSO algorithm is then applied to find the optimal values of these decision variables.

To ensure the convergence of the long-run maintenance cost rate, the simulation must be done with a very long period. Figure 5.4, including 20 curves, illustrates the convergence of the long-run maintenance cost rate with respect to the number of inspection intervals. The result shows that the convergence reaches from 1.2x10^4 (inspection intervals).

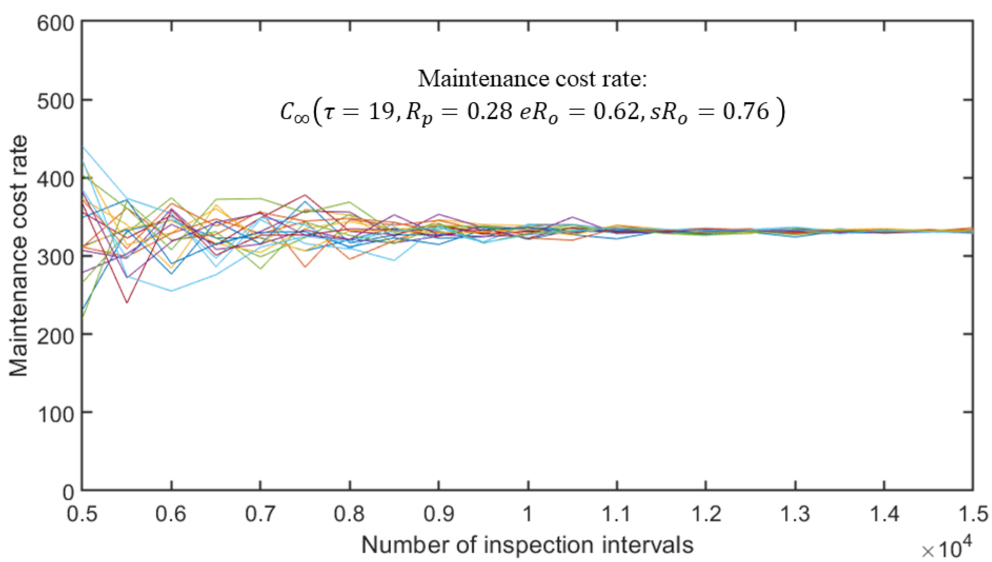

Figure 5.4 Illustration of the convergence of the long-run maintenance cost rate

By applying the optimization process presented in section *4.3.2.2*, the optimal maintenance policy is obtained with a minimum maintenance cost rate $C_\infty^*(\tau^*, R_p^*, eR_o^*, sR_o^*) = 332.40$ (acu) at $\tau^* = 19, R_p^* = 0.28, eR_o^* = 0.62$ and $sR_o^* = 0.76$. The convergence of PSO algorithm with respected to the number of iterations is illustrated in Figure 5.5 (a). It is shown that the convergence is searched from 58 iterations.

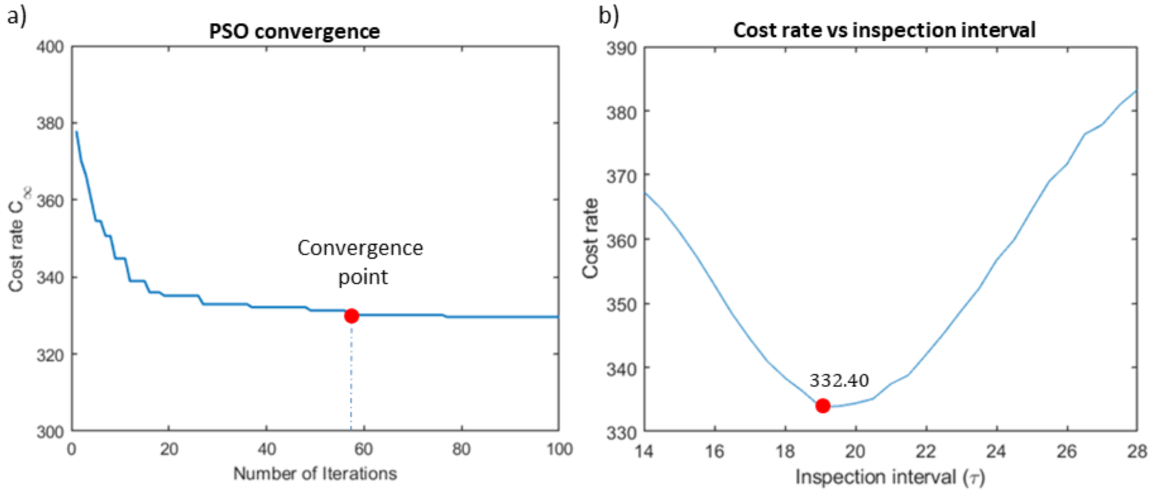

Figure 5.5 (a)-Convergence of PSO and (b)-Maintenance cost rate as a function of τ when $R_p^* = 0.28, eR_o^* = 0.62$ and $sR_o^* = 0.76$

Figure 5.5 (b) shows the maintenance cost as a function of inspection interval, τ, when $R_p^* = 0.28, eR_o^* = 0.62$ and $sR_o^* = 0.76$. The obtained result shows that the maintenance cost rate is a convex function of the inspection interval and reaches the minimum value at $\tau = 19$ (10^2h). This can be explained by the fact that the shorter inspection interval could reduce the corrective maintenance cost as the components are inspected more frequently. However, it will increase the total inspection cost. On the other hand, increasing the length of inspection interval results in an increase of likelihood of failure of the components between the two consecutive inspection epochs, and the corrective maintenance cost is much more expensive than the preventive maintenance cost.

5.4. Maintenance policy comparison

To study the impact of structural dependence in maintenance decision-making, a special case of the proposed multi-level opportunistic maintenance policy is considered by setting $eR_o = sR_o = R_o$. The proposed policy (τ, R_p, eR_o, sR_o) becomes a single level opportunistic maintenance policy, which is hereafter denoted as policy (τ, R_p, R_o). In fact, policy (τ, R_p, R_o) is likely similar to a conventional single level opportunistic policy, see for instance (Huynh, Barros, et al., 2014). However, it is important to note that this existing single level opportunistic policy has been introduced to multi-component system to consider only economic dependence between components without considering the structural dependence. It needs therefore to be extended to consider the structural dependence in a single opportunistic threshold R_o. A short description of policy $\left(\tau, R_p, R_o\right)$ is presented in appendix A. To highlight the effects of structural dependence, a performance comparison of the proposed policy $\left(\tau, R_p, eR_o, sR_o\right)$ with policy $\left(\tau, R_p, R_o\right)$ is conducted. It must be noticed that the impacts of both economic and structural dependence are considered in the maintenance decision optimization process in the two above mentioned maintenance policies.

The relative excess-cost is used as criteria for performance comparison between the two maintenance policies, which is defined as follows:

$$P_{(\tau,R_p,eR_o,sR_o)/(\tau,R_p,R_o)} = \frac{C_\infty^*(\tau^*,R_p^*,R_o^*) - C_\infty^*(\tau^*,R_p^*,eR_o^*,sR_o^*)}{C_\infty^*(\tau^*,R_p^*,eR_o^*,sR_o^*)}.100\% \qquad (5.1)$$

Where $C_\infty^*(\tau^*, R_p^*, R_o^*)$ are the minimum maintenance cost rate of policy $\left(\tau, R_p, R_o\right)$. From Eq. (5.1), the two following cases are specified:

- If $P_{(\tau,R_p,eR_o,sR_o)/(\tau,R_p,R_o)} > 0$, the proposed policy is more profitable than policy $\left(\tau, R_p, R_o\right)$ in terms of maintenance cost rate. The higher $P_{(\tau,R_p,eR_o,sR_o)/(\tau,R_p,R_o)}$, the more cost-effective the proposed maintenance policy is;
- If $P_{(\tau,R_p,eR_o,sR_o)/(\tau,R_p,R_o)} = 0$, both the policies are equally profitable. Note that the case $P_{(\tau,R_p,eR_o,sR_o)/(\tau,R_p,R_o)} < 0$ does not exist because policy $\left(\tau, R_p, R_o\right)$ is a special case of the proposed policy when $eR_o = sR_o$.

By applying the same optimization process, expressed above, to the policy $\left(\tau, R_p, R_o\right)$, the minimum maintenance cost rate is $C_\infty^*(\tau^*, R_p^*, R_o^*) = 363.00$ with optimum values for decision variables $\tau^* = 19.5, R_p^* = 0.48, R_o^* = 0.89$. When compared to the proposed maintenance policy, the maintenance cost rate of the policy $\left(\tau, R_p, R_o\right)$ is about 9.2% higher. Figure 5.6 shows the maintenance cost rate of the two maintenance policies as a function of inspection interval when the other parameters are as their optimal values.

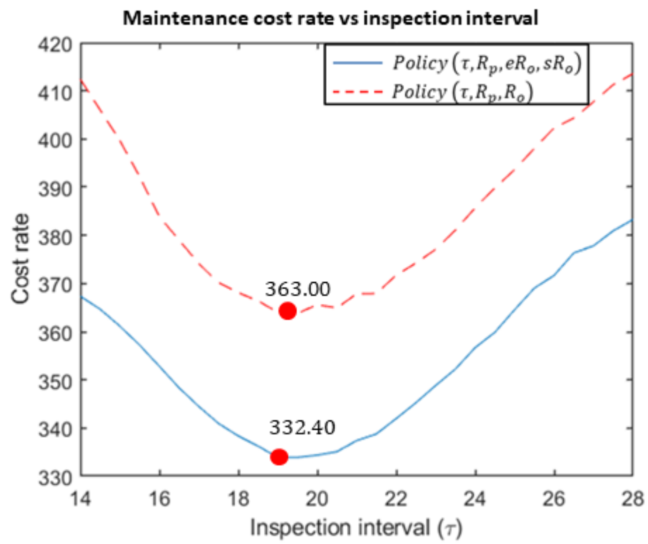

Figure 5.6 Maintenance cost rate of the two maintenance policies as a function of inspection interval

Figure 5.6 underlines that the maintenance cost of the proposed maintenance policy is always lower than that of policy (τ, R_p, R_o). Policy (τ, R_p, R_o) equally considers all components for opportunistic maintenance without considering the differences of dependences between components. However, the benefit of opportunistic maintenance on the disassembled and non-disassembled components are different. The proposed policy considers components for opportunistic maintenance based on their dependences with the maintained components. Therefore, the proposed policy can exploit the higher benefit of opportunistic maintenance. Of course, the policy (τ, R_p, R_o) is simpler than the proposed maintenance policy since it requires only three decision variables (τ, R_p, R_o) while four decision variables (τ, R_p, eR_o, sR_o) are needed for the proposed policy.

5.5. Sensitivity analysis

The result in section 5.4 shows that the proposed multi-level opportunistic maintenance policy is significantly more cost-effective than conventional opportunistic maintenance policy $(\tau, \mathrm{R_p}, \mathrm{R_o})$. However, the result is obtained with given values of system parameters. To study the impacts of economic and/or structural dependence in maintenance cost rate in a more general way, several sensitivity analyses to degree of dependences need to be investigated. In that way, several sensitivity analyses are carried in this section.

5.5.1. Sensitivity analysis to the structural dependence

Structural dependence has two different impacts on the maintenance modeling: (1) impact on degradation process of the components and (2) impact on disassembly duration. In that way, two sensitivity analyses on structural dependence are conducted.

5.5.1.1. Sensitivity analysis to the disassembly impact on degradation process

First, to study how the impact of disassembly operations on the degradation process of the components influence the maintenance decision variables and performance of the proposed maintenance policy, a sensitivity analysis on the impact of disassembly impact is conducted. The impact of disassembly operation parameter (H_i) is decreased from the current value (set as 100%) (shown in table 5.1) to zero (0%).

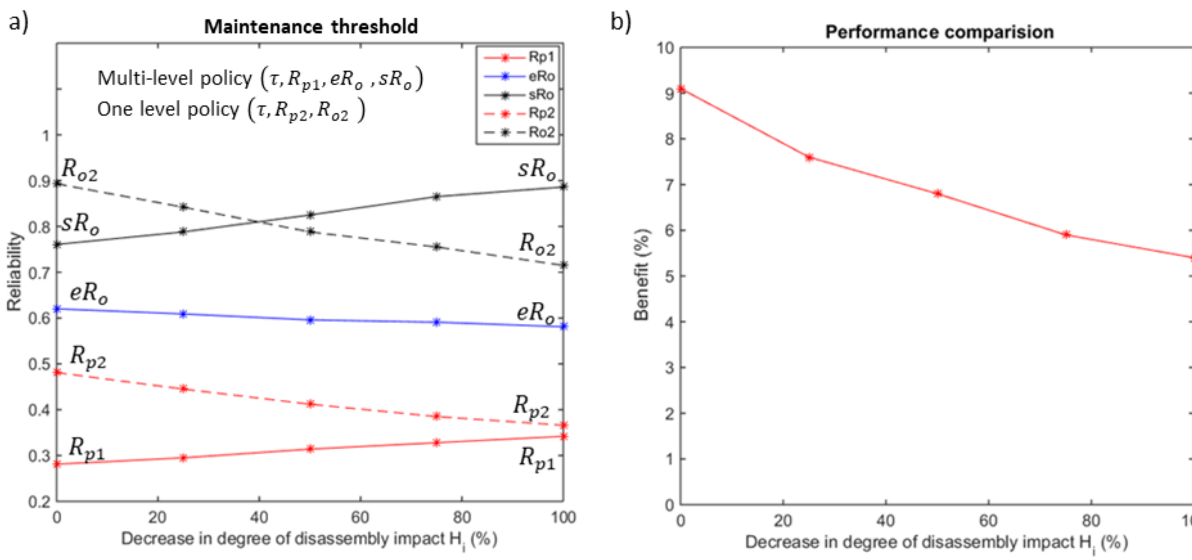

Figure 5.7 (a)-Optimal maintenance thresholds and (b)-performance comparison between the two maintenance policies as a function of the degree of disassembly operations impact

Figure 5.7 (b) shows that when the degree of disassembly impact approaches zero, the relative excess-cost between the two policies is decreased. Since the policy (τ, R_p, R_o) does not take into account the disassembly operations impact on the degradation process of the components in maintenance decision-making process, it means that omitting the disassembly operations impact in maintenance decision-making process results in suboptimal maintenance plan. Figure 5.7 (a) shows that when the degree of damage due to disassembly operations on the disassembled components approaches zeros, the opportunistic maintenance threshold (R_o) of the policy

(τ, R_p, R_o) tends to be centered between the structural based and economic based opportunistic maintenance thresholds (eR_o and sR_o) of the policy (τ, R_p, eR_o, sR_o). It seems that R_o is the average of eR_o and sR_o accounting for the weighting of the degree of structural and economic dependence. To confirm this conclusion, a sensitivity analysis to the disassembly duration is conducted in the next subsection.

5.5.1.2. Sensitivity analysis to the disassembly duration

Now, to study the influence of disassembly duration on the maintenance decision variables and the performance of the proposed maintenance policy, a sensitivity analysis to the disassembly duration is conducted. The disassembly duration of all components is varied from 100% (the current values shown in Table 5.1) to 0% $(\tau_i^{pd} \to 0)$. Note that this study is conducted when the impact of disassembly operation on the degradation process of the component approaches zero $(H_i = 0)$, following the sensitivity analysis in section 5.5.1.1.

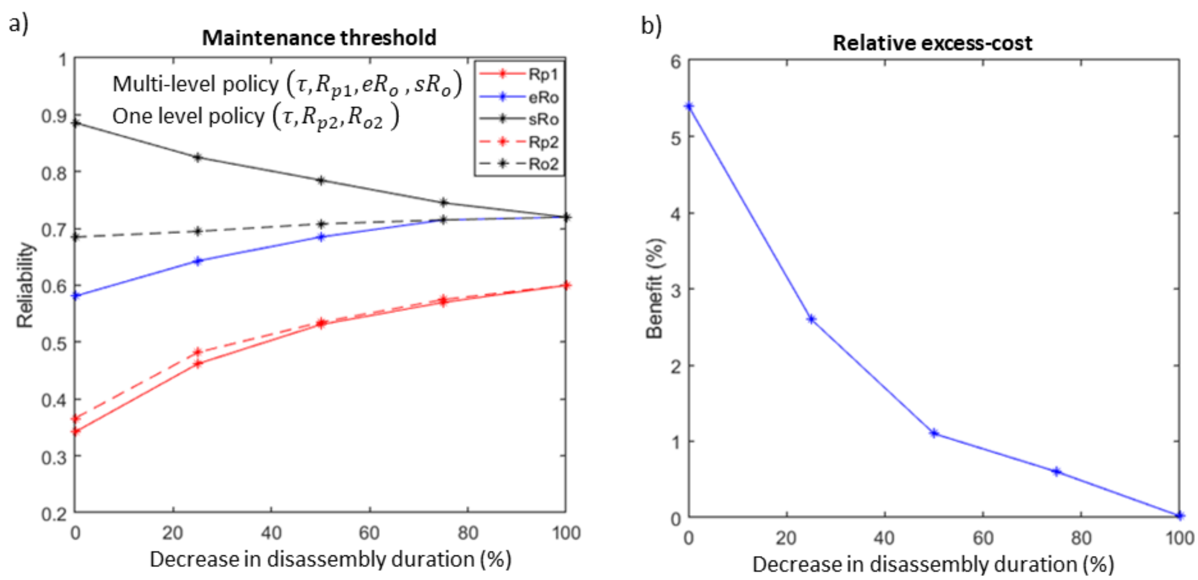

Figure 5.8 (a)-Optimal maintenance thresholds and (b)-performance comparison between the two maintenance policies as a function of the degree of disassembly duration

Figure 5.8 (a) shows the optimal maintenance thresholds of the two policies when the disassembly duration (τ_i^{pd}) decreases from the current value (100%) to zero (0%). Note that the discrete line represents the maintenance thresholds of policy (τ, R_p, R_o), while continuous line represents the maintenance thresholds of the proposed opportunistic policy. R_{p1} and R_{p2} denote the preventive maintenance thresholds of the two policies (τ, R_p, eR_o, sR_o) and (τ, R_p, R_o) respectively; R_{o2} denotes the opportunistic maintenance threshold of policy (τ, R_p, R_o).

The obtained results show that the gap between eR_o and sR_o is getting smaller when the disassembly duration is decreasing, and finally, converges to the opportunistic maintenance threshold, R_o, of the policy (τ, R_p, R_o) when the disassembly duration approaches zero. Figure 5.8 (b) shows that the advantages of the proposed opportunistic policy decreases when the disassembly duration decreases. When the disassembly duration is equal to zero, the proposed opportunistic policy becomes policy (τ, R_p, R_o). It is noticeable that when the disassembly duration approaches zero, the preventive maintenance threshold (R_p) increases significantly. It can be explained by the fact that the preventive maintenance threshold depends on the ratio between the PM cost and CM cost (C_i^p/C_i^c). If C_i^p/C_i^c is small, i.e., $C_i^c \gg C_i^p$, then R_p is high, because CM cost is much higher than PM cost. It is shown in Eq. (3.1), Eq. (3.2), and Eq. (3.3) that when the disassembly duration decreases to zero, the downtime cost c_i^d tends to zero $(c_i^d \to 0)$, hence C_i^p/C_i^c is smaller.

5.5.2. Sensitivity analysis to the maintenance setup cost

In addition, to analyze the contribution of economic dependence, it is necessary to analyze how economic dependence influences the maintenance decision variables and the performance comparison between components. The degree of economic dependence between components is represented by the maintenance setup cost. Therefore, the degree of economic dependence between components can be varied by changing the value of setup cost. In that way, the maintenance setup cost is varied from 100% (the setup cost in Table 5.1) to 0%.

Figure 5.9 (a) shows that the policy (τ, R_p, eR_o, sR_o) is not converse to policy (τ, R_p, R_o) even the economic dependence is totally released, i.e., all components are economically independent. Figure 5.9 (b) shows that even all components are economically independent, the proposed opportunistic maintenance is always better than policy (τ, R_p, R_o). This is because the benefits of the policy (τ, R_p, R_o) mainly comes from the economic dependence, while the policy (τ, R_p, eR_o, sR_o) comes from both economic and structural dependences. Therefore, when the degree of economic dependence (maintenance setup cost) decreases, the benefit of the policy (τ, R_p, R_o) decreases faster than that of the policy (τ, R_p, eR_o, sR_o).

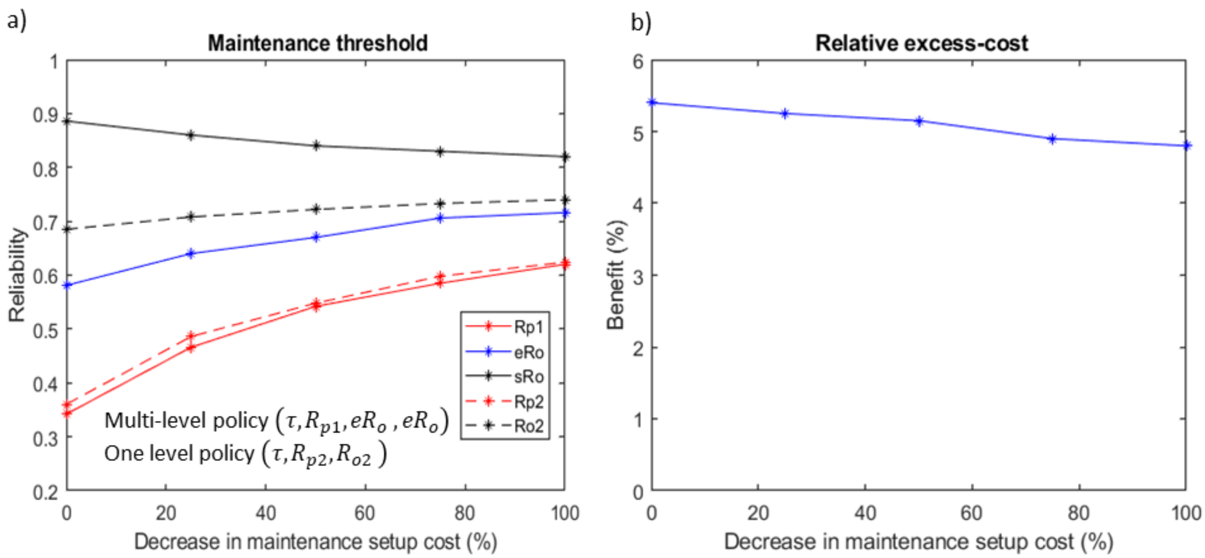

Figure 5.9 (a)-Optimal maintenance thresholds and (b)-performance comparison between the two maintenance policies as a function of the degree of economic dependence

5.5.3. Sensitivity analysis to joint consideration of both setup cost and disassembly duration

The sensitivity analysis on the impact of economic dependence and structural dependences on the maintenance thresholds and performance have been conducted separately in the previous sections. In this section, the degree of both economic and structural dependences are simultaneously varied from 100% (the setup cost and disassembly duration in Table 5.1) to 0%. Figure 5.10 (a) and 5.10 (b) show the influence of simultaneously changing the disassembly duration and setup cost on the maintenance thresholds and the maintenance performance comparison between the two maintenance policies, policy (τ, R_p, eR_o, sR_o) and policy (τ, R_p, R_o), respectively. It is shown that when both economic and structural dependences are completely released, both policy (τ, R_p, eR_o, sR_o) and policy (τ, R_p, R_o) become the conventional preventive maintenance without any opportunistic maintenance, i.e., policy (τ, R_p).

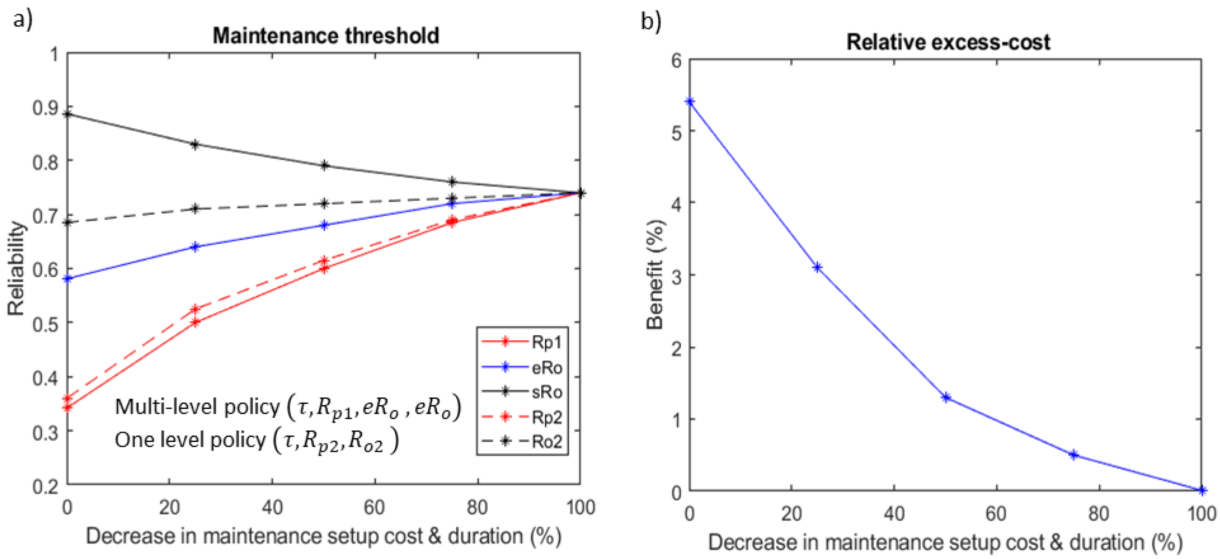

Figure 5.10 (a)-Maintenance thresholds and (b)-performance comparison when the degree of economic and structural dependence simultaneously decrease

5.6. Conclusions

This chapter illustrate the contributions proposed in chapter 4 through a case study of an industrial conveyor system. The economic and structural dependence between components in the conveyor system is modeled. The proposed multi-level predictive opportunistic maintenance approach is then applied for maintenance of the conveyor system. To find the optimal maintenance policy, the long-run maintenance cost rate is evaluated with different values of the decision variables (τ, R_p, eR_o, sR_o) by stochastic Monte Carlo simulation. PSO algorithm is then applied to find the optimal values of these decision variables. A performance comparison between the proposed multi-level opportunistic maintenance approach and the conventional opportunistic maintenance approach is conducted. The numerical results show that the proposed multi-level opportunistic maintenance approach results in significant lower long run maintenance cost compared to the conventional opportunistic maintenance approach. Several sensitivity analyses are also carried out to study the impact of different factors on the performance of the proposed maintenance approach. The results show that, when the degree of structural dependence approaches zeros (disassembly duration approaches zeros), the two opportunistic maintenance thresholds approach to each other, i.e., the proposed multi-level opportunistic maintenance approach tends to the conventional opportunistic maintenance approach which has only one opportunistic maintenance threshold. The sensitivity analysis also show that the impact of disassembly operations significantly influences the long run maintenance cost. That is because the higher disassembly impact results in increasing the failure risk of the components.

The study developed in this chapter highlights the potential achievement of our proposals and shows the advantages of the proposed multi-level predictive opportunistic maintenance approach.

Chapter 6 – General conclusions

The core idea defended in this thesis is to take into account both economic and structural dependences in maintenance modeling and optimization for multi-component system in the framework of predictive maintenance. The economic and structural dependences significantly influence the maintenance cost and degradation process of the components. In that way, the thesis addressed 3 issues (see chapter 2) in relation to modeling the impact of economic and structural dependence in maintenance modeling, taking the advantages of structural and economic dependences in maintenance optimization.

From these issues, it is promoted 3 contributions. The first contribution is related to modeling the structural and economic dependences between components. For that purpose, a maintenance cost model is established to model the economic impact of economic and structural dependence. The economic dependence is presented by the saving maintenance setup cost when several components are maintained simultaneously. Simultaneously maintenance on several components also leads to saving maintenance duration, thanks to the structural dependence. In that way, the directed graph and disassembly matrix are proposed to present the disassembly sequences between components. Based on the disassembly path model, the disassembly duration of a components and a group of several components are established. The second contribution is related to investigation the impact of structural dependence on the degradation process of the components. In that way, an investigation on the factors influencing the impact of disassembly operations on degradation process of the components is conducted, including properties of the components, degree of expertise of technician and tools suitability and the structural dependence between components. Based on this investigation, the formulation of the disassembly operations impact on degradation process of the disassembled components is proposed. A model is then developed to integrate the impact of disassembly operations into the degradation process of the components.

The third contribution related to the development of a novelty multi-level opportunistic predictive maintenance approach to take into account the properties of both economic and structural dependences. The existence of economic and structural dependence means that there are two groups of components subjected to different level of dependence when maintenance occurs, called as disassembled and non-disassembled components. The disassembled components are subjected to both structural and economic dependences, while the non-disassembled components are subjected to only economic dependence. The maintenance cost saving factor of opportunistic maintenance on the two groups of components are different. In that way, a multi-level opportunistic predictive maintenance approach is proposed for maintenance optimization of multi-component system with structural and economic dependences. The proposed opportunistic maintenance approach consists of one preventive threshold and two opportunistic thresholds. The preventive threshold, R_p, is used to select the components for preventive maintenance. If corrective/preventive maintenance occurs, the economic dependence-based opportunistic threshold, eR_o, is defined to select components for opportunistic maintenance. This first opportunistic maintenance decision allows considering the economic dependence between components. The maintenance of the selected components may require disassembling other components which could be also good candidates to be opportunistically maintained. The structural dependence-based opportunistic threshold, sR_o ($sR_o \geq eR_o$), is then developed to select disassembled components to be opportunistically maintained. This second opportunistic threshold allows promoting both structural and economic dependences, i.e., the setup cost and downtime cost saving. In that way, the proposed multi-levels opportunistic maintenance approach promises to be more profitable in considering both economic and structural dependences in maintenance optimization. For maintenance optimization, a long run maintenance cost rate is used as the objective function to be optimized. To find the optimal maintenance decision variables, e.g., inspection interval τ, preventive and opportunistic maintenance thresholds, R_p, eR_o and sR_o, an implantation process of the PSO algorithm is then proposed for maintenance optimization.

According to these contributions, the main originality claimed in this thesis are the modeling the impact of economic and structural dependence on maintenance modeling (maintenance cost and degradation process of the components), and proposing a multi-level opportunistic predictive maintenance approach taking into account these impacts in maintenance optimization. The contributions are generic and thus can be applied for different types of manufacturing system and their maintenance.

The proposed contributions (mainly those of chapter 4) are then illustrated through an industrial conveyor system. The dependence between components of the conveyor system is firstly modeled. The proposed multi-level predictive opportunistic maintenance approach is then applied for maintenance of the conveyor system. To find the optimal maintenance policy, the long-run maintenance cost rate is evaluated with different values of the decision variables (τ, R_p, eR_o, sR_o)

by stochastic Monte Carlo simulation. PSO algorithm is then applied to find the optimal values of these decision variables. A performance comparison between the proposed maintenance approach and the conventional opportunistic maintenance approach is conducted. The numerical results shown that the long run maintenance cost provided by the proposed maintenance approach is significantly lower than the one provided by the conventional opportunistic maintenance approach. Several sensitivity analyses are carried out to analyze the influence of different factors on the performance of the proposed maintenance approach such as the degree of economic dependence, degree of structural dependence, the disassembly operations impact. The results show that, when the degree of structural dependence approaches zeros (disassembly duration approaches zeros), the two opportunistic maintenance threshold approach to each other, i.e., the proposed multi-level opportunistic maintenance approach tends to the conventional opportunistic maintenance approach which has only one opportunistic maintenance threshold. The sensitivity analysis also show that the impact of disassembly operations significantly influences the long run maintenance cost. That is because the higher disassembly impact results in shortening the remaining useful life of the components.

Although the proposed maintenance approach moves a step toward solving the maintenance optimization for multi-component system with structural and economic dependences, there are still remaining issues. For example, the proposed maintenance approach should be tested with more complex system to prove the feasibility and the real benefit. Moreover, the existence of the disassembly operations impacts on the degradation process of the components open several ways of research. For example, the degree of expertise of maintenance technician may significantly affect the impact of disassembly operations on the degradation of the disassembled components. Therefore, development of a maintenance approach to consider the maintenance technician skills in maintenance decision-making and optimization process could be considered. In addition, for a more complex industrial system, e.g., system consisting of hundreds of components, such as aircraft engine, the disassembly matrix that allows quantifying the structural dependence between components should be automatically calculated to prevent the human errors. Development of a tool to automatically build the disassembly matrix of the system based on the CAD (Computer-Aided-Design) model remains also an interesting research topic. The impact of disassembly operations on the degradation process of the components also should be considered in production designing state. Therefore, a design for disassembly methodology considering the disassembly operations impact could also be another research way.

Appendix

Appendix A. Short description of the maintenance policy (τ, R_p, R_o)

For this policy, τ, R_p, R_o are three decision variables. The system's components are inspected regularly at $T_z = z.\tau, (z = 1,2, \dots)$. The maintenance decision rules at each inspection are as follow:

- *CM decision:* if the component is failed, i.e., its degradation level reach its failure threshold, it is correctively replaced.
- *PM Decision:* if component is surviving, its reliability at the next inspection is evaluated. The component is preventively replaced if its predicted reliability is less than the preventive maintenance threshold, R_p.
- *OM decision:* if there is at least one corrective and/or preventive maintenance action, other components can be opportunistically replaced if their predicted reliability is below the opportunistic maintenance threshold, R_o. To consider both economic and structural dependence between components, the selection process of OM decision is divided into two phases. In phase 1, the OM decision is applied to all surviving components without considering the disassembly impacts on the degradation process of these components. After phase 1, several surviving components may be selected to be opportunistically maintained with maintenance of components selected from CM or PM decision. Maintenance on the selected components may require to disassembly several no-selected components. In phase 2, OM decision is applied again on these disassembled components by integrating the disassembly impacts on their degradation process when evaluating their predicted reliability.

Similarly, as presented in section 3.3.1, the cost model of policy (τ, R_p, R_o) can be formulated as:

$$C_\infty(\tau, R_p, R_o) = \frac{\mathbb{E}[\sum_{z=1}^{N}(C_{insp}^{z} + C_{G^z} + C_{lost}^{z})]}{\mathbb{E}[t_{end} - t_{down}]}$$

The optimal maintenance decision variables of this policy can be obtained by minimizing the long run maintenance cost rate:

$$C_\infty^*(\tau^*, R_p^*, R_o^*) = \min_{(\tau, R_p, R_o)} C_\infty(\tau, R_p, R_o), (\tau > 0, 0 < R_p < 1, R_p \leq R_o < 1)$$

Publications of Ph.D candidate

Journal articles

(1) Dinh, D. H., Do, P., & Iung, B. (2020). Degradation modeling and reliability assessment for a multi-component system with structural dependence. *Computers & Industrial Engineering*, 144, 106443.

(2) Dinh, D. H., Do, P., & Iung, B. (2020). Maintenance optimisation for multi-component system with structural dependence: Application to machine tool sub-system. *CIRP Annals*, 69(1), 417-420.

(3) Dinh, D. H., Do, P., & Iung, B. (2021). Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts. Reliability Engineering & System Safety, 217, 108055.

Conference presentations

(1) Dinh, D. H., Do, P., & Iung, B. (2019, June). Modeling the impact of disassembly operations on the degradation process of multi-component systems. In *11th International Conference on Mathematical Methods in Reliability, MMR 2019.*

(2) Dinh, D. H., Do, P., & Iung, B. (2021, July). Multi-level opportunistic predictive maintenance policy for multi-component system with multiple dependences. In *11th IMA International Conference on Modelling in Industrial Maintenance and Reliability (MIMAR 2021)*

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