



HAL
open science

Development of a dynamic grouping maintenance strategy for a geographically dispersed production system

Ho Si Hung Nguyen

► **To cite this version:**

Ho Si Hung Nguyen. Development of a dynamic grouping maintenance strategy for a geographically dispersed production system. Automatic. Université de Lorraine, 2019. English. NNT : 2019LORR0131 . tel-02461107

HAL Id: tel-02461107

<https://hal.univ-lorraine.fr/tel-02461107>

Submitted on 30 Jan 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



AVERTISSEMENT

Ce document est le fruit d'un long travail approuvé par le jury de soutenance et mis à disposition de l'ensemble de la communauté universitaire élargie.

Il est soumis à la propriété intellectuelle de l'auteur. Ceci implique une obligation de citation et de référencement lors de l'utilisation de ce document.

D'autre part, toute contrefaçon, plagiat, reproduction illicite encourt une poursuite pénale.

Contact : ddoc-theses-contact@univ-lorraine.fr

LIENS

Code de la Propriété Intellectuelle. articles L 122. 4

Code de la Propriété Intellectuelle. articles L 335.2- L 335.10

http://www.cfcopies.com/V2/leg/leg_droi.php

<http://www.culture.gouv.fr/culture/infos-pratiques/droits/protection.htm>

Développement d'une stratégie de regroupement dynamique d'actions de maintenance pour un système de production géographiquement dispersé

THÈSE

présentée et soutenue publiquement le 10 Septembre 2019

pour l'obtention du

Doctorat de l'Université de Lorraine

(en Automatique, Traitement du Signal et des Images, Génie Informatique)

par

Ho Si Hung NGUYEN

Composition du jury

<i>Rapporteurs :</i>	A.Barros	Professeur à NTNU, Norvège
	B. Castanier	Professeur à l'Université d'Angers
<i>Examineurs :</i>	A.Grall	Professeur à l'Université de technologie de Troyes
	K.Nguyen	Maître de conférences à l'Université de Toulouse (ENIT)
<i>Encadrants :</i>	B. Iung	Professeur à l'Université de Lorraine
	P. Do	Maître de conférences à l'Université de Lorraine
<i>Invité :</i>	H.C. Vu	Enseignant-chercheur à l'Université de technologie de Troyes

Centre National de la Recherche Scientifique (CNRS)

Centre de Recherche en Automatique de Nancy (CRAN)— UMR 7039



Mis en page avec la classe thesul.

Development of a dynamic grouping maintenance strategy for a geographically dispersed production system

THÈSE

présentée et soutenue publiquement le 10 Septembre 2019

pour l'obtention du

Doctorat de l'Université de Lorraine

(en Automatique, Traitement du Signal et des Images, Génie Informatique)

par

Ho Si Hung NGUYEN

Composition du jury

<i>Rapporteurs :</i>	A.Barros	Professeur à NTNU, Norvège
	B. Castanier	Professeur à l'Université d'Angers
<i>Examineurs :</i>	A.Grall	Professeur à l'Université de technologie de Troyes
	K.Nguyen	Maître de conférences à l'Université de Toulouse (ENIT)
<i>Encadrants :</i>	B. Iung	Professeur à l'Université de Lorraine
	P. Do	Maître de conférences à l'Université de Lorraine
<i>Invité :</i>	H.C. Vu	Enseignant-chercheur à l'Université de technologie de Troyes

Centre National de la Recherche Scientifique (CNRS)

Centre de Recherche en Automatique de Nancy (CRAN)— UMR 7039



Mis en page avec la classe thesul.

Acknowledgements

First of all, I would like to express my deepest gratefulness and sincerest thanks to my supervisor Professor Benoit IUNG. With his erudition, he has given me precious counsels and invaluable suggestions throughout the period of my PhD study at CRAN and University of Lorraine. Since the first working days at CRAN, he has guided me many things, which I would need to succeed, with his enthusiasm, tremendous patience and huge efforts. My work could not be achieved without his great guidance.

I also deeply expressed my gratitude to my co-supervisor Dr. Phuc DO who has given me useful advises in both academic research as well as life. He was the first person to give me the opportunity to work at Cran laboratory and was also a great influence on my research orientation. It must be said that my successes and publications today cannot be achieved without his enthusiastic guidance and help. In addition, his attitude and passion in work always creates me great motivations in research.

Moreover, it is my honor to express indispensable gratitude to all members in CRAN as well as member of ISET team who I have had a chance to interact Sara, Hoang Anh, Dang Hoa , for their assistance, support during my study, specially, Mr VU Hai Canh who is a brother and a great colleague. He assisted and supported me so much in during research progress. I also present sincere thanks to all my Vietnamese friends who work and study in Nancy, Dinh-Hoan Trinh, Dinh-Lam Dang, Van-Duy Tran, Hoai-Le, Mr My, Mrs Nga and many others for sharing with me the living experiences that could not learn at school.

In addition, and much importantly, I am greatly thankful the funding by the Ministry of Education and Training, Vietnam (MOET) together with Vietnam International Education Development (VIED). This funding gave me a chance to persuade and realize my studied desire.

Last but not the least, I would like to send my thankfulness to my beloved parents, my lovely wife and specially my 1 year old son who have always been with me, shared and supported me during my research progress.

Abstract

In the recent years, the Geographically Dispersed Production System (GDPS) with a number of advantages such as saving the product delivered costs (closed to the clients), improving quality of services (short delivery time, high quality after-sales services) has been extensively developed by many manufacturing companies to ensure their competitiveness. In operation, the GPDS faces many challenges concerning standards, regulation, production management, and especially maintenance planning and optimization due to the geographical dispersion of production sites. However, few studies have been developed for maintenance strategies of GDPSs.

To face this challenge, the main objective of this thesis is to develop a dynamic grouping maintenance strategy for a GDPS with consideration of dependencies between at both component and site level (economic, geographical dependencies) and impacts of dynamic contexts (i.e. varying deterioration rate of components, change of maintenance routes, maintenance opportunities, etc.). In this strategy, maintenance routing and scheduling are jointly considered in a global model. The model aims at finding an optimal maintenance and routing plan. For this purpose, a cost structure and a dependence model jointly considering economic and geographical dependence are formulated. They are used as a basis for the development of the global model of maintenance routing and scheduling. In addition, to find a joint optimal maintenance and routing plan, advanced algorithms using jointly Genetic Algorithm and Branch and Bound are proposed. Finally, a numerical study is investigated to evaluate the performance and the advantage as well as limits of the proposed maintenance strategy.

Keywords: Geographically dispersed production systems, dynamic grouping maintenance, economic dependence, geographical dependence, maintenance routing, joint optimization, genetic algorithm.

Résumé

Ces dernières années, un nouveau type de système de production nommé système de production géographiquement dispersé (GDPS) est prôné par de nombreuses entreprises manufacturières internationales. Par cette vision « dispersée », il présente un certain nombre d'avantages tels que l'économie des coûts du produit livré (puisque proche des clients), l'amélioration de la qualité des services (délais de livraison courts, services après-vente de haute qualité) favorisant la pérennité et la compétitivité des entreprises dans un contexte de compétition mondiale. Cependant l'exploitation multi-sites d'un GPDS est confronté à de nombreux défis concernant les normes, les réglementations, la maîtrise des flux de production, et en particulier la planification et l'optimisation de la maintenance en raison de la dispersion géographique des sites de production. Sur ce dernier point et plus globalement la définition d'une stratégie de maintenance adaptée au GDPS, peu d'études ont été menées compte tenu de la jeunesse du sujet et de la complexité des GDPSs (ex. multi-sites, multi-composants).

Cette thèse se positionne donc sur ce sujet émergent avec comme objectif de développer une stratégie de maintenance de regroupement dynamique pour un GDPS en tenant compte de dépendances à la fois aux niveaux composants et sites de production (dépendances économique et géographique) et des impacts des contextes dynamiques (à savoir, taux de détérioration variable des composants, modification des itinéraires de maintenance, possibilités de maintenance, etc.) auxquels il est soumis. Dans cette stratégie, les itinéraires de maintenance et l'ordonnancement sont considérés conjointement dans un modèle global. Le modèle vise à trouver un plan optimal de maintenance et de routage des ressources de maintenance. A cette fin, une structure de coûts et un modèle de dépendance qui prend en compte conjointement la dépendance économique et géographique sont formulés. Ils servent de base à l'élaboration du modèle global de planification et d'ordonnancement de la maintenance et du routage. De plus, pour la recherche de la solution optimale, des algorithmes d'optimisation basés sur l'algorithme génétique et l'algorithme Branch and Bound sont proposés. Enfin, une étude numérique est investiguée pour évaluer la performance, les avantages et aussi les limites de la stratégie proposée.

Mots-clés: Systèmes de production géographiquement dispersés (GDPS), Regroupement dynamique de maintenance, dépendances économique et géographique, itinéraire de maintenance, optimisation conjointe, algorithme génétique.

Contents

List of Tables	xi
List of Figures	xiii
Abbreviations	xv
Notations	xvii
General introduction	xxi

Chapter 1	
Overview about geographically dispersed production systems and their maintenance	1
1.1 Introduction	1
1.2 Geographically dispersed production system (GDPS)	2
1.2.1 Background on a GDPS	2
1.2.2 Main characteristics of a GDPS	4
1.3 Maintenance for GDPSs	6
1.3.1 Architectures and influence factors	6
1.3.2 Consideration of dependencies on maintenance for GDPSs	10
1.3.3 Maintenance strategies for GDPSs	12
1.3.4 Mathematical models for maintenance routing and scheduling	13
1.3.5 Maintenance optimization methods	14
1.4 Conclusion	14

Chapter 2	
Scientific problem statement on maintenance for GDPSs	17
2.1 Introduction	17

2.2	State of the art on dependence modelling	17
2.2.1	Economic dependence	18
2.2.2	Geographical dependence	21
2.3	State of the art on grouping maintenance strategies	23
2.3.1	Stationary grouping maintenance	24
2.3.2	Dynamic grouping maintenance	30
2.4	State of the art on maintenance scheduling and maintenance routing	33
2.5	State of the art on optimization methods	37
2.5.1	Analytical methods	37
2.5.2	Exact algorithms	38
2.5.3	Heuristic and metaheuristic algorithm	40
2.5.4	Hybrid/combination algorithm	43
2.6	Conclusion	45

Chapter 3	
Dependence modelling for maintenance of a GDPS	47

3.1	Introduction	47
3.2	Cost structure at component level	47
3.3	Economic and geographical dependence-based cost model for a GDPS	50
3.3.1	Tentative maintenance plan under individual optimization	51
3.3.2	Dependence modelling	55
3.4	Numerical application	59
3.4.1	Economic and geographical dependence and cost model	61
3.4.2	Sensitivity analyses	62
3.5	Conclusion	63

Chapter 4	
Dynamic grouping maintenance strategy for a GDPS	65

4.1	Introduction	65
4.2	General assumptions	65
4.3	Dynamic grouping maintenance strategy for a GDPS	67
4.3.1	Phase 1: Individual maintenance optimization	68
4.3.2	Phase 2: Individual planning	68
4.3.3	Phase 3: Grouping maintenance optimization	69
4.3.4	Phase 4: Update and rolling horizon	74

4.4	Procedure for updating maintenance and routing plan in a dynamic context	74
4.5	Conclusion	76

Chapter 5

Mathematical models for maintenance routing and scheduling problem 77

5.1	Introduction	77
5.2	Mathematical modelling of maintenance routing	77
5.3	Mathematical modelling of maintenance routing and scheduling	80
5.3.1	Sequential consideration of maintenance routing and scheduling	80
5.3.2	Joint consideration of maintenance routing and scheduling	82
5.4	Conclusion	85

Chapter 6

Development of optimization algorithms for dynamic grouping maintenance strategy 87

6.1	Introduction	87
6.2	At group level	88
6.2.1	Optimization algorithm for SMaRS approach	88
6.2.2	Optimization algorithm for JMaRS approach	94
6.3	At grouping structure level	98
6.4	Conclusion	102

Chapter 7

Numerical study for the proposed dynamic grouping maintenance strategy 103

7.1	Introduction	103
7.2	Given data of a typical GDPS	104
7.3	Performance study for SMaRS and JMaRS approaches at group level	105
7.4	Optimal maintenance and routing plan	108
7.4.1	Optimization of maintenance and routing plan based on JMaRS approach	108
7.4.2	Optimization of maintenance and routing plan based on SMaRS approach	111
7.4.3	Updating of maintenance and routing plan in dynamic context	112

7.5	Sensitivity analysis	114
7.5.1	Sensitivity analysis on the transportation cost rate	115
7.5.2	Sensitivity analysis on the site-preparation cost	115
7.6	Performance study of the proposed GAB algorithm	116
7.6.1	At group level	117
7.6.2	At grouping structure level	119
7.7	Conclusion	119
	General conclusion	121
	Publication of the author	125
	Bibliography	127
	Résumé de la thèse en Français	145

List of Tables

3.1	Distance matrix between sites	60
3.2	Given information related to the site level	60
3.3	Components' data and individual maintenance optimization	60
3.4	Preventive maintenance cost of components	61
3.5	Maintenance plan of the GDPS	62
3.6	Maintenance cost provided by the predetermined maintenance plan	62
7.1	Travel distances among sites and their global maintenance center	104
7.2	Travel times among sites and their maintenance center	105
7.3	Components, downtime cost rate and site-preparation cost of each produc- tion site	105
7.4	Components' data and individual maintenance optimization results	106
7.5	Maintenance routes and departure times provided by SMaRS and JMaRS approaches	106
7.6	Maintenance costs provided by SMaRS, JMaRS and individual mainte- nance optimization (IMO) approaches	106
7.7	Optimal grouping structure and maintenance costs provided by JMaRS	109
7.8	Optimal maintenance routes and optimal departure times provided by JMaRS	110
7.9	Optimal grouping structure and maintenance costs provided by SMaRS	111
7.10	Optimal maintenance routes and optimal departure times provided by SMaRS	111
7.11	Optimal maintenance itineraries after updating	113
7.12	Sensitivity analysis of grouping structure to transportation cost rate	115
7.13	Sensitivity analysis of grouping structure to site-preparation cost	116
7.14	Comparison of search time between the jBAB and ES	118
7.15	A population of GA	118
7.16	Search time of GAB and GAaES	119

List of Figures

1.1	The architecture of GDPSs	3
1.2	The architecture of a distributed computing system	3
1.3	Geographically dispersed production model of Honda corporation ¹	4
1.4	Maintenance architectures of a GDPS	6
1.5	Centralized maintenance architecture on preventive maintenance of hydro power plants	8
2.1	Different types of maintenance strategies for multi-component systems [1] .	24
3.1	Structure cost of component i in GDPS context	50
3.2	Tentatively individual maintenance plan of three considered components 1,2,3	54
3.3	Illustration of change of maintenance execution date of component i	57
3.4	Impacts of maintenance routes on the PM dates and travel distance	57
3.5	A typical GDPS containing 5 production sites	59
3.6	Sensitivity analysis of economic profit to transportation cost rate for the proposed dependence model	63
4.1	A model of the dynamic grouping maintenance strategy of a GDPS	67
4.2	Flow chart of an optimization process [2]	72
4.3	The updating procedure for a dynamic grouping maintenance approach . . .	75
5.1	A Traveling Salesman Problem	78
5.2	The procedure formulating economic profit model by the SMaRS approach	81
5.3	The procedure formulating economic profit model by the JMaRS approach	82
6.1	Optimization procedure based on SMaRS	88
6.2	Search tree for the group $G_k = \{1, 2, 4, 5, 7, 8\}$	89
6.3	The principle of GAB for grouping maintenance and routing optimization problem	99

6.4	Encoding for a grouping structure	99
6.5	Example of crossover and mutation operators.	100
7.1	A typical GDPS containing 6 production sites	104
7.2	Tentative execution dates of components provided by individual maintenance planning	107
7.3	Optimal grouped maintenance plan	109
7.4	Updating tentative individual planning	113
7.5	Updating the grouping maintenance planning in the presence of a road interruption	114
7.6	Sensitivity analysis of grouping economic profit to transportation cost rate	116
7.7	Sensitivity analysis of grouping economic profit to site-preparation cost . .	117
8	L'architecture des GDPS	147
9	Différents itinéraires pour effectuer un groupe de tâches	147

Abbreviations

GDPS	Geographically dispersed production system
GDPSs	Geographically dispersed production systems
CPS	Centralized production system
CM	Corrective maintenance
PM	Preventive maintenance
O&M	Operation and maintenance
GMC	Global maintenance center
LMC	Local maintenance center
ABM	Age-based maintenance
CBM	Condition-based maintenance
MTTF	Mean time To failure
MTW	Maintenance time window
IMO	Individual maintenance optimization
SMaRS	Sequential maintenance routing and scheduling
JMaRS	Joint maintenance routing and scheduling
GA	Genetic algorithm
BAB	Branch and Bound
sBAB	Branch and Bound algorithm based on SMaRS approach
jBAB	Branch and Bound algorithm based on JMaRS approach
GAB	Advanced algorithm based on GA and BAB

Notations

n	The number of components of the system
n_s	The number of production sites of the system
$r_i(t)$	Failure rate of component i
L_{0j}	Travel distances from the global maintenance center (denoted by 0) to site j
L_{j0}	Travel distances from site j to the global maintenance center
AS	Average speed of transport vehicles
d_{mj}	Travel time from site m to site j
β_i, λ_i	Shape and scale parameters of the Weibull distribution of component i
ω_i	Preventive maintenance duration of component i
C_i^{sp}	Spare part cost of component i
C_i^{dt}	Downtime cost of component i
R_j^{dt}	Downtime cost rate at site j
S_{ij}^0	Site-preparation cost of components i at site j
S_{ij}^{tr}	Transportation cost from a global maintenance center to site j containing maintained component
R^{tr}	Transportation cost rate
C_i^{lb}	Labor cost for a preventive maintenance activity of component i
l_i	Skill level of a maintenance team required by component i
$R_i^{lb}(l_i)$	Labor cost rate of maintenance team corresponding to skill level l_i
Δh_i	Penalty cost of component i
x_i^*	Preventive maintenance cycle of component i
ϕ_i^*	Minimal long-term average maintenance cost of component i
t_i^e	Total operational time of component i elapsed from the last replacement
ω_{ij}^{Σ}	Cumulative downtime of component i at site j
t'_{iz}	Maintenance execution date of component i at the z^{th} times
t_{iz}	The tentative maintenance date of a component i at the z^{th} times
Δt_{iz}	The difference between maintenance execution date and tentative maintenance date of component i
T_{begin}	Beginning date of planning horizon

T_{end}	Ending date of planning horizon
G_k	The k_{th} group of maintenance activities in the planning horizon
$n_j^{G_k}$	The number of components located at site j of group G_k
t_{G_k}	Departure time at global maintenance center of group G_k
$t_{G_k}^*$	Optimal departure time at global maintenance center of group G_k
I_{G_k}	Maintenance itinerary that maintenance team follow to maintain components of group G_k
$I_{G_k}^*$	Optimal maintenance itinerary of group G_k
X	Matrix of routing plan
J_v	Visit order to sites associated with itinerary I_{G_k}
L_{G_k}	Total distance of a maintenance itinerary
$\Delta S_j^{G_k}$	Site-preparation cost saving at site j of the group G_k
$\Delta S_{G_k}^0$	Site-preparation cost saving of group G_k
ΔH_{G_k}	Penalty cost of group G_k
$\Delta C_{G_k}^{lb}$	Labor loss cost of group G_k
l_{G_k}	The highest skill level of maintenance team of group G_k
EPE_{G_k}	Economic profit of group G_k yielded from economic dependence
$\Delta S_{G_k}^{tr}(I_{G_k})$	Transportation cost saving thanks to geographical dependence
EPG_{G_k}	Economic profit of group G_k
$C_{G_k}^p$	Maintenance cost of group G_k
GS	Grouping structure of several groups
EPS	Economic profit of a grouping structure
X	Matrix of routing plan
J_v	Visit order of a maintenance team
$LBTC_q(I_{G_k})$	Lower bound of transportation cost of the routes containing node q
$L_{0 \rightarrow q}$	Total travel distance of the planned part of the routes from a global maintenance center to node q
$\hat{L}_{q \rightarrow 0}$	Expected total travel distance of the unplanned part of the routes from node q to a global maintenance center
$LBPC_q(I_{G_k}, t_{G_k})$	Lower bound of penalty cost of the routes containing node q
$H_{0 \rightarrow q}$	Total penalty cost related to the planned part of the routes from the maintenance center to node q
$\hat{H}_{q \rightarrow 0}$	Expected total penalty costs related to the unplanned part of the routes
$t'_{i_s}{}^{min}$	The smallest travel time if the maintenance team directly go to site m after leaving node q
$t'_{i_s}{}^{max}$	The longest travel time if the maintenance team directly go to site m after leaving node q

$h_i(t'_{i_s}, t_{i_s})$ The minimum penalty cost expected
 LBC_q Lower bound cost at node q

General introduction

In the context of current globalization, in order to remain competitive, companies define their activities and priorities according to several factors related to their production systems, such as flexibility, productivity and quality. Therefore, maintenance, which is defined as "all activities necessary to restore equipment to, or keep it in, a state in which it can perform its designated functions" [3], plays an increasingly support role. On the one hand, it allows equipment to be sustained in good working condition and to increase their service life. On the other hand, it also allows production to be ensured by meeting all the expected performances such as the required time, quality and safety requirements. In perceiving the very important role of maintenance, companies are investing more in maintenance operations. Both the portion of maintenance cost and maintenance worker have been increasing [4]. According to statistic, maintenance costs occupies about 15-70% of the total production costs [5,6]. The amount of money spent on building engineering structures and infrastructures serving maintenance activities has been increasing continuously [7]. Another report [8] shows that the United States annually spends more than \$300 billion on maintenance and plant operations in 1990s. About 80% of this cost is estimated to pay for chronic failures. Eliminating these failures can reduce maintenance costs by 40% to 60%. Whereas, in the chemical industry, over 30% of the total workforce and up to a quarter of operation cost was devoted to maintenance activities [9]. Moreover, the study [10] highlighted that maintenance budgets represent, on average, 20% of the total plant operating budget, ranging from a few percent in light manufacturing, to very high percentages in equipment-intensive industry (i.e. steelmaking, petrochemical, mining industry, etc.) or in the so-called utilities sector (i.e. electrical energy, oil and gas, etc.).

To better control budgets, the choice of maintenance strategies should be considered carefully. The chosen strategy must be adapted to the maintenance objective (i.e. reduce the production cost, improve the availability of the system, etc.), the characteristics of the system (i.e. mono or multi-component, etc.) and the operating conditions of the system (stable or dynamic). In the literature [11], a lot of studies addressed the development and optimization of maintenance strategies. The question is how to give an

optimal maintenance decision which satisfies desired objectives (i.e. minimizing maintenance cost, maximize system availability, etc.) among many maintenance options relating to frequency of execution, level of intervention (perfect or imperfect) [12]. As a result, many maintenance strategies have been developed since the 1990s [7, 11, 13]. However, these works were often limited to a class of system: single production system (or centralized system). In the recent years, with the growth of international trade, the development of distributed control, information, and logistic technologies, many manufacturing companies pursued the goal of building a geographically dispersed production system (GDPS) to improve their competitiveness [14]. A GDPS is a geographically dispersed production network in which production sites are located far away from each other and subjected to management of an administration center. The GDPSs are mainly characterized by the following features: multi-component, multi-site, dynamic contexts and routing. Indeed, the GDPS is a multi-component and multi-site system because it is constructed by many different production sites in which each site is composed of different subsystem and components. Moreover, due to large-scale system constructed by many subsystems and many production sites, the operation and maintenance of a GDPS is affected by many operating/dynamic contexts such as changes of transportation capacity, disruptions due to maintenance road [15, 16], etc. Another crucial feature of geographically dispersed production network is routing. The routing is the process of selecting a route to perform the given tasks under constraints such as vehicle capacity, time window, manpower, etc. Normally, to perform a group of many tasks at different production sites, personnel leaves administration center and performs sequentially all tasks of the group, then returns to the administration center only when all tasks in the group is completed. In this case, the routing helps managers to find the best route with the given objectives when performing a group of tasks.

Thanks to geographical dispersion of a GDPS, enterprises can save labor cost (located in low labor cost location) and delivered costs (closed to the clients) [14], improve quality of service or product (short delivery time, high quality after-sales activities, fresh foods in case of food industry). Especially, this type of production system judged to be sustainability in manufacturing [17] because its dispersed production can help to reduce risks of disruption in manufacturing and production distribution [18]. Although the GDPSs have many advantages, in real applications, they have to face many challenges concerning standards, regulation, production management, and especially, maintenance planning and optimization due to the geographical dispersion of production sites [19]. Thus, in the framework of maintenance planning and optimization, the main challenge addressed by this PhD is:

How to extend conventional maintenance strategies for GDPSs in considering its features in terms of multi-component, multi-site, dynamic contexts and routing?

According to this challenge and by considering the specific features of the GDPS, new scientific issues are necessary to be attacked.

Firstly, in the framework of maintenance optimization, the dependencies between components have important impacts on the performance of maintenance planning and need to be considered in the maintenance modelling and optimization [11, 20]. Due to multi-component and multi-site system, the GDPS promotes dependencies between components and between sites. In practice, the dependencies between components are classically classified in three main types as in [11, 20, 21]: structural dependence (i.e. maintenance of a failed component implies maintenance of working components or, at least, dismantling them); stochastic dependence (i.e the condition of components influences the life distribution of other components) and economic dependence (i.e the cost of joint maintenance of a group of components does not equal the total cost of individual maintenance of these components). In addition, due to geographical dispersion of GDPSs, another dependence, called geographical dependence, exists if the total distance/time of a joint maintenance a group of several components is smaller than the total distance/time of individual component. Geographical dependence is mentioned that grouping maintenance activities can not only save transportation cost but also reduce travel time thanks to reduction of travel distance. Whereas, economic dependence only considers economic profit when grouping maintenance activities. From the economic aspect, geographical dependence is a special type of economic dependence. However, it is not true when considering travel time aspect. For GDPSs, economic and geographical dependencies are two of the most important dependencies considered widely in development of maintenance strategy [22–27]. However, several studies investigated either economic or geographical dependence. Others investigated separate consideration of these dependencies. It means that interaction between economic and geographical dependencies is not counted. For these reasons, the first scientific issue is here **"How to formulate a dependence model for a GDPS in which economic and geographical dependencies are jointly considered?"** (*scientific issue 1*).

Secondly, the main issue, we want to attack, is relating to maintenance approaches for the development of maintenance strategies within GDPSs. In practice, a large number of maintenance approaches have been introduced, developed and successfully applied to multi-component systems considering several types of dependencies in literature [1, 20]. Among existing maintenance approaches, dynamic grouping maintenance approach initially proposed in [28] seems to be an efficient one since it can take into account several

kinds of dependencies between components and easily update the maintenance planing in dynamic contexts (varying deterioration rate of components, maintenance opportunities, etc.) [29]. However, in the literature this approach is usually investigated for centralized system where geographical dependence does not exist. Therefore, the existing approaches cannot be directly applied for the maintenance strategies of a GDPS because they are inefficient due to omission of geographical dependence. In addition, a GDPS is seen as a large-scale system impacted by many dynamic contexts compared to a centralized system. Therefore, updating maintenance plan under impacts of dynamic contexts is really necessary in order that a current maintenance plan is an optimal one always. For these reasons, the scientific issue is here **"How to develop a dynamic grouping maintenance strategy for GDPS with consideration of the economic, geographical dependencies and the impacts of dynamic contexts?"** (*scientific issue 2*).

The third issue, we want to attack, is to develop economic profit models supporting maintenance optimization for a GDPS. In fact, to address difficulties related to features of GDPSs (multi-site, routing), many researchers investigated maintenance routing problem in their studies. These studies focus on formulating a maintenance routing model that supports to find an optimal route (see for instance [25,30,31]). In these models proposed, the maintenance schedule is usually considered as a constraint rather than the second optimization objective. In practice, simultaneously considering both maintenance routing and scheduling makes global maintenance model become more complex because these processes interact together in establishing maintenance strategy. For this reason, few studies have mentioned to formulate economic profit models of maintenance routing and scheduling. Therefore, the third scientific issue is **"How to formulate economic profit models of maintenance scheduling and routing in GDPS context?"** (*scientific issue 3*).

Finally, another issue relates to maintenance optimization methods/algorithms for maintenance strategies in GPDS context. From economic point of view, maintenance optimization can be understood as optimization of maintenance planning with minimum maintenance cost [11]. For centralized systems, maintenance optimization process tries to find the best maintenance schedule of components so that total maintenance cost is minimum. In the literature, many optimization methods/algorithms have been developed to support maintenance optimization for centralized systems such as analytical methods, exact algorithms, heuristic algorithm [32, 33], etc. However, these existing algorithms, developed for maintenance optimization within centralized systems, cannot be directly applied for GDPSs due to difficulties related to their geographical dispersion (multi-site). Indeed, to perform joint maintenance of several components located at different sites, maintenance team travels from the maintenance center to all production sites containing

maintained components and returns to the maintenance center only when maintenance activities are completed. By that way, maintenance routing is as important as maintenance scheduling. Therefore, developing optimization algorithm for maintenance optimization in GDPS context should consider both maintenance planning and routing. For this reason, the last scientific issue is "**How to develop advanced algorithms to support maintenance optimization for GDPS in considering maintenance planning and routing?**"(*scientific issue 4*).

To face with all these issues in the way to support the maintenance challenge of a GDPS, we defend in this PhD work a global contribution on "A dynamic grouping maintenance strategy for a geographically dispersed production system."

To proceed the defense, we formulate four scientific contributions based on the four scientific issues mentioned:

- **Formulating a dependence model of economic and geographical dependencies for a GDPS (*contribution 1*).**
- **Developing a dynamic grouping maintenance strategy for a GDPS with consideration of economic, geographical dependence and impacts of dynamic contexts (*contribution 2*).**
- **Formulating economic profit models of maintenance scheduling and routing (*contribution 3*).**
- **Developing an advanced algorithm using Genetic Algorithm and Branch and Bound method to solve maintenance optimization problem for the grouping maintenance strategy in GDPS context (*contribution 4*).**

According to these main contributions, the thesis is organized as follows.

Chapter 1 introduces an overview about geographically dispersed production systems (GDPSs) and their maintenance. First, we explore the definition and general characteristics of the geographical dispersed production systems. Then, we mention several factors impacting on maintenance for such systems. Through this introduction, research questions related to difficulties in establishing maintenance strategies for GDPSs are given.

Chapter 2 presents a review of the literature relevant to previous research questions including aspects on: dependence modelling, grouping maintenance strategies, maintenance routing and scheduling problem, and maintenance optimization methods. Through the state of art on these aspects, the four scientific issues related to these aspects are drawn.

In link to the first scientific issue, Chapter 3 is devoted to formulate a dependence model for a GDPS taking into account economic and geographical dependencies. In this dependence model, the reduction of transportation cost due to geographical dependence coupled with the reduction of preparation cost due to economic dependence make total maintenance cost decreasing significantly when several components are jointly maintained.

In link to the second scientific issue, Chapter 4 is devoted to develop a dynamic grouping maintenance strategy for a GDPS with consideration of economic, geographical dependence and impacts of dynamic contexts. In this strategy, components of the system are maintained preventively and jointly to take cost saving of preparation (economic dependence) and transportation (geographical dependence) instead of performing separately. In addition, the maintenance strategy allows updating the optimal solution when the dynamic contexts (change of vehicle capacity, change of maintenance routes, etc.) occur.

In link to the third scientific issue, Chapter 5 is devoted to formulate economic profit models of maintenance scheduling and routing. In framework of grouping maintenance for GDPSs, to do preventive maintenance of a group of several components, maintenance team can follow different maintenance routes/itineraries to maintain these components before turning back to maintenance center when all maintenance activities are completed. Different maintenance itineraries lead to different maintenance schedule and different maintenance cost due to impacts of travel distance and travel time. In addition, maintenance routing depends on allocation of maintenance resources (i.e repairman, vehicle, etc.). Therefore, maintenance routing impacts considerably to formulate the economic profit models. It is reasonable that economic profit models in considering both of maintenance routing and scheduling is developed in this chapter.

In link to the last scientific issue, Chapter 6 is devoted to develop an advanced algorithm aiming to optimize maintenance planning. For this purpose, an advanced algorithm using Genetic Algorithm (GA) and Branch and Bound method (BAB), named GAB, is investigated. This algorithm does not require to find a strictly optimal solution, however it has to ensure that: (i) it can integrate many constraints and dynamic context easily; (ii) it can reduce and adjust computational time.

In Chapter 7, the numerical study are done to evaluate the proposed maintenance strategy.

Finally, general conclusions and perspectives are drawn from our works.

Chapter 1

Overview about geographically dispersed production systems and their maintenance

1.1 Introduction

In the framework of maintenance for production systems, initially, most of studies deal with maintenance strategies for centralized production systems whose labor and equipment are completely located in a certain geographic area. Nevertheless, with development of distributed control, information and logistic technologies, production systems have also changed to improve competition level and meet customer's demand. Particularly, to adapt to geographical dispersion of customers, a new model of production system, named geographically dispersed production system (GDPS), has emerged [14]. On the one hand, the GDPS brings many competitive advantages such as saving the product delivered costs (closed to the clients), improving quality of services (short delivery time, high quality after-sales services) or products (fresh foods in case of the food industry),etc. On the other hand, it has to face many challenges concerning standards, regulation, production management, and especially, maintenance planning and optimization [19]. The consideration of the GDPS challenges and mainly those related to its maintenance opens new scientific issues. In this way, this chapter provides an overview about geographically dispersed production systems and several important problems related to their maintenance.

In consistency with this global objective, Section 1.2 presents a general introduction of a GDPS. This section focuses on clarifying what is a GDPS, and then its characteristics. Section 1.3 is devoted to discuss several issues related to maintenance for a GDPS. From analysis of these aspects on GDPS, four research questions are introduced.

1.2 Geographically dispersed production system (GDPS)

1.2.1 Background on a GDPS

For improving competitive ability, the manufacturing companies always seek and change their production models to adapt them to market. In particular, to adapt to geographical dispersion of customers, a manufacturing system, named geographically dispersed production system (GDPS), is emerged. Before mentioning the GDPS concept, we should define what is production system. According to system theory [34], a system is an organized collection of personnel, machines, and methods required to accomplish a set of specific actions. Whereas, production is the process of creating goods through a combination of material, work, and capital [35]. Thus, we can understand that production system is as a collection of integrated machines and personnel whose function is to perform one or more processing and/or assembly operations on a raw material. A set of operations performed on material which brings them closer to the desired final form [35]. From that, concepts of distributed manufacturing system is given in [36]. Distributed manufacturing system is a form of decentralized manufacturing system built by a network of geographically dispersed manufacturing facilities that are coordinated by using information technology. To emphasize the role of geographical dispersion of production sites (factories, plants and workshops) in distributed manufacturing system, a new concept, geographical dispersed production system (GDPS), is defined. The GDPS is a distributed manufacturing system in which production sites are located far apart from each others. The production sites have to be connected and subjected to management of an administration center while between production sites can exist connections or not, it depends on structure of each system. The production sites are subsystems constructed by multiple components. The architecture of GDPSs is shown in Figure 1.1. Because production sites are far away from each other, operation and maintenance of the GDPS are significantly affected by factors such as travel time and travel distance. There are some confusion between concept of GDPS, DS (distributed system) and GDS (geographical distributed system). DS and GDS are wider concept than GDPS. In these systems, the distributed objects are not only physical entities (factories, workshops, production sites) but also technologies (distributed computing system, distributed information system [37](see in Figure 1.2)). For a GDPS, only physical entities of production system are considered.

Thanks to geographical dispersion of a GDPS, enterprises can save labor cost (located in low labor cost location) and delivered costs (closed to the clients) [14], improve quality of service or product (short delivery time, high quality after-sales activities, fresh foods in case of food industry). Especially, this type of production system is judged to be sustainable in manufacturing [17] because it avoids negative environmental impacts (reduce

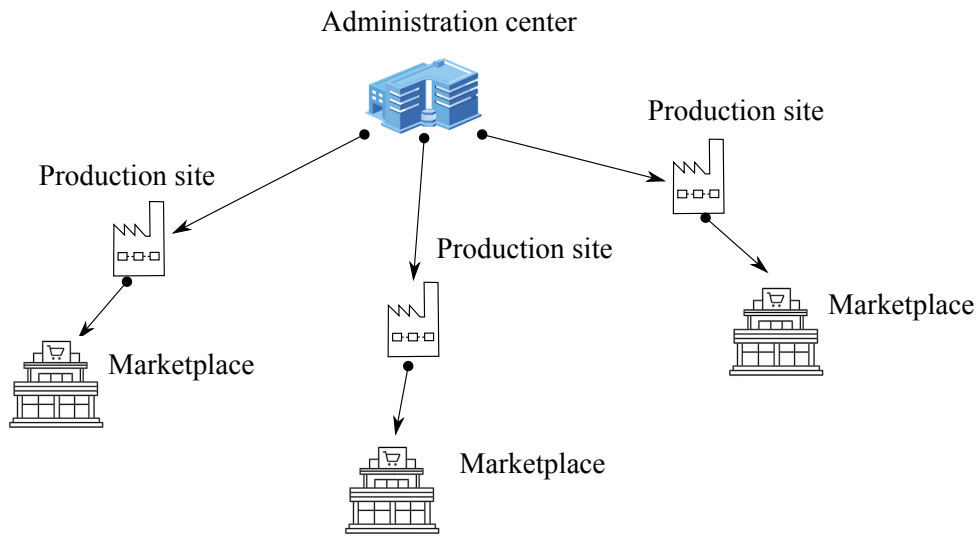


Figure 1.1: The architecture of GDPSs

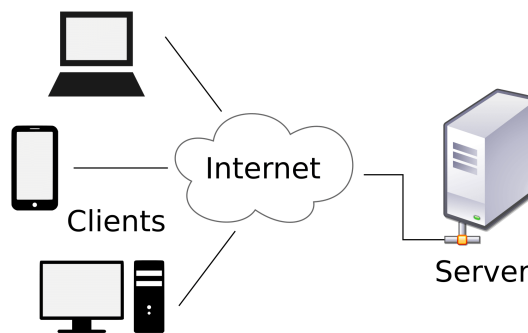


Figure 1.2: The architecture of a distributed computing system

energy consumption in goods transportation) [18] as well as reduces risks of disruption in manufacturing and production distribution. Imagines that when disruption occurs at a production site due to extreme weather, tornado, floods, earthquake, and other unforeseen circumstances, other sites still operate normally because they are not in the sphere of influence. As a result, products are always supplied to customer in any cases. Due to the mentioned advantages in above, the GDPS model is applied by many large corporations. For example, Honda corporation has built five engine production bases located at five countries: Japan, China, Thai, Italia and USA. The five divisions are managed by Kumamoto headquarter located at Ozu-machi, Kikuchi-gun, Japan (Figure 1.3). With the distributed manufacturing operation, Honda corporation saves costs for transport logistic, limits negative environmental effects as well as improve quality of their service and product, meet the customer’s demand in a better way ¹. The study in [38] also shows

¹<https://engines.honda.com/oem-resources/manufacturing-locations>

that distributed mini-factory networks are trend in future. This paper mentioned applications of the GDPS model for furniture company, glass production company and tires manufacturing company.

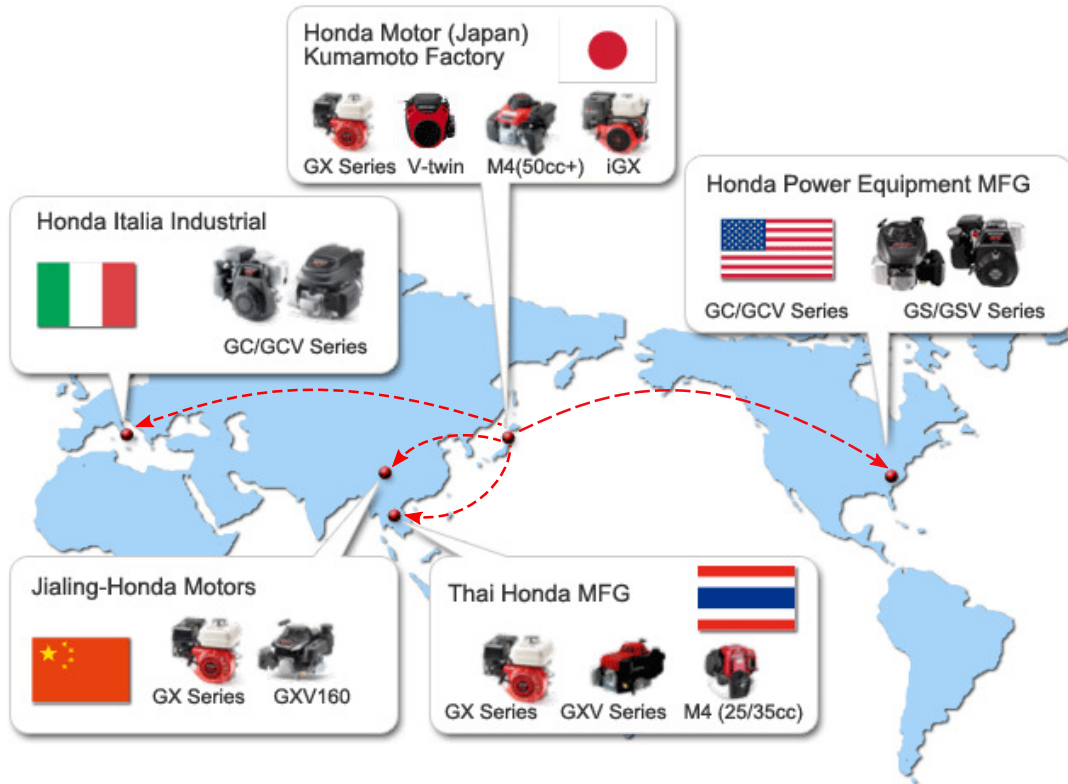


Figure 1.3: Geographically dispersed production model of Honda corporation¹

1.2.2 Main characteristics of a GDPS

Differing of the centralized production system (CPS) whose labor and equipment are completely located at a certain geographic area, a GDPS is constructed by many production facilities/ sites located far apart each other. Its properties therefore is more complex than CPS system. The main characteristics of a GDPS can be identified as follows:

- Multi-component: a GDPS is constructed by many different production sites. Each production site is composed of different subsystems and components which may depend on each others. These dependencies are classically classified by three main types as in [11, 39, 40]: structural dependence, stochastic dependence and economic dependence. Structural dependence means that the dismantling of a component

has to force to dismantle one or many others. Stochastic dependence means that the deterioration or failure of a component influences the lifetime distribution of other components. Economic dependence implies that the cost of joint execution of missions does not equal the total cost of individual execution of these missions.

- Multi-site: According to above definition, a GDPS is a set of production sites located geographically at different places. Thus, a GDPS can be seen as a multi-site system where distance plays an important role in operation and maintenance. Due to this characteristic, normally missions at different sites are jointly performed to reduce travel distance/time. For instance, operators daily transport employees from mainland bases to offshore oil platforms in an adequate itinerary to reduce travel distance [41]. It is depicted as geographical dependence which exists if the total distance/time of a joint execution of missions is not equal to the total distance/time of separate execution of these missions [42].
- Dynamic contexts: A system in operation is usually impacted by dynamic contexts. These contexts can come from internal and external factors of system. Dynamic contexts are related to uncertainties associated with the operations and degradation processes. Sources of uncertainty include degradation processes of the working components, unpredictable transportation interruptions/delays, changing environmental parameters, unreliable parametric estimations, etc. The operation and maintenance (O&M) decisions are made based on consideration of these contexts.
- Routing: The routing supports the process of selecting a route to perform the given tasks under constraints such as vehicle capacity, time window, manpower, etc. As an example, Petrobras, a Brazil company, manages about 80 offshore oil platforms². It transports approximately 1,900 employees daily between these platforms from mainland bases, using more than 40 helicopters that vary in capacity, operating costs, and performance characteristics [41]. Each day, flight planners must select the helicopter routes and schedules that satisfy passenger demands. In this case, the routing helps managers to generate optimized flight plans that meet operational guidelines, improve travel safety, and minimize operating costs. Another example, when a factory does not produce enough products to supply its market or stops production because of failures, other factories will produce more to supplement this shortage. In this case, routing helps managers find an optimal route with the lowest cost to transport products from operating factories to the shortage area [17].

²<http://www.petrobras.com.br/en/>

1.3 Maintenance for GDPSs

The aim of this section is to show some important aspects on establishing maintenance strategies for a GDPS like maintenance architecture, dependencies between components and between sites, maintenance strategies, mathematical models of maintenance routing and scheduling problem, and maintenance optimization methods. Based on the analysis of these aspects, the research questions are identified.

1.3.1 Architectures and influence factors

In relation to above GDPS features, the preventive maintenance of a GDPS can lead generally to three types of architecture [43] (Figure 1.4) which we name local, centralized and hybrid maintenance architecture. Local maintenance architecture (architecture 1) is defined as maintenance system in which each production site is completely maintained by its local maintenance center without supporting external resources. In the contrast, in centralized maintenance architecture (architecture 2), the spare parts and repairman are centralized at a global maintenance center (GMC) and are transported from GMC to maintenance sites when required. The last one, a hybrid maintenance architecture (architecture 3), is combination of the two previous types (1 and 2). This architecture is constituted by two parts.

1. Global maintenance center (GMC) consists of expensive spare parts and high-tech labor serving major maintenance activities. Maintenance center is responsible for maintaining several essential components at all production sites.
2. Local maintenance center (LMC) composed of common spare parts and labor at production sites performing medium and minor maintenance activities.

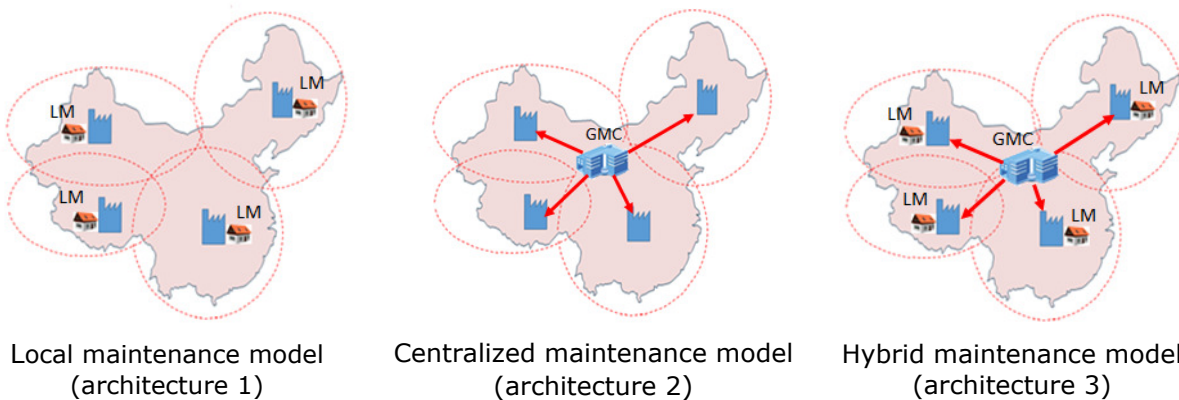


Figure 1.4: Maintenance architectures of a GDPS

Depending on different objectives of managers, one of these architectures is constructed to develop maintenance strategies for GDPSs. In fact, each type of architecture has cons and pros. In the architecture 1, each production site seems to be an independent entity with others. Hence, maintenance strategies of whole system can be combination of individual maintenance strategies of production sites. This architecture ensures that a production site is restored as soon as possible when failures occur because a local maintenance center is near to the production site. It also means that downtime duration is as minimal as possible, therefore, we can minimize production loss cost. However, storing a lot of expensive spare parts and high-tech repairman for major or special replacements during long time can cause a waste of money and time because these replacements rarely occur. In contrast, the architecture 2 can solve these limitations thanks to sharing maintenance resource (spare parts, repairman, etc). More precisely, the spare parts and repairman are centralized at a global maintenance center (GMC) and are transported from GMC to maintenance sites when required. The operators only store a small amount of spare part and repairman at GMC to perform maintenance activities by sharing these resources instead of keeping the identical resources at each sites. By that way, inventory cost is reduced significantly. In addition, investment cost of facilities can reduce because we only build a global maintenance center. However, centralizing all maintenance resources at a location can lead to increase downtime duration and downtime cost due to transportation issues of maintenance resources. The architecture 3 considering both local and global maintenance is a way to ease the disadvantages of architecture 1 and 2. However, this architecture increases investment costs because there are too much maintenance centers to be constructed. It also complicates the process of establishing maintenance strategies because too many constraints and parameters must be considered. In addition, it is not completely relevant for all cases, especially production systems obliged to have only one maintenance center serving maintenance activities for all sites such as offshore wind farm, oil offshore platform, etc . In these cases, centralized maintenance architecture (architecture 2) is applied.

Indeed, maintenance architecture for a geographically dispersed system of hydro power plants is a typical example (see Figure 1.5). This system consists of many plants located far apart each other. Each plant is constructed by many components such as rotor, stator, generator shaft, etc. Considering centralized maintenance architecture on preventive maintenance of such system can reduce inventory cost, investment cost of facilities as well as take advantages on the allocation of maintenance resource. Thus, this architecture could be an appropriate choice in the GDPS context.

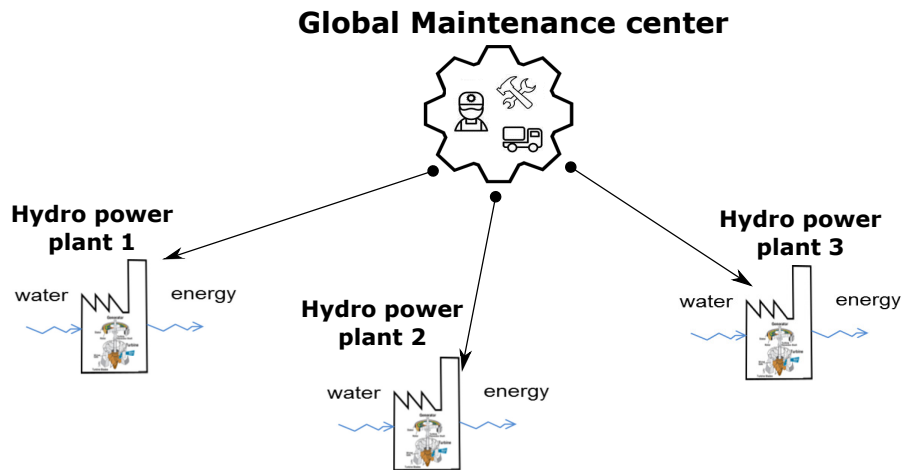


Figure 1.5: Centralized maintenance architecture on preventive maintenance of hydro power plants

In our PhD work, we used architecture 2 for preventive maintenance in GDPS context. It allows to establish preventive maintenance plan for components located at production sites around a GMC.

In this way, the centralized maintenance for a GDPS is defined as a maintenance approach based on the sharing of common maintenance resources (spare parts, maintenance team, etc.) of a GMC to perform maintenance tasks for a production system composed of several production sites dispersed in a geographical area where the distances are important. To perform the centralized maintenance in the frame of a GDPS, the following aspects are considered [44]:

- Spare parts: Spare parts are "items intended to replace failed or degraded components" [45]. Spare parts are an indispensable item of any replacement task in maintenance. The quality, quantity, availability of spare parts impact maintenance planning significantly. For centralized maintenance of a GDPS, spare parts are transported from a GMC to production sites when required. In our study, it is assumed that

ASSUMPTION 1: Spare parts are always adequate and available to be used for maintenance tasks.

- Maintenance routing: For centralized maintenance of a GDPS, to perform maintenance activities, the maintenance team and spare parts have to be transported from the GMC to the maintenance site. There are two ways to perform maintenance tasks. First way, maintenance team can travel from the maintenance center to the

maintenance site where the component is located on, and then come back to the maintenance center when the maintenance is completed. Other one, to perform a group of maintenance tasks at different sites, maintenance team replaces sequentially all components of the group following a specific maintenance route and returns to the maintenance center only when these components are maintained completely. In fact, the second way should be usually considered in maintenance strategies for a GDPS because travel distance/travel time is significantly saved.

- Maintenance team/repairman (number and skill): It is one of factors directly impacting on establishing maintenance strategies [46]. Maintenance team is usually considered under two aspects: number and skill. Indeed, depending on type and level of failures, operators decide the number of worker required for maintenance tasks. The shortage of workers can make maintenance duration become longer or even not perform maintenance operations [47]. In addition, skill levels of repairman also play an important role in guarantee of the success of maintenance tasks [48]. As an example, in a system, each component requires a kind of repairman with different skill levels. Repairing component 1 requires repairman possessing electric skill ; repairing component 2 requires repairman possessing electric and electronic skill; repairing component 3 requires repairman possessing electric, electronic and mechanical skill, etc. Thus, skill of repairman can be divided into different levels. For example, level 1 can repair electric failures; level 2 can repair electric and electronic failures; level 3 can repair electric, electronic and mechanical failures, etc. The higher level of repairman can repair components requiring lower level. It should be noted that the repair cost depends on skill levels of repairman. It means that the higher skill level of repairman is required, the higher repair cost is paid. When performing individual maintenance, the lowest level of repairman is required to ensure the minimum repair cost. In the contrast, when performing joint maintenance of a group of several components, the highest level of repairman of the group is required to guarantee the success of all maintenance tasks. In our study, it is assumed that
ASSUMPTION 2 : One maintenance team is available to perform any maintenance tasks. The maintenance team is a set of many repairman. The number of repairman is always adequate to develop any maintenance task. The skill of repairman is divided into three levels. When performing joint maintenance of a group of several components, the highest level of repairman of the group is required to guarantee the success of all maintenance tasks.

- Vehicle fleet/Van: To transport repairman and spare parts from a GMC to maintenance sites, a fleet of vehicle including car, truck, crane, etc is a necessity. The size

of the fleet depends on the scale of maintenance activities. In some cases, investing purchase of specialized means to transport a special component is unnecessary. When requiring a specialized means, we can rent them to reduce cost of investment. In our study, it is assumed that

ASSUMPTION 3 : Vehicle is always adequate and available to develop any maintenance task.

In this thesis, the architecture 2 is used to develop preventive maintenance strategy for a GDPS. In addition, the influence factors and their assumptions as mentioned above are considered on establishing maintenance strategy for a GDPS.

1.3.2 Consideration of dependencies on maintenance for GDPSs

As known, a GDPS is a form of multi-component and multi-site system so that it has characteristic of multi-component system. In any multi-component systems, interactions/dependencies between components always exist. In the framework of maintenance, these interactions/dependencies have to be considered due to their great impacts in maintenance planning. Dependencies between components can be classified into three different types (economic, stochastic and structural dependence) [39, 42]:

1. Economic dependence: The maintenance cost structure has inter-dependencies between components. As a result, the maintenance cost of a group of several components is not equal to total cost of individual maintenance of these components. For this type, we distinguish two following cases:
 - Positive economic dependence: It implies that the cost of joint maintenance of a group of several components is less than the total cost of individual maintenance of these components. This dependence is often modeled as a setup cost that needs to be paid one time if maintenance is performed for a group of components. It means that if setup cost of component is a fixed cost S , we only have to pay a fixed cost S when a group including n components is maintained. The saving setup cost is equal to $(n - 1)S$. Normally, this dependence appears in grouping maintenance strategy [47].
 - Negative economic dependence: This one occurs when maintaining components simultaneously is more expensive than maintaining components individually. According to [11], such negative economic dependence can be present in systems with manpower restrictions, safety requirements, or production-loss, which is usually incorporated by imposing restrictions in the maintenance model. For example, this type of economic dependence refers to [28]. The authors give

an example of the maintenance of blast furnaces. The disturbance due to maintenance is substantially more, the more furnaces that are out of operation. That is, the cost of overhauling the furnaces increases more than linearly with the number of furnaces out of action.

2. Stochastic dependence: It means that the deterioration or failure of components influences the lifetime distribution of other components. In other words, the behavior of one component depends on the behavior of others. This type of dependence occur in two difference ways. Firstly, the failure of one component can lead to an immediate increase of the deterioration level of other components or even an immediate failure of these components. Secondly, working components have to operate harder to compensate for the shortcomings caused by failure components, therefore, their deterioration increase more fast.
3. Structural dependence: It concerns the structural, static relationships between different components. Originally, structural dependence focus on the situation where the replacement of a certain component requires the dismantling or replacement of other components. The physical structure is well known as series, parallel, series-parallel, k-of-N [11]. However, more situations exist that components are not dependent through the physical structure of the system. As an example, the tires of an airplane are always replaced jointly to ensure that their thickness is always the same. This type is mentioned as technical dependence [21].

Recently, a new type of dependence, called geographical dependence, appears [49]. This dependence exists if the total distance/time of a joint maintenance a group of several components is not equal to the total distance/time of individual maintenance of these components. This type of dependence may impact on the maintenance planning and/or total maintenance cost. This is specially true when only one maintenance team located far from production sites is responsible for performing the maintenance of different sites. In fact, no much studies have investigated this dependence for GDPSs [23,27]. Therefore, the consideration of the geographical dependence of GDPSs to implement its maintenance opens a new scientific issue.

The dependencies between sites and between components have important impacts on the performance of a maintenance planning. In fact, many papers ([22–27]) consider these dependencies on development of maintenance strategies for GDPS. However, considering all dependencies in establishing maintenance strategies is impossible because it make maintenance model too complex. Therefore, the maintenance strategies should only consider a few dependencies in their establishment. This raises the following questions:

"What kind of the most impacted dependencies exist in a GDPS? How to model and formulate these dependencies?" (RQ 1).

1.3.3 Maintenance strategies for GDPSs

To better control budgets, the choice of maintenance strategies is a great importance. There are many ways to classify maintenance strategies thanks to differently desired objectives. Depending on the nature of performing maintenance activities, we can distinguish types of maintenance strategies: individual maintenance strategy and grouping maintenance strategy [1].

- Individual maintenance strategy: In this type, each component is maintained independently with each others. To optimize maintenance execution date of a component, we can apply time-based maintenance or condition-based maintenance policy. For the time-based maintenance policy, it is built on life time distribution of components. This policy is widely applied in industries because it is relatively easy to be implemented and can only rely on the long-term statistical behavior of the degradation processes of components and personnel's experience [13]. Normally, the maintenance cycle time of a component can be determined by this policy. Whereas, condition-based maintenance policy is built on information of the health condition of the components thanks to monitoring the actual condition of the component/system. Condition based maintenance policy takes into account the relatively accurate current state of the components. A component is maintained when its status overcomes a limitation threshold [50].
- Grouping maintenance strategy: It is a strategy based on joint maintenance of several components to save preparation/setup cost, time or take advantages of maintenance opportunities [20]. In fact, maintenance execution time of components provided by this strategy usually differ to their maintenance cycle time, therefore a penalty cost is incurred due to the shift of the maintenance time. However, normally this penalty cost is less than economic profit thanks to grouping maintenance. The grouping maintenance strategy can be categorized in following: stationary grouping maintenance strategy and dynamic grouping maintenance strategy. This classification is based on how dynamic contexts are considered on the grouping maintenance strategies [40]. Dynamic contexts have uncertainties associated with the operations and degradation processes. Dynamic contexts considered in a GDPS can be degradation processes of the working components, unpredictable transportation interruptions/delays, changing transportation capacity,etc.

- Stationary grouping maintenance strategy: Grouping maintenance decisions do not take into account the dynamic contexts that is only known on a short-term horizon. This strategy usually outlines a maintenance plan that does not change over the life of the system.
- Dynamic grouping maintenance strategy: Grouping maintenance decisions can take into account the dynamic contexts. The maintenance plans provided by this strategy can be updated when the dynamic contexts occur on the planning horizon.

For the stationary grouping maintenance strategy, maintenance models are often less complicated than those of dynamic one. In addition, the management and organization of maintenance actions of a stationary grouping maintenance strategy are simpler too. However, the stationary grouping maintenance strategy is evaluated less flexible than the dynamic one because maintenance plan cannot be updated when a dynamic context occurs. Therefore, for systems impacted mainly with dynamic contexts, the dynamic grouping maintenance strategy is usually chosen.

In practice, for a multi-component system, grouping maintenance strategies are widely applied to aim reduction of maintenance cost thanks to the save of preparation cost [1, 29, 51]. Applying this one into a GDPS is absolutely appropriate because grouping maintenance for such system not only saves setup cost but also transportation cost. However, developing a grouping maintenance strategy for GDPSs faces many difficulties related to interaction/dependencies between components and sites, impacts of dynamic contexts on maintenance planning. In that way, raising question is: **"How to extend grouping maintenance strategy for a GDPS taking into account the dependencies and impacts of dynamic contexts?" (RQ 2).**

1.3.4 Mathematical models for maintenance routing and scheduling

In order to increase competitive ability, one of companies's aims is to minimize maintenance cost. Thus, maintenance strategies usually focus on finding an optimal maintenance schedule with the lowest cost. To do this, maintenance scheduling models, supporting to find optimal maintenance execution dates of components, has been usually formulated [39]. However, for a GDPS, maintenance problem becomes more complex due to its geographical dispersion. Establishing a maintenance strategy for a GDPS not only depends on maintenance scheduling but also maintenance routing. It is specially true with centralized maintenance architecture that one global maintenance center is in charge to perform

maintenance tasks for different production sites located around. Obviously, to do joint maintenance of several components located at different sites, maintenance team has to travel from the GMC to all production sites containing maintained components and returns to the maintenance center only when maintenance activities is completed. In that case, many papers [25,30,31] formulated maintenance routing models to support maintenance optimization for GDPSs. However, these model are inefficient because maintenance scheduling is ignored. For this reason, raising questions are: **"Which is a maintenance routing and scheduling approach that is appropriate for a GDPS? How to formulate mathematical models representing this approach?" (RQ 3).**

1.3.5 Maintenance optimization methods

Maintenance optimization is defined as an approach that aim to find optimal maintenance solutions with possible objectives including minimization of the maintenance cost, or maximization of the system availability and reliability [33]. Maintenance optimization for a maintenance strategy can be understood as optimization of maintenance planning [11]. In the framework of maintenance optimization, for centralized systems, many optimization methods are used such as analytical methods, exact algorithms, heuristic algorithm [32, 33],etc. However, these methods/algorithms cannot directly be applied to solve the grouping maintenance optimization problems for GDPSs due to difficulties related to maintenance routing. Indeed, the maintenance optimization for GDPSs not only relates to maintenance scheduling but also maintenance routing. Therefore, optimization algorithms/methods should try to simultaneously solve optimization problem of maintenance planning and routing. This raises the following question **"What kind of methods/algorithms should be developed for maintenance optimization of a GDPS in joint consideration of maintenance planning and routing?" (RQ 4).**

1.4 Conclusion

In this chapter we provided an overview about GDPSs, their characteristics and several issues related to their maintenance planning and optimization. A GDPS is a production system which the production is done over a number of production sites geographically located far apart from each other. A typical GDPS is mainly characterized by four properties: multi-components, multi-sites, dynamic contexts and routing. These characteristics are usually considered in majority of development of maintenance strategies for GDPSs. Related to preventive maintenance for GDPSs, in the framework of our research, the centralized maintenance system where spare parts and repairman are centralized at

a global maintenance center is chosen. Based on this architecture, establishing maintenance strategies for a GDPS should consider different aspects: dependence modelling (structural, stochastic, economic and geographical), maintenance strategies, optimization of maintenance routing and scheduling problem and maintenance optimization methods. By considering these aspects in maintenance planning, four research questions have been highlighted:

- What kind of the most impacted dependencies exist in a GDPS? How to model and formulate these dependencies? (RQ 1)
- How to extend grouping maintenance strategy for a GDPS taking into account the dependencies and impacts of dynamic contexts? (RQ 2)
- Which is a maintenance routing and scheduling approach that is appropriate for optimization problem of a GDPS? How to formulate mathematical models representing this approach? (RQ 3)
- What kind of methods/algorithms should be developed for maintenance optimization of a GDPS in joint consideration of maintenance planning and routing? (RQ 4)

To identify the gap between the existing work on maintenance strategies for the GDPS and what it is expected to achieve the research questions, a scientific problem statement on maintenance for a GDPS is developed in next chapter.

Chapter 2

Scientific problem statement on maintenance for GDPSs

2.1 Introduction

The Chapter 2 aims to overview the existing works related to the four research questions identified in Chapter 1. Thus, the state of the art is developed with regards to each of these research questions. From the state of the art, the scientific issues to be attacked for contributing to research questions are highlighted.

More precisely, in Section 2.2, we present a state of the art on dependence modelling for production systems, especially a GDPS. For the types of dependencies promoted by a GDPS, economic and geographical dependencies are underlined in our analysis. Then, in Section 2.3, a state of the art on maintenance strategies is reviewed. After that, Section 2.4 presents a state of the art on mathematical model of maintenance routing and scheduling in GDPS context. Finally, in Section 2.5, a state of the art related to optimization algorithms/methods is presented. Through the perception of each section, scientific issues for establishing maintenance strategy in GDPS context are given at end of these sections.

2.2 State of the art on dependence modelling

As mentioned in chapter 1, a GDPS is seen as a multi-component system, therefore it is existing the following types of dependencies between components: structural dependence (i.e. maintenance of a failed component implies maintenance of working components or, at least, dismantling them); stochastic dependence (i.e the condition of components influences the life distribution of other components) and economic dependence (i.e the cost

of joint maintenance of a group of components does not equal the total cost of individual maintenance of these components) [11, 20, 21]. In addition, due to multi-site characteristic of GDPS, it exists another dependence, called geographical dependence [42, 49]. The geographical dependence implies that the total distance/time of a joint maintenance of several components is smaller than the total distance/time of individual component. All these dependencies directly influence maintenance planning in GDPS. However, integrating many dependencies into a maintenance strategy makes it too complicated to be analyzed or to be solved, therefore most maintenance strategy consider only one or two of these dependencies. For GDPSs, economic and geographical dependence are two of the most important dependencies in establishing maintenance strategy. It is specially true when maintenance activities are jointly performed. The joint maintenance of components can save both setup cost thanks to economic dependence and transportation cost (reduce travel distance) thanks to geographical dependence. Therefore, investigating these dependencies and integrating them into maintenance strategies have received big attention of many researchers [22–27]. In that way, in the following section, we present a state of the art on dependence modelling related to economic and geographical dependence. From this analysis, a scientific issue related to development of dependence model taking into account economic and geographical dependence in GDPS context is drawn.

2.2.1 Economic dependence

Economic dependence implies that the maintenance cost of a group of components is not equal to total of maintenance costs of the individual components of this group [11]. The nature of this difference is often based on the following three costs:

1. Setup cost: This cost is paid for maintenance preparation tasks. It often includes costs related to dismantling and assembly activities and opening devices. Set-up cost can be saved when maintenance activities of the different components are performed jointly, because setup cost paid on a group of these components counts only on one component [52] instead of all components. In the literature, there are two types of implementation cost [20, 52]: (i) when the setup cost is the same for the maintenance of all components in the system, this type is single setup cost [20, 53–55]; (ii) when the setup cost is shared between specific groups of components and it is different for each group, this type is defined as a multi-setup cost [42, 56]. In a GDPS, the components are located in different production sites. So, the preparation tasks required for the maintenance of each site are not the same. They depend on the site characteristics. The setup cost therefore should not be identical for all sites. For this reason, a **multi-setup cost model** needs to be developed for modeling the

economic dependence between the components of GDPS with taking into account the characteristics of production sites.

2. Downtime cost: This cost appears due to system shutdown. The stopping can cause the loss of production costs, cost to restart the system, loss of product quality or quality of services [57–60]. Normally, this cost depends on downtime required to restore the system. The longer downtime is, the more lost cost is. The downtime cost is often distinguished into two categories.
 - Unplanned shutdown cost: So the breakdowns in a system are random, these failures generate the unplanned shutdown cost of the system. This unplanned shutdown cost is often an opportunity to replace a group of failed components or to combine corrective and preventive maintenance activities [54, 61–65]. For a GDPS, the unplanned shutdown cost is usually large because operators take long time to transport spare parts and repairman from GMC to maintenance sites for repairing unforeseen failures.
 - Planned shutdown cost: The preventive maintenance actions are always performed in schedule. If these actions drive the system off, the shutdown cost is incurred. This cost is called as the planned shutdown cost of a system. Due to proactive maintenance, the downtime down up significantly, thus downtime cost is also reduced sharply. For a GDPS, the planned shutdown cost is usually much less than the unplanned shutdown cost because the unplanned one has to take into account downtime caused by transportation time of spare parts and repairman from GMC to maintained sites.
3. Penalty cost: The cost is paid when components are not maintained at their maintenance cycle dates. In fact, in framework of grouping maintenance, components are usually maintained at the same date (at the grouping execution date). This grouping execution date is usually different with most of the maintenance cycle dates of components of this group. The difference generates penalty cost due to:
 - Reducing the useful life of the components if maintenance execution dates of them occur in advance.
 - Increasing the probability of component failure which could lead to increase of the total corrective costs or the total unplanned downtime cost, if maintenance execution dates of components are delayed.

It should be noted that the joint execution of maintenance activities can save costs in some cases (e.g. due to economies of scale). On the other hand, grouping maintenance

may also lead to higher costs (e.g. due to manpower restrictions) or may not be allowed. In the literature, economic dependence is analyzed in both aspects: negative and positive one [1, 11, 66].

Negative economic dependence between components occurs when joint maintenance of components is more expensive than separately one of individual components. According to [52], such negative economic dependence can be present in systems with manpower restrictions, safety requirements, or production-loss, which is usually incorporated by imposing restrictions in the maintenance model. As an example of this type, paper [67] present the maintenance of blast furnaces where there are several identical pieces of equipment, and the only cost is an 'out-of-service' one, which increases more than linearly with the number of items out of service. In this study, the disturbance due to maintenance is substantially more, the more furnaces that are out of operation. That is, the cost of overhauling the furnaces increases more than linearly with the number of furnaces out of action. Whereas, paper [68] solve the scheduling maintenance problem for electrical power transmission networks. There is negative economic dependence in the network due to redundancy/ production-loss. Grouping certain maintenance activities in the network may prevent a cheap electricity generation from running, so requiring a more expensive generator to be run in its place. The negative economic effect is unexpected by planners. They try to find solutions improving profit economic. As a result, a large number of studies exploited the positive economic dependence [54, 69–76].

The positive economic dependence implies that the maintenance cost of a group of several components is less than the total maintenance cost of individual components [52, 77, 78]. It is a result when total saving cost thanks to sharing of logistic costs such as set-up cost, downtime cost is higher than penalty cost. In fact, most of planers have desire to establish a maintenance plan with positive economic dependence to minimize maintenance cost, therefore a large number of studies were investigated [54, 69, 70, 73–76, 79–82]. For a GDPS, the studies [22, 23] model economic dependence for a network of offshore wind turbines by applying the grouping maintenance policies to share the set-up costs. By that way, joint maintenance cost is lower than total maintenance cost of components. The similar work was also studied in paper [24]. The objective of this paper is to develop a preventive replacement strategy for wind farms taking into account economic dependence. These wind farms are located in remote areas or off-shore sites. Each wind farm consists of multiple wind turbines, and each wind turbine has multiple components including main bearing, gearbox, generator, shafts, etc. Obviously, there are economic dependencies among wind turbines and their components. That is, once a maintenance team move to the wind farm, it may be more economical to take the opportunity to maintain multiple turbines. If a turbine is stopped for maintenance, it may

be more economical to replace or repair multiple components which have shown high risks of failures. These studies showed the importance of economic dependence in establishing maintenance strategies for GDPSs. However, the economic dependence usually studies independently with other dependencies. Therefore, it reduces the effectiveness of model in several practical applications.

2.2.2 Geographical dependence

Geographical dependence is an inherent characteristic existing in GDPSs. It implies that for a GDPS, performing joint maintenance of several components along a maintenance itinerary can reduce the total distance/time/cost compared to separate maintenance. However, no much researchers have been considered this dependence in their studies due to (i) integrating this dependence into maintenance models make it become more complex and cause difficulties to optimization issues, (ii) in several cases, impacts of geographical dependence to maintenance planning is negligible and can be ignored. As an example, with a GDPS whose production sites located nearly together, the transportation cost for maintenance activities occupies a very small part in total of maintenance cost, therefore it can be ignored in optimization process of maintenance planning.

However, when considering a large-scale GDPS whose production sites are located far apart each others (distance between sites is important), integrating geographical dependence into maintenance model is extremely meaningful because impacts of travel distance and time on optimization process of maintenance cost or maintenance resource allocation are very big. In the literature, geographical dependence can be considered by three aspects [23, 25–27, 42, 44, 83–85]:

- Distance: In centralized maintenance architecture for a GDPS, repairs and replacement for components are undertaken by global maintenance center whose location is far away production sites. In this case, the cost paid for transportation of maintenance team, tool and spare part is quite large. A number of studies considered travel distance as an important factor to affect transportation cost. Paper [42] developed a maintenance strategy for geographically dispersed production system in which considering impacts of travel distance to maintenance itinerary, execution dates of components and departure time from maintenance center for each maintenance group. Meanwhile, paper [44] proposed maintenance schedules in which incorporating distance factor and other constraints such as limit for daily work duration, spare parts availability, etc.
- Time: Transporting a maintenance team and spare parts for maintaining sites at the right time is an extreme importance so it can help to reduce downtime cost

and penalty costs due to delay of maintenance. In these cases, time factor should be investigated. Paper [25] investigated geographical dependence for maintenance routing and scheduling problem in the electricity networks. The aim of routing problem is to determine travel itinerary of each worker such that the downtime of power lines and the travel effort of workers are minimized. The similar problem was studied in paper [26]. The authors optimized maintenance planning for geographically distributed assets in which the travel time between geographically distributed assets should be incorporated in the maintenance planning. It assumed that one technician (or team) is responsible for the maintenance of multiple assets. Whereas, paper [27] solves the combined maintenance and routing optimization problem for a set of geographically distributed machines in which considering the time window for each customer. In this paper, impacts of travel time to time window were analyzed and modeled.

- Risks: The frequent moves from global maintenance center to production sites and between these sites increase accident probability. The increase of maintenance cost due to unforeseen accident need to be considered in proposals of maintenance strategy. In study [23], the authors gave a maintenance strategy for offshore wind farm in which set up cost take into account both travel cost and accident cost. The probability of access ability, accident ability, collision ability is considered in maintenance process. Meanwhile, paper [83] planned a maintenance strategy for wind turbine systems in presence of weather conditions. The weather factor is considered to limit risks in maintenance process.

Summary of section 2.2: As argued, economic and geographical dependence are relevant for GDPSs that impact directly on maintenance planning, especially when maintenance activities are jointly performed. In fact, most of existing studies [23–27, 44, 83] usually investigate one type of these dependencies in establishing maintenance strategies for GDPSs. Only few studies [22, 23] consider both economic and geographical dependencies in establishing maintenance strategies for GDPSs. Unfortunately, in these studies, economic and geographical dependencies are investigated separately. It means that interactions between them are not be taken into account. By this approach, the maintenance strategies proposed by these studies are less effective in practice. Joint consideration of economic and geographical dependencies is hence seen as appropriate approach for modeling dependencies for GDPSs. So, it leads to define a scientific issue to be attacked in our PhD thesis:

How to formulate a dependence model for a GDPS in which economic and geographical dependence are jointly considered?

2.3 State of the art on grouping maintenance strategies

For GDPSs, planners usually consider joint maintenance of several components to take advantage of cost-saving from preparatory work (economic dependence) and transportation (geographical dependence). Indeed, preparatory or setup work (erecting a scaffolding, opening a machine, etc.) can be shared when several components are maintained simultaneously. Preparation costs can be saved when maintenance activities on different components are executed simultaneously, since execution of a group of activities requires only one set-up [11, 29]. Besides, the joint maintenance of components in an adequate maintenance itinerary can reduce travel distance, travel time and transportation cost compared to perform individual maintenance. For this reason, a large number of studies are interested in developing the maintenance grouping strategies for these systems [1, 11, 52, 55, 86]. These strategies try to find a better way for grouping maintenance activities of degraded components together to maximize positive economic dependence and to minimize the negative economic dependence between components.

In the literature, grouping maintenance strategies are classified as shown in Figure 2.1: stationary grouping maintenance (see section 1.3.3) and dynamic grouping maintenance (see section 1.3.3). For the first group (stationary grouping maintenance), a long-term stable situation is assumed and most of studies assume an infinite planning horizon. By verifying the nature of the maintenance actions (preventive/corrective) for grouping maintenance, three types of stationary grouping maintenance strategies can be catalogued: grouping preventive maintenance, grouping corrective maintenance, opportunistic maintenance. In the contrast, the dynamic grouping maintenance take short-term information into account such as nonlinear degradation of components, unexpected events, etc. Therefore, it adapts better in real applications. This group is divided into two categories: finite horizon and rolling horizon. The finite horizon considers the system in this horizon only, and hence assume implicitly that the system is not used afterwards. Whereas, rolling horizon models also use a finite horizon, but they do so repeatedly and based on a long-term (infinite-horizon) plan.

In the next subsections, we present the definition, characteristics and strategies of each type of grouping.

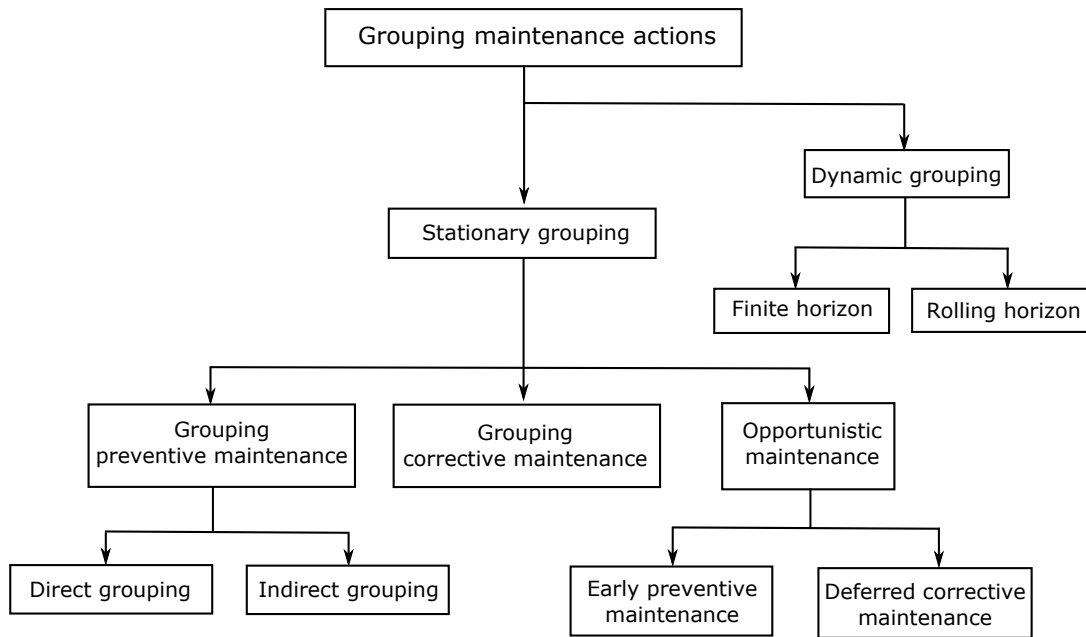


Figure 2.1: Different types of maintenance strategies for multi-component systems [1]

2.3.1 Stationary grouping maintenance

The stationary grouping provides a grouping maintenance plan on infinite horizon in which the operating conditions of the system are stable and the frequency occurring the dynamic contexts is low. Compared to dynamic grouping maintenance, the stationary one seems to be less complicated. Looking at the nature of maintenance actions (preventive or corrective) for grouping maintenance activities, we can catalogue stationary grouping maintenance into three groups as follows:

- Grouping corrective maintenance.
- Grouping preventive maintenance.
- Opportunistic maintenance.

Grouping corrective maintenance

Grouping corrective maintenance is often applied to maintenance for systems with redundancy where we can leave down failed components without interrupting the operation of the system. Paper [82] proposed a grouping corrective maintenance strategy for a parallel system with n components. This system is maintained every T time unit by repairing all the components that are down at that time. T is the decision variable of this strategy and is determined by minimizing the average cost per time unit over infinite horizon. By considering the similar model, paper [79] built a maintenance strategy in which maintenance

activities are performed as soon as the number of failed components has passed a given threshold. This threshold is as a corrective maintenance decision parameter. For this strategy, all failed components are jointly replaced when the number of failed components reaches a threshold.

Grouping preventive maintenance

The strategies in this category are considered as a grouping maintenance plan that only contains preventive maintenance actions. A big advantage of grouping preventive maintenance is that it can given a tentative plan in advance. This is important when preparation tasks is necessary so that spare parts can be ordered in time and maintenance crew can be available in preventive maintenance periods. In framework of maintenance optimization, grouping preventive maintenance policies can be divided into two groups: direct grouping and indirect grouping.

- a *Direct grouping*: The word "direct" here means that the grouping plan is modeled directly as decision variables. More concretely, we must determine: (i) a grouping structure $SG = \{G_1, G_2, \dots, G_m\}$ is defined as collection of groups in which all components are maintained in these groups; (ii) the optimal preventive maintenance cycle of each group in the grouping structure ($t = \{t_{G_1}, t_{G_2}, \dots, t_{G_m}\}$). As a result, the grouping maintenance problem is directly formulated as follows:

$$\begin{aligned} & \text{Minimize } CA = f \{SG, t_{SG}\} \\ & \text{which } SG = \{G_1, G_2, \dots, G_m\}, \forall SG \in PSG \\ & t = \{t_{G_1}, t_{G_2}, \dots, t_{G_m}\}, \forall t_{G_k} \in [0, +\infty), k = 1, \dots, m \end{aligned}$$

where CA is the long-term average costs. It is a function of the grouping structure and optimal preventive maintenance cycles of these groups; PSG is the set of possible grouping structures. The number of possible solutions is equal to 2^N .

The grouping optimization problem is very difficult to solve with this straightforward approach, as we need to find both the optimal grouping structure and the optimal preventive maintenance cycles for these groups simultaneously. As a result, the development of direct grouping is few and is applied only for systems with few components. In order to reduce the complexity of direct grouping problem, paper [87] considered that the optimal maintenance cycle of a group of G_k components is determined as follows: $t_{G_k} = \min_{i \in G_k} t_i$, where t_i is the optimal maintenance cycle for the component i . Dynamic programming is used to search for the optimal grouping structure. According to this strategy, the preventive maintenance of the components is determined in advance.

b *Indirect grouping*: For indirect grouping, the grouping plan is obtained indirectly.

- The first indirect grouping approach is to consider that each component i has an optimal preventive maintenance cycle at the time $k_i \cdot T$, where $T > 0$ is a real value and k is an integer. Then, the decision variables T and k_i (with $i = 1, \dots, n$) are determined by minimizing the long-term average cost of the system. This indirect grouping approach is studied by a number of works. The papers [88–91] consider indirect grouping problems as follows:

$$\text{Minimize } CA(k_i, T) = AS + \sum_i^n \frac{C_i^{sp} + MC_i(k_i \cdot T)}{k_i \cdot T}$$

with k_i is an integer and $T > 0$ is a real value

Where AS is the long-term average cost; C_i^{sp} is the specific cost of preventive replacement of component i ; $MC(x)$ is the total cost of corrective maintenance of the component i incurred over the interval $[0, x]$.

Papers [88, 89] consider the form of $MC(x)$ following $MC_i(x) = a_i \cdot x + b_i \cdot x^e$. Considering that the setup cost must be paid at each T , we have $AS = S/T$. Note that when k are greater than one, there are periods of T where the setup cost is not paid, because no component is maintained at these "empty" periods. Papers [90, 91] consider the general models of $MC(x)$ and give a correction factor for the calculation of AS in the case where there are "empty" periods.

Paper [56] solves the problem of indirect grouping by considering production systems with a multi setup cost model. Whereas, paper [92] gave complementary mathematical analyzes for the model proposed in paper [88, 89] and proposed a new algorithm to find the optimal values of the decision variables. Recently, taking into account the duration of preventive and corrective maintenance, paper [93] proposes a new way of calculating the long-term average cost:

$$CA(k_i, T) = \frac{\sum_{j=1}^k C_{mr}^i + C_{pr}^j}{k \cdot T + \omega_k^p}$$

where: k is the number of preventive maintenance times on a system renewal cycle; C_{mr}^j is the total cost of corrective maintenance of all components between two consecutive maintenance times $(j - 1)_{th}$ and j_{th} ; C_{pr}^j is the total cost of preventive maintenance on the first time; ω_k^p is the total period of preventive maintenance in k cycles.

- Another way of modeling the indirect grouping problem was presented in [94–97]. According to these papers, the system was renewed every T time unit. In addition, each component i of the system was maintained every T/k time unit.

Decision variables were determined by minimizing the long-term average cost which is calculated as follows:

$$CA(k_i, T) = AS + \frac{\sum_{i=1}^n (k_i - 1) \cdot C_i^{sp} + k_i \cdot MC_i \left(\frac{T}{k_i} \right)}{T}$$

- For previous indirect grouping approaches, the number of decision variables increases with the number of system components. As a result, the clustering optimization problem is complicated and requires a lot of computing time especially when the number of system components is large. To address the problem of previous computational time, an indirect clustering approach based on thresholds is proposed. The thresholds (the decision variables) optimized are usually very few, the grouping optimization problem is thus less complicated. The best-known strategy using this approach is the block replacement strategy [98, 99]. According to this strategy, all components are replaced at every T. When a component breaks down between two replacement periods, it is immediately repaired by minimal repair or replacement. The decision variable T is determined by minimizing the long-term average cost:

$$CA(T) = \frac{S + \sum_{i=1}^n (C_i^{sp} + MC_i(T))}{T}$$

where S is the setup cost

The block replacement strategy is simple and easy to implement. However, in the case where the components are replaced when they failed, the replacement is sometimes wasted especially when the time interval between component failure and the next period of preventive maintenance is short. To avoid this disadvantage, a modified block replacement strategy is proposed in [100, 101]. According to this modified strategy, at the time of preventive replacement, the components are replaced only if their age is greater than an age limit a . Two decision variables (T and a) are determined by minimizing the long-term average cost.

Opportunistic maintenance

For this type, the grouping plan contains both preventive and corrective maintenance activities. Depending on how the corrective and preventive maintenance actions are grouped, we can divided them into two types of opportunistic maintenance: early preventive maintenance and deferred corrective maintenance

- Early preventive maintenance:* Preventive maintenance activities are maintained earlier than tentative plan proposed to take advantage of maintenance opportunities.

More concretely, by taking advantage of the maintenance (preventive/corrective) of a component, the other components in the system can be repaired and replaced. These strategies are often applied for the maintenance of the series systems where the shutdown of any components will lead to the shutdown of the system and this shutdown is considered as an opportunity to do preventive maintenance on the other components.

Opportunistic maintenance presented in paper [101] considers a two-component series system. When a component fails, the other component is replaced on that occasion if its age reaches a threshold. An extension of this strategy was developed in [102]. The strategy is based on four thresholds m_1, m_2, M_3, M_4 . The component i is replaced (corrective replacement) when it breaks down or when its age reaches the threshold limit M_i (preventive replacement). When a component is replaced (corrective or preventive), the other component is replaced jointly if its age reaches the threshold limit m_i .

Paper [103] presented an early preventive maintenance strategy for the maintenance of systems of n different components. According to this strategy, a component is minimally repaired when it is failed and its failure rate at the point of failure is between 0 and $L - u$. The component is replaced in two cases: (i) it is broken down and its failure rate is between $L - u$ and L ; (ii) its failure rate reaches the limit threshold L . L and u are the two decision variables. When a component need to be replaced, it provides the opportunity to maintain the other components to save the downtime cost and maintenance cost.

Paper [104] proposed an early preventive maintenance strategy for the maintenance of offshore wind turbines. According to this strategy, a component i is replaced when it is failed. The failure of component i is also an opportunity to replace other components j that satisfy the following condition: $age_j \geq p \cdot MTTF_j$ with $j \neq i, p = p_1$ if component j is in a failed turbine and $p = p_2$ if component j is in a running turbine. The strategy succeeded in providing a different opportunistic replacement threshold for each component based on its $MTTF$ (Mean Time To Failure). Recently, early preventive maintenance strategies are widely developed and applied for the maintenance of practical industrial systems. Other studies of this type can be found in papers [105–109].

- b *Deferred corrective maintenance*: Deferred corrective maintenance means that corrective and preventive maintenance activities are grouped together by delaying corrective maintenance activities. Specifically, when a component fails, no maintenance action is performed at the time of failure and the component is down. The failed

component will be maintained jointly during other maintenance activities upon failure of another component or the next preventive maintenance period. It should be noted that, on the one hand, the setup cost and/or the repair cost can be reduced when the corrective maintenance activities are grouped together with the preventive maintenance periods. But, on the other hand, the risk cost or penalty cost must be paid when the component is left out of order. For this reason, deferred corrective maintenance often applies to the maintenance of redundant systems (parallel, k to n , etc.) where stopping some components does not always lead to system shutdown.

Deferred corrective maintenance began to be developed for parallel structured systems in papers [110–113]. According to these papers, when a component of this parallel system is broken down, this system still sustains its operation. The components is maintained at an optimum threshold that are out of order and is determined by minimizing the long-term average cost of the system.

The deferred corrective maintenance was developed for systems with structure k on n in papers [114, 115]. Paper [114] proposed a preventive replacement strategy based on the set of critical components. According to this strategy, the component is replaced when it is failed and it is in the set of critical components. On the other hand, the component is left out if it is not in the set of critical components. Paper [115] presented a preventive replacement strategy based on a threshold limit m . Specifically, if the number of components failed on a maintenance cycle τ is less than m , the system is replaced at the preventive maintenance period $k \cdot \tau$, ($k = 1, 2, \dots$). On the contrary, if the number of failed components is equal to m , all m failed components are replaced immediately at the moment of the m_{th} failure.

Paper [58] considered repairable systems with a model of failure and more general structures. A two-phase maintenance strategy is proposed: the first phase is in $(0, T)$, and the second phase is in $(T, T + W)$. A component of the system has two types of failure: (i) minor failures that are treated by a minimal repair on both phases, (ii) major failures are treated by a replacement if they occur on the first phase $(0, T]$, and for which one does nothing if they appear on the second phase $[T, T + W)$. The system is replaced at time $T + W$ or at the moment of k component failure on $[T, T + W]$. Decision variables T, W, k are determined by minimizing the long-term average cost of the system.

When systems has a long-term stable situation, the stationary grouping maintenance strategy is usually chosen. For this strategy, mathematical models and maintenance optimization are not too complicated because this strategy usually ignores impacts of dynamic context on maintenance planning. However, this strategy usually outlines a

maintenance plan that does not change over the life of the system. In the contrast, for system with the high frequency of the dynamic contexts, a dynamic grouping maintenance strategy is usually chosen. This strategy allows to update the maintenance planing in dynamic contexts. A state of the art on dynamic grouping is presented below.

2.3.2 Dynamic grouping maintenance

Dynamic grouping strategies are grouping strategies that allow to update maintenance plan in presence of the dynamic contexts (i.e. degradation processes of the working components, unpredictable transportation interruptions/delays, changing transportation capacity,etc.). This strategies can be classified into two types: finite horizon and rolling horizon.

Finite Horizon:

This approach integrates dynamic contexts into maintenance decisions in considering a system on a finite horizon [116]. The maintenance model is optimized on this horizon because the system is no longer operational at the end of the horizon. The calculation of the maintenance cost has to overcome this restriction by integrating remaining useful life of the components in order to estimate the remaining useful life of the system at the end of the finite horizon. Finite horizon models are less investigated in the literature because the optimal policy is often complex and time dependent. These models are often applied for the case where the operating time of the systems is finished. As an example, in military applications, a missile launch system should only operate over its designated useful life [117]. The maintenance strategies proposed for the finite horizon are often applied only for the maintenance of systems with series structure [118–120]. Recently, paper [121] proposed a maintenance strategy for serial-parallel systems on finite-horizon. The strategy contains two main steps: initially, a maintenance plan on the planning horizon is determined separately for each component by minimizing the maintenance cost and maximizing the availability of the component on the planning horizon at the same time. Then, at the system level, a maintenance time window (interval time, noted MTW) is proposed to: (i) separating the maintenance dates of the components in parallel when the maintenance of these components causes the shutdown of the system ; (ii) grouping the maintenance dates of the components in series in order to reduce the downtime of the system.

Rolling Horizon:

This approach of dynamic grouping maintenance is the rolling horizon approach. The basic idea of this approach is to group the maintenance activities in order to get the best benefits. More concretely, the steps can be described as follows:

- *Individual maintenance optimization:* The aim of the individual optimization is to determine the optimal preventive maintenance cycle of each component by minimizing its average maintenance cost on an infinite horizon (long-term average maintenance cost). At this step, stationary maintenance models for single-component systems, such as time-based/age-based replacement strategy or block replacement, can be applied.
- *Individual maintenance planning:* The aim of this step is to establish an individual maintenance plan in a finite planning horizon $PH = [t, \max_{i=1 \rightarrow n} \{t_i^*\}]$, where t_i^* is the optimal execution date of a component i after time t deduced by considering optimal PM cycle of each component and short-term information.
- *Optimization process:* The aim of this step is to find an optimal grouping maintenance plan based on maintenance models and search algorithms. A complete maintenance plan is achieved when each component is maintained at least one time on finite horizon (PH). In this plan, maintenance activities of components is arranged into several groups. It should be noted that the execution dates of components based on grouping maintenance can be different to their optimal maintenance cycle, therefore penalty cost due to the shift of the execution date appears. A penalty cost function is formulated to take account these changes. Besides, the grouping maintenance activities also take economic profit from saving preparation cost, so it should be investigated in maintenance model. From economic point of view, the optimal maintenance plan is a plan with the lowest maintenance cost. Hence, a grouping structure including m mutually exclusive groups covering all activities is an optimal one if total maintenance cost of its groups is minimal when comparing to other grouping structures. The optimal grouping structure is found based on optimization search algorithm.
- *Rolling and updating:* The aim of this step is to propose a new maintenance planning for the next horizon or new horizon. When ending a finite horizon, the rolling should be performed because new missions or new maintenance constraints can be required on next horizon. Whereas, in presence of dynamic contexts, the current maintenance planning may be no longer the optimal one or even unusable, so it should be updated on new horizon.

The rolling horizon approach is proposed for the first time in paper [86]. In this paper, grouping optimization was formulated as an overall partitioning problem. Despite the assumptions proposed by the authors in order to reduce the computational time, the algorithm was limited to a small number of maintenance activities (10 activities) over the planning horizon. Then, paper [20] improved the rolling horizon approach by proposing the theorem of consecutive maintenance activities where the maintenance activities of an optimal group must be consecutive. With the proposed theorem, dynamic programming can be used to search for the optimal quadratic grouping scheme. As a result, the proposed consolidation strategy can be applied to the maintenance of multi-component systems. Unfortunately, this theorem was only valid for systems with serial structure. Therefore, the grouping strategy based on dynamic programming is applied only for the maintenance of systems with serial structure. The authors also show how their strategy can be used for changes in component utilization rates in grouping maintenance planning. In addition, paper [122] addressed the problem of comparing the rolling horizon approach with the stationary maintenance approach. Considering a considerable frequency of occurrence of dynamic contexts (the change of utilization rate or the opportunity to maintain), this paper showed that the rolling horizon approach gives the best results (the minimum cost) compared to stationary maintenance approaches. So far, work on a rolling horizon has been realized by considering simple models: series systems, negligible maintenance time, single and fixed implementation cost, life-time models.

By considering the benefits of the rolling horizon approach, much work has been done to develop this maintenance approach for multi-component. Paper [123] developed the models for a non-negligible preventive maintenance period. The authors were interested in the problem of dynamic grouping under constraints of system availability and limited number of operators. In this case, the optimal grouping plan not only reduces the cost of maintenance, but also ensures system availability level on the planning horizon. This problem was extended in paper [55]. The authors solved the problem for several maintenance activities of a component on the planning horizon and proposed a new method for updating the grouping plan when an opportunity occurs. It is completely different if papers [20, 86, 122] or which each component is considered to be maintained only one time on the planning horizon. Paper [72] developed the rolling horizon approach for the maintenance problem of multi-component systems with gradual deterioration. In order that maintenance planning was adapted to the actual use conditions, the grouping decisions was based on the health states of the components that were inspect in daily. Whereas, a dynamic grouping strategy developed for application of the industrial vehicles maintenance was presented in paper [47]. The authors developed an approach for complex multi-component systems where there is both economic and stochastic dependence be-

tween components. The grouping decisions are based on the degradation level and the remaining useful life of components.

Summary of section 2.3: For GDPSs, planners usually consider joint maintenance of several components (grouping maintenance) to take advantage of cost-saving from preparatory work and transportation. Indeed, preparatory or setup work (erecting a scaffolding, opening a machine, etc) can be shared when several components are maintained simultaneously thanks to economic dependence. Besides, the joint maintenance of components in an adequate maintenance itinerary can reduce travel distance, travel time and transportation cost compared to perform individual maintenance thanks to geographical dependence. Hence, grouping maintenance strategies should take into account economic and geographical dependence in maintenance planning. In addition, an appropriate maintenance approach should be also taken into account. For systems with long-term stable situation, the stationary grouping maintenance is a reasonable solution. It makes maintenance model become more simple when ignores insignificant impacts of dynamic contexts on an infinite planning horizon. Unfortunately, the maintenance for GDPSs have to face a lot of difficulties related to the dynamic route, transportation capacity, etc. These kinds of situations, referred to dynamic contexts, may have significant impacts on the maintenance planning. In the presence of the dynamic contexts, the current maintenance grouped plan and maintenance route may be no longer optimal ones and need to be updated. The proposed grouping maintenance strategy should be a dynamic one which allows to update the optimal solution when the dynamic contexts occur. It means that a dynamic maintenance strategy taking into account short-term information should be considered in the developments. So, it leads to define another scientific issue to be attacked in our PhD thesis:

How to develop a dynamic grouping maintenance strategy for GDPS with consideration of the economic, geographical dependencies and the impacts of dynamic contexts?

2.4 State of the art on maintenance scheduling and maintenance routing

Preventive maintenance (PM) aims to restore equipment reliability and reduce downtime costs by replacing degraded components before failures occur. To make sure that the production is operated at a high efficiency and with minimum breakdowns, it is important that the components are in good health and that preventive maintenance is performed

frequently on right time. This can be done by scheduling maintenance to change parts or repair degraded components. Maintenance scheduling determines the set of time intervals to conduct maintenance activities [124]. In a centralized system, sometimes maintenance planning can be understood as maintenance scheduling. However, for a large and distributed system, maintenance planning not only includes maintenance scheduling but also maintenance routing. It is completely true with centralized maintenance architecture where all maintenance actions are performed by global maintenance center or semi-centralized maintenance architecture where only a few critical components are performed by global maintenance center. It is easy to see that in these architectures, a part of maintenance cost is paid for transporting maintenance team and spare part from global maintenance center to sites and then returning back. Therefore, maintenance routing become important part in optimizing maintenance planning because maintenance cost can be reduced drastically if maintenance route is chosen in reasonable way.

In a number of papers, when the number of preventive maintenance (PM) activities in a short-term planning horizon is always assumed to be known in advance, the main objective is then to find the optimal route configuration for the technicians along with the optimal execution dates of the PM activities that minimize maintenance costs, including travel, labor and penalty costs. The paper [48] considers maintenance routing problem for offshore wind farms in which technician crew with different skills performs predetermined maintenance tasks. This paper carried out sharing of technicians between wind farms over multiple periods, while determining the time for delivering and picking up technicians. The problem can be seen as a new variant of the pickup and delivery problem. The same problem has been studied in [125] in which maintenance routing process for offshore wind farms considers the risk of collisions between maintenance vessels and wind turbines. Paper [126] considers two main types of decisions: which types of vessels have to be used, and how and when to acquire them for the maintenance of offshore equipment within the planning horizon? The uncertain number of failures and the weather conditions are taken into account in the vessel fleet optimization mathematical model. Whereas, paper [127] addressed the problem of maintenance routing for large-scale infrastructure system with geo-distributed units. The objective is to determine the periodic inspection interval for each unit of the system with minimum maintenance and operational constraints (budget and workforce). To deal with the huge number of units, the system is partitioned into a number of clusters. The paper [128] considered maintenance routing problem for a distributed system as vehicle routing problem with time windows. This paper formulated a mathematical model allowing to determine an optimal maintenance itinerary with several constraints about time windows and vehicle capacity. The maintenance planning and routing of electricity network has been studied in paper [25]. The goal is to assign each

task to a worker and to determine a schedule such that the downtime of power lines and the travel effort of workers are minimized. Papers [30] and [31] consider the operational aircraft maintenance routing problem. Given the set of flights for a specific homogeneous fleet type (group of aircraft), this short-term planning problem requires building feasible aircraft routes that cover each flight exactly once and that satisfy maintenance requirements. Basically, these requirements enforce an aircraft to undergo planned maintenance at a specified station, and remain grounded for some durations before accumulating a maximum number of flying hours. Papers [129] and [26] consider the problem of maintenance routing and scheduling for a general GDPS. While the paper [129] focuses on finding the optimal schedule which maximizes the total reward associated with the completing of a task on a given day within the scheduling horizon. Paper [26] integrates the prognostic information (predicted failure probabilities of assets) in the proposed model.

These above works mainly focus on the problem of maintenance routing rather than maintenance scheduling and optimization ones. In these studies, maintenance scheduling is introduced as a constraint for the maintenance routing model. These models is completely acceptable in case that maintenance schedule is determined in advance. However, when maintenance schedule is not predetermined, maintenance planning should be considered in both domains: maintenance routing and scheduling. Recently, paper [130] removes the assumption about the number of PM activities and builds two different models for maintenance scheduling and maintenance routing. This paper developed a scheduling model combining maintenance and routing optimization for a set of geographically distributed machines. Maintenance operations are performed on the machines by a set of technicians at the customers'sites. The approach is based on two steps. Firstly, they determine the optimal PM period, the number of expected corrective and preventive maintenance operations over the planning horizon, and the time window for each PM operation. In the second step, given the directed complete graph and the travel times, they determine the set of routes for each technician and the start time for each PM operation, which minimizes the total maintenance cost. The linkage between the two models is the expected waiting time prior to the beginning of the corrective maintenance (CM) activity on machines when they fail before the start of the PM activity. Paper [44] studies the maintenance optimization problem for offshore wind farms. This study determines the optimal planning of maintenance operations and the optimal routes for the crew transfer vessels with the number of technicians required for maintaining the turbine, taking into account a number of constraints such as weather conditions, vessel personnel capacity, vessel load capacity, vessel availability, spare part availability. The same problem has been studied in [131] with vessels that can stay offshore for several shifts.

However, in these studies, maintenance routing and maintenance scheduling are inves-

tigated sequentially or separately, therefore the obtained plans do not guarantee that both maintenance routing and scheduling are optimized simultaneously. Besides, dependencies existing between components were not considered because all components assume to be independent each other in these studies. It should be noted that for a GDPS as well as a multi-component system, some dependencies such as economic, structural and stochastic dependencies usually exist between components [39, 132]. The maintenance planning should therefore take into account dependencies among components in its optimization process. Recently, economic dependence was analyzed in paper [22, 23] when grouping maintenance policy was applied for establishing maintenance strategies of an offshore wind farm. However, reduction of transportation cost due to geographical dependence existing when grouping maintenance activities was not investigated in these studies. It leads that maintenance planning process is not performed in the most effective.

Summary of section 2.4: Optimization of preventive maintenance (PM) planning for GDPSs is a challenging problem because of difficulties related to their geographical dispersion. Indeed, this optimization process has to consider both optimization of the maintenance scheduling and routing. In practice, many companies usually plan PM operations of their system independently from the optimization of the maintenance scheduling and routing. Maintenance scheduling aims to optimize maintenance execution dates of components. Maintaining components at the right time can reduce penalty cost due to: (i) a reduction of components useful life if the maintenance dates of components are in advanced; (ii) an increase of components failure probability if maintenance dates are postponed. This issue is discussed widely in maintenance framework of multi-component system [133, 134]. Whereas, the maintenance routing aims to find an optimal maintenance itinerary satisfying one of objectives such the shortest distance, time window, etc [135, 136]. These approaches, as fragmented approaches, are easily implementable in realistic systems. However, these approaches are lack of consideration of the interactions between maintenance routing and scheduling potentially and leaves significant inefficiencies in optimizing maintenance planning. This is especially visible in the case of large networks of geographically dispersed subsystem, such as oil/gas extraction companies or airlines, where maintenance routing is as important as maintenance scheduling. To improve the efficiency of the mathematical model for optimization problem of a GPDS, economic profit models with consideration of maintenance routing and scheduling is seen as an appropriate approach. By using these economic profit models, both an optimal maintenance itinerary and an optimal maintenance schedule can be found. So, it leads to define a scientific issue to be attacked in our PhD thesis:

How to formulate economic profit models with consideration of maintenance routing and scheduling in GDPS context?

2.5 State of the art on optimization methods

Optimization algorithms/methods are seen as tools to find optimal solutions for maintenance models/strategies. With an identical mathematical model, there can be many different algorithms that can implement it. These algorithms can lead an identical result, however their efficiency level is different. The efficiency level of an algorithm is evaluated through criteria such as computational time, exact degree, etc. Ideally, an optimization algorithm is a perfect one when it can find an exact solution and its computation speed is fast enough. However, in fact the two criteria are usually opposite to each other. Therefore, building an optimization algorithm should balance between these criteria.

In this subsection, we present a state of the art on maintenance optimization methods that have been developed for optimization problems in the grouping maintenance strategies. Through this analysis, a scientific issue related to develop optimization algorithms for maintenance problem of GDPSs is drawn.

2.5.1 Analytical methods

In framework of grouping maintenance optimization, a number of researchers used analytical methods. These methods have been formulated based on deterministic programming, stochastic optimization and dynamic programming, etc, to achieve optimal maintenance and replacement schedules. Paper [137] proposed an optimization model to find an optimal preventive maintenance plan for a serial multi-station manufacturing system. He said that most of models usually used a simulation approach at that time but his model proposed a mathematical programming approach. His computational results show that the operating features of the stations are interrelated, therefore one has to consider the impacts of preventive maintenance activities of all stations simultaneously. Another study in paper [138] presented an optimization model that minimizes total maintenance costs and penalty costs. Assume that a Weibull distribution function represents a failure rate of equipment. They proposed a 4-parameter model, and a 4-stage algorithm based on an analytical approach to optimize maintenance planning. Their model was applied for several numerical examples to find optimal maintenance plans in each situation. Whereas, paper [51] presented a stationary grouping maintenance strategy for multi-component systems whose structure is changed over time. This change leads to

many difficulties in evaluating the maintenance cost. Therefore, an analytical calculation and hybrid simulation-analysis were developed to evaluate the long-run expected maintenance cost rate of the proposed grouping strategy. These methods help to effectively find the optimal maintenance plan and well adapt to changes of structure.

Though these mathematical models can be proposed a strictly optimal solutions for small scale decision-making problems, but they have two major defectives. Firstly, applying these methods for large-scale maintenance problems are impossible because the candidate solution space usually grows exponentially with the number of components and decision variables. Secondly, the production systems in practice are complex, hence it is hard to faithfully formulate by a tractable mathematical model.

2.5.2 Exact algorithms

Exact optimization methods are used to find the optimal solution of a problem. For grouping maintenance optimization problem, paper [139] proposed a two-layer hierarchical model that optimizes the preventive maintenance schedules in semiconductor manufacturing operations. This paper designed a Markov decision process and optimized this model via a mixed-integer linear programming model in considering a time window for preventive maintenance activities and limitation of resources as nonlinear constraints. The profit of cluster tools was defined as the objective function. In order to obtain a global optimal maintenance plan, they transformed the nonlinear functions into linear functions by using EasyModeler and OSL as the optimization software. In addition, this paper used AutoSched AP as the simulation software to simulate optimization model and evaluated the performance of this model. A real case study with 11 preventive maintenance activities in an one-week planning horizon was realized and the obtained optimal results were compared to the actual preventive maintenance plan. Later, this model was improved in [140] to be more general. This extended model was applied for a production line of a semiconductor manufacturing system.

Another study in paper [141] presented an optimization model on long-term planning horizon to design a preventive maintenance plan for a real power plant. This paper considered the total cost of various maintenance activities as the objective function and used Bender's decomposition to solve a mixed-integer linear programming model. Paper [53] proposed two mixed-integer linear programming models for preventive maintenance planning problems. In these models, the objective function was the total cost including possession costs, maintenance costs, and the penalty costs of early consecutive maintenance activities. The authors presented and proved a theorem about the NP-hard structure of the preventive maintenance planning problems and use GAMS software to implement the optimization models. They used CPLEX as the optimization software to

find an optimal maintenance plan. This model was applied for a case study of railway maintenance planning. In addition, this study also proposed four heuristic optimization algorithms, two for each model. The computational results obtained from heuristic optimization algorithms were compared to exact algorithms in CPLEX to draw the advantages of each solution methodology. Whereas, paper [142] developed a binary integer linear programming model to find the best preventive maintenance plan. The authors defined the availability of equipments as the objective function under considering constraints such as the maintenance time window, maintenance completion duration, logical operational, resource limitation, maintenance crew availability, efficiency measures, and demand as the set of constraints. Their model was applied in two co-generation plants with 7 units and 42 pieces of equipment in Kuwait, over a 52-week planning horizon, and utilize LINGO as the optimization software to optimize the model. Besides, a sensitivity analysis on the model is performed to assess the robustness and analyze the impacts of expanding the planning horizon, decreasing the resources, and reducing the demand on the maintenance strategies.

For GDPSs, many studies addressed optimal maintenance planning as an optimization problem of maintenance routing by exact algorithms [143–145]. From optimization point of view, exact methods are more appropriate to solve maintenance routing problems. It is completely true in cases that the number of production sites is not too large, where computational time by exact methods is not too longer than heuristic methods. The exact methods were mentioned in literature as Exhaustive Search [143], Branch and Bound [145–147], Brute-force, Cutting Planes [144], Branch and Cut [148], etc. In these methods, Branch and Bound (BAB) method emerges as effective methods due to (a) reducing computational time compared to exhaustive search thanks to trying to rule out parts of the search space that cannot contain the best solution; (b) easily to simulate [148]. Indeed, paper [149] presents a novel approach in preventive maintenance scheduling of thermal generating systems. The authors develop a large-scale multi-objective combinatorial optimization model with three objective functions and a set of constraints. They consider minimization of total fuel costs, maximization of reliability in terms of expected unserved energy, and minimization of technological concerns as the objective functions. In addition, they define maintenance duration, maintenance continuity, maintenance season, maintenance sequence of thermal units of the same class, limitation on simultaneous maintenance of thermal units, and limitation on total capacity on maintenance due to labor and resources as the constraints of the model. They develop a multi-objective preventive maintenance scheduling software based on a multi-objective branch-and-bound algorithm implemented in FORTRAN. Finally, the researchers apply their methodology to a real system of 8 power plants with thermal units with maintenance classes over 31

weeks as the planning horizon. They show that BAB method is an effective solution to address maintenance routing optimization problems.

The exact algorithm always ensures that obtained results is global optimal ones. However, if the computational time of this method increases exponentially with the number of components, numerous maintenance activities or constraints, then exact methods are only desirable to a certain extent.

2.5.3 Heuristic and metaheuristic algorithm

In the grouping maintenance optimization problem for multi-component system with numerous constraints, using analytical methods or exact algorithms are impossible due to difficulties from modelling and computational time, hence heuristic or metaheuristic algorithms have been considered. Heuristics/ metaheuristics are algorithms designed to solve a wide range of optimization problems without having to find an optimal solution strictly. In other words, they are local optimization methods that can not find the global optimal solution always, but they can be applied to find the best solution to the problems in reasonable time. The quality of such algorithms depends on each specific problem. In some cases it is possible to give an upper bound on the gap between the optimal solution and the solution found by the heuristics. Paper [150] presented a heuristic-based optimization algorithm for on-line scheduling and assignment of preventive maintenance jobs to processors. The authors developed an optimization model that considers total cost of maintenance actions as the objective function and subject to availability constraints, time-window. They showed that this model is NP-hard to solve and they therefore proposed a heuristic optimization algorithm to solve the model. They proved that proposal algorithm has a low complexity through the different running times of the corresponding programs fed by simulated parameters. Monte Carlo based simulation paradigm, known as a heuristic method, is widely used for maintenance optimization problem. Paper [151] presented an application of Monte Carlo simulation to optimal maintenance scheduling in a parallel-redundant system. A Monte Carlo simulation approach was applied to obtain the total failure frequency and optimum maintenance interval for a parallel-redundant system where each component can enter its wearout period. The effectiveness of simulation procedure was shown through two examples. Another study in paper [151] proposed a Monte Carlo continuous time simulation modelling to improve preventive maintenance scheduling. This method allowed the assessment of alternative scheduling policies that could be implemented dynamically on the shop floor. By using this method, authors estimated measures of performance by treating simulation results as a series of realistic experiments and using statistical inference to identify reasonable confidence intervals. Nevertheless, the solution space of maintenance optimization problems is usually so large

that an exhaustive evaluation of all candidate solutions via Monte Carlo simulations is generally unfeasible. Therefore, many researchers turn their eyes to meta-heuristic approaches to optimization as methods for maintenance planning optimization.

A metaheuristic is an algorithm designed to solve a wide range of optimization problems without having to deeply adapt to each one. Typical metaheuristic approaches can be mentioned as the Tabu search (TS), simulated annealing method (SA) and genetic algorithm (GA), etc. Paper [152] presented a maintenance optimization method for multi-components system based on a Tabu search algorithm. The authors developed a maintenance model with minimizing the total generator operating cost and leveraging the reserve as the objective function and considering constraints such as: maintenance completion, crew size, precedence, reserve and reserve constants. The effectiveness of the proposal was evaluated through two numerical examples containing 4 units and 22 units respectively. Similarly, paper [153] presented a Tabu search for the preventive maintenance scheduling problem. The aims of preventive maintenance planning problem were to maximize the total priority of the scheduled tasks subject to resource availability constraints. The proposed algorithm considered three basic moves - adding a PM task to the current schedule, dropping a task from the schedule and swapping craft-combination assigned to a task. The obtained results showed that by applying this algorithm the average optimality gap was reduced from 2.26 % to 0.6 % compared to local heuristics. Whereas, paper [154] solves the generator maintenance scheduling problem based on a simulated annealing method. The authors defined generation cost as an objective function and it is subjected to a number of constraints about time window and the number of crews for some generation technologies. The obtained results showed that the Simulated Annealing application has a good performance and it is able to produce good maintenance schedules with short computational times. In framework of metaheuristic methods, a genetic algorithm, as a popular optimization approach, has been presented in a lot of research. The GA is very robust, and there are many researchers that can be implemented differently according to the problem [155, 156]. The paper [157] presented a preventive maintenance optimization problem to a multi-state system in which all or some of the components have different performance levels, from proper functioning to complete failure and the reliability of the system as its ability of satisfying the demand levels. The authors formulated an optimization model in considering the effective age of components. Their model was based on minimization of cost subject to a required level of reliability. They applied an universal generating function technique and use a genetic algorithm to determine the best maintenance strategy. The paper [158] presented additional research in which an optimization model was developed to find an optimal replacement schedule in multi-state systems. The authors considered an increase of failure

rate based on the expected number of failures during time intervals and defined the total of maintenance activities cost along with cost of unsupplied demand due to failures of components as the objective function. Finally, they applied a genetic algorithm to find an optimal maintenance plan. Another study in paper [159] proposed new genetic algorithm for maintenance planning optimization problem for power systems. The basic operators, crossover and mutation operators of a standard genetic algorithm were modified based on the specific characteristics of the problem. This new GA improved GA computation performance by considering a code-specific and constraint-transparent integrated coding method to achieve faster convergence sequence and to refrain from the occurrence of unfeasible solutions. The effectiveness of the new genetic algorithm was shown via theoretical analysis and simulation results to compare with a traditional genetic algorithm. Whereas, paper [160] proposed a preventive maintenance optimization model considering two activities: imperfect maintenance and replacement. Modeling imperfect maintenance activities was based on the concept of an improvement factor which was defined by a quantitative assessment procedure. A genetic algorithm whose the objective function is unit-cost life was used to find an optimal preventive maintenance schedule. The proposed model and algorithm were tested to a mechatronic system to show their effectiveness.

Additional research on the application of genetic algorithms to maintenance optimization has been done in paper [161]. This study presented an optimization model to seek optimal solution of the maintenance scheduling for multi-component system. In this study, a genetic algorithm was used as the optimization methodology to determine the best preventive maintenance plan. Note that the objective function of this algorithm considers the effect of reliability as well as economy. Therefore, this model can find a most economic solution under reliability constraints. The optimization model applied for system including six electric generators showed that the proposal algorithm was useful for maintenance optimization problem considering multi constraints. Paper [162] developed maintenance model by considering recursion relationship of failure rate between preventive maintenance cycles. The non-linear optimal model of equipment preventive maintenance cycle in finite horizon planning was proposed considering repair cost, preventive maintenance cost and production loss cost. They applied a genetic algorithm as the optimization technique to give maintenance decision and job shop scheduling. The obtained results showed that the GA is an effective approach to find the global optimal cycle in limited time. One of the most notable studies in the area of reliability and maintenance optimization for multi-state multi-component systems is found in paper [163]. The authors developed a model for maintenance planning by a genetic algorithm based on cost and reliability. The mathematical model considered preventive and corrective maintenance activities and the incurred cost of them, reliability of the system, probability of imperfect maintenance and

outage times. Because this model was a nonlinear large-scale optimization model, a genetic algorithm was used to solve grouping maintenance planning optimization problem. The results were applied for a high-pressure injection system to measure the effectiveness of this proposal. Similarly, paper [164] presented an age based maintenance scheduling model linked with production planning optimization model to maximize availability of a production machine. The authors used a heuristic algorithm to find an optimal plan that minimizes the makespan. They also applied a simulation approach to validate the heuristic algorithm and to demonstrate its effectiveness in optimizing maintenance planning which integrated production planning and maintenance scheduling.

Recently, paper [165] developed a powerful and flexible metaheuristic optimization models is developed to solve daily maintenance planning for offshore wind farms. In this study, the maintenance planning taking into account numerous constraints on weather conditions, shifts, vessel and technician capabilities and availability made maintenance optimization process become more difficult. Therefore the authors applied Genetic Algorithm to find the best possible Transfer Plans from the very large set of possible maintenance itineraries. By that way, this approach allowed much simpler incorporation of realistic constraints and reduced computational time.

The heuristic/ metaheuristic algorithms prove their effectiveness in solving maintenance planning optimization problem for large-scale system including multi-components and multi-constraints. The aim of these algorithms are to find the best solution in reasonable computational time instead of the global optimal one. Besides, speed and duration of computational time can be adjusted by changing iteration or the special parameters of an algorithm. Of course, the accuracy level of obtained results is proportional to computational time. That is the strong point of this method compared to analytical and exact methods. This strength can be raised many times if heuristic/ metaheuristic algorithms can be combined together.

2.5.4 Hybrid/combination algorithm

As mentioned in above, the hybrid/combination algorithms can improve the performance of algorithms such as accuracy, speed and duration of computational time, etc because they can combine advantages of different algorithms. The hybrid/combination algorithms used for maintenance planning optimization have widely been investigated in literature. Paper [166] combined a genetic algorithm with a simulated annealing to optimize maintenance planning in long-term. In this study, the individual survival in the genetic algorithm was measured by the acceptance probability of a simulated annealing method. Applying this approach, the obtained solution is a near optimal one implemented in a shorter period than the computational time of a simple genetic algorithm. A case study was

presented to show the effectiveness of their model in maintenance planning optimization. Whereas, paper [167] developed a general framework for maintenance optimization problems in chemical process operations. The authors proposed a methodology that combines a Monte Carlo simulation with a genetic algorithm to solve opportunistic maintenance problems with a non-deterministic objective function. This approach applied in two case studies came a conclusion that this combination is more effective than an analytic approach, and the Monte Carlo simulation with a neural network. A similar combination between Monte Carlo simulation model and genetic algorithm for maintenance planning problem in multi-components systems is found in paper [168]. The authors applied genetic algorithm to optimize the degradation level after maintenance actions in a multi-objective optimization model whose objectives include economic profit and availability. Besides, a Monte Carlo simulation model was considered to describe the dynamics of a stress-dependent degradation process in load-sharing components. Through the achieved results, the authors came to conclusion that the combination between Monte Carlo simulation and a genetic algorithm is an effective approach to solve combinatorial maintenance planning optimization models.

Another study in paper [169] proposed an optimization model and use a genetic algorithm combined with simulated annealing for maintenance planning in power system. In this study, maintenance planning is established based on an optimization objective with customer satisfaction. The authors tested the method on 62-unit state electrical system of Victoria and show the advantages of the their proposed approach. Paper [170] proposed a combination of an ant colony algorithm and a genetic algorithm to optimize a large-scale maintenance planning problem. In this paper, the objective function of their problem was divided into two sections and then each algorithm was utilized to improve each section separately. The proposed algorithm proved its effectiveness in solving maintenance planning optimization problem for a large-scale problem compared to a simple genetic algorithm. While, paper [171] proposed a maintenance optimization model for a multi-component production process. This study considered a combination of mechanical service, repair, and replacement activities for each component as well as used Markov decision process to formulated the transition function of probability for maintenance activities in the planning horizon. Besides, the authors defined total preventive maintenance cost as the objective function of the model and considered required reliability of the system as a constraint. This study is shown that considering the combination of maintenance activities can significantly reduce cost in comparison with the situation that different activities are performed separately. Paper [134] presented a maintenance grouping approach for multi-component systems and developed the heuristic optimization scheme for the maintenance decision by implementing a combination algorithm between genetic algorithm and MULTIFIT.

The combination prove the effectiveness in optimizing maintenance planning under both availability and limited repairmen constraints. The algorithm is extremely flexible when computational time can be adjusted through changes of iteration and some parameters.

Summary of section 2.5: As argued, maintenance optimization for the grouping maintenance strategies can be seen as optimization of maintenance planning [11]. Its aim is to find the best maintenance schedule of components in groups with objective function such as minimum maintenance cost or maximum availability, etc. The optimization process can be implemented by different methods: analytical methods, exact algorithms, heuristics and metaheuristic algorithms, hybrid/combination algorithms. Unfortunately, majority of existing algorithms are usually developed for centralized system, therefore they cannot directly apply for maintenance optimization for GDPSs due to difficulties related to geographical dispersion of GDPSs. In practice, because maintained components of a group can be located far apart each other, so a part of maintenance cost comes from transportation cost which is impacted directly by maintenance routing. Optimization of maintenance routing can lead to a reduction of maintenance cost. Therefore, maintenance optimization for GDPSs not only relates to maintenance planning but also maintenance routing. In addition, for large-scale geographically dispersed systems with numerous maintenance activities and constraints as GDPSs, using analytical methods or exact algorithms are impossible due to difficulties related to modelling and computational limitation. In that case, advanced algorithms are seen as a more appropriate solution. So, it leads to define a scientific issue to be attacked in our PhD thesis:

How to develop an advanced algorithm to support maintenance optimization for GDPS in considering maintenance planning and routing?

2.6 Conclusion

From the state of the art developed in this chapter, the dynamic grouping maintenance strategy initially proposed in [28] seems to be appropriated since it can take into account several kinds of dependencies between components and easily update the maintenance planning in dynamic contexts. However, extending the dynamic grouping maintenance strategy in GDPS context faces several problems related to dependence modelling, impacts of dynamic contexts on maintenance planning, mathematical model and maintenance optimization algorithms/methods. The underlining of these problems, in this chapter, led to identify four scientific issues to be attacked:

- How to formulate a dependence model for a GDPS in which economic and geographical dependence are jointly considered? (*scientific issue 1*)
- How to develop a dynamic grouping maintenance strategy for GDPS with consideration of the economic, geographical dependencies and the impacts of dynamic contexts? (*scientific issue 2*)
- How to formulate economic profit models with consideration of maintenance routing and scheduling in GDPS context? (*scientific issue 3*).
- How to develop an advanced algorithm to support maintenance optimization for GDPS in considering of maintenance planning and routing? (*scientific issue 4*)

To address these scientific issues, four original contributions are developed. The detailed description of these contributions are presented respectively in chapters 3,4,5 and 6.

Chapter 3

Dependence modelling for maintenance of a GDPS

3.1 Introduction

This chapter describes our contribution with regards to the first scientific issue identified in the Chapter 2: "How to formulate a dependence model for a GDPS in which economic and geographical dependencies are jointly considered?". More precisely, firstly, a cost structure of one component is formulated and used as a basis for the development of our dependence model. Then, we formulate a dependence model which takes jointly into account economic and geographical dependencies.

To construct this contribution in a consistent way, Section 3.2 presents the cost structure for a component. Based on this cost structure, Section 3.3 formulates the dependence model. Then in section 3.4, a numerical application for a typical GDPS constructed by 5 production sites is carried out to illustrate the proposed model.

3.2 Cost structure at component level

The objective of this section is to formulate a cost structure of a preventive maintenance activity of a component . It will be used as a basis for the development of a dependence model of economic and geographical dependence in next step. Remind that, for a GDPS system, to do a PM action, the maintenance team and spare part have to be transported from the global maintenance center to the production site where the maintained component is located on. Then, maintenance team goes back the global maintenance center when the maintenance activity is completed. By that way, maintenance cost includes direct and indirect maintenance cost. Direct maintenance cost is defined as the

expenses paid for direct replacement/repair activities like spare part cost, labour cost, etc. Whereas, indirect one is usually paid for preparation process and loss of product due to stopping of a system. More precisely, the maintenance costs for a component includes:

Spare part cost (C_i^{sp}): This cost includes physical cost of a component and costs paid for management and inventory before a preventive maintenance task is performed [46]. Normally, the physical cost depends on supplier and sometime impacted by market fluctuation. Whereas, management and inventory cost of spare parts depend on their management and inventory policies [46, 172, 173]. The spare part cost can be expressed as follows (see [172]):

$$C_i^{sp} = c_i^{ph} + c_i^m + c_i^h \quad (3.1)$$

Where

- C_i^{sp} : spare part cost of a component i
- c_i^{ph} : physical cost of a component i
- c_i^m : management cost of a component i
- c_i^h : inventory holding cost of a component i

To simplify calculations, in several cases the spare part cost of a component can be seen as fixed value over the time C_i^{sp} .

Downtime cost (C_i^{dt}): It (also called shutdown cost) is paid for loss of revenue when a production system stops to perform preventive maintenance tasks. Downtime cost can be reduced by reducing downtime. By this way, grouping of maintenance activities is a good solution when many maintenance actions can be performed simultaneously to reduce downtime [174]. In general models, it is supposed that the loss of revenue due to downtime is a linear function of the downtime. $C_{i_j}^{dt}$ denotes the downtime cost which occurs when site j is stopped during the maintenance of component i . $C_{i_j}^{dt}$ can be calculated as (see [26])

$$C_{i_j}^{dt} = R_j^{dt} \cdot \omega_i \quad (3.2)$$

Where

- R_j^{dt} : the downtime cost rate at site j .
- ω_i : the PM duration of component i .

Site-preparation cost ($S_{i_j}^0$): The preparation cost is associated with preparation tasks such as erecting a scaffolding, opening a machine, etc. To simplify calculations, preparation cost of each component in a system can be seen as the same [47], called single-setup cost. This cost can be saved when different components are joint maintained, since execution of a group of activities requires only one setup cost. The single setup cost model seems to be now not sufficient for a GDPS whose production sites are dispersed.

Due to geographical dispersion of production sites, the preparation tasks required for the maintenance of each site are not the same. They depend on the site characteristics. The preparation cost therefore should not be identical for all sites. For this reason, a multi-setup cost model as [11] is suitable in this case. In our study, we consider that different sites require different preparation cost, while components at the same production site have identical setup cost. The site-preparation cost of a component i located at site j is a fixed cost, denoted S_{ij}^0 .

Transportation cost (S_{ij}^{tr}): For a GDPS, it is cost paid for transportation of spare parts and repairman in maintenance itineraries. In general models, transportation cost is constructed as a linear function of time or distance [26]. In this model, a transportation cost/travel cost rate represents the paid expense over time or distance unit. For a GDPS, let L_{0j} and L_{j0} be the travel distances from the global maintenance center (denoted by '0') to site 'j' and back again respectively, the transportation cost is calculated as follows (see [26]):

$$S_{ij}^{tr} = R^{tr} \cdot (L_{0j} + L_{j0}) \quad (3.3)$$

where R^{tr} is the transportation cost rate.

Labor cost (C_i^{lb}): It can be understood as expenses paid for maintenance works of repairman/maintenance team. Each component usually requires a skill level of repairman and maintenance duration [48]. It means that different components can lead to different requirements related to skill level and maintenance duration. Of course, the higher the technician's skill is required and the longer the maintenance duration is, the more expensive the labor cost is. In general models, the labor cost is proposed as a linear function of the labor cost rate and maintenance duration. The labor cost of component i , denoted C_i^{lb} , can be expressed by (see [48]):

$$C_i^{lb} = R_i^{lb}(l_i) \cdot \omega_i \quad (3.4)$$

Where

$R_i^{lb}(l_i)$: the labor cost rate of repairman with skill level l_i who maintain component i .

ω_i : the maintenance duration of component i .

As a consequence, the maintenance cost structure of component i includes spare part cost, downtime cost, labor cost, site-preparation cost and travel cost shown in Figure 3.1. This structure can be formulated as:

$$C_i^p = C_i^{sp} + C_{ij}^{dt} + C_i^{lb} + S_{ij}^0 + S_i^{tr} = c_i^{ph} + c_i^m + c_i^h + R_j^{dt} \cdot \omega_i + R_i^{lb}(l_k) \cdot \omega_i + S_{ij}^0 + R^{tr} \cdot (L_{0j} + L_{j0}) \quad (3.5)$$

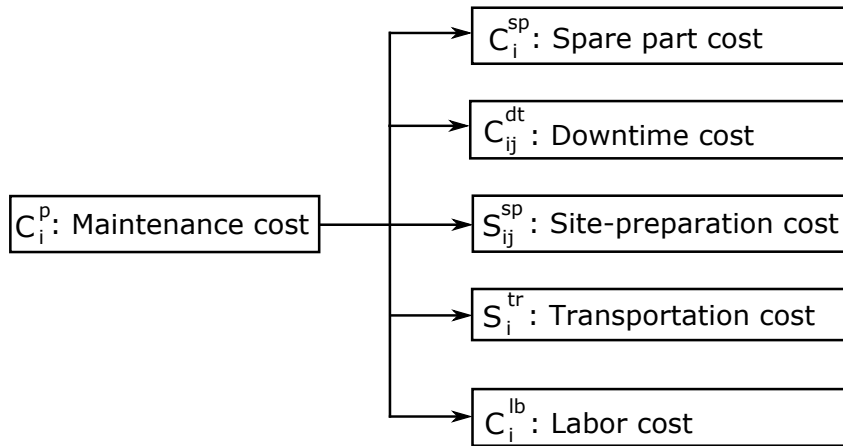


Figure 3.1: Structure cost of component i in GDPS context

According to the above cost structure, the site-preparation cost and downtime cost generally may be different for different components in the system or even for identical components located on the different sites. Whereas, travel cost of components is identical if they are located in the same site, and it may be different if they are not in the same site.

3.3 Economic and geographical dependence-based cost model for a GDPS

The objective of this section is to develop a dependence model considering economic and geographical dependencies based on cost structure formulated in previous section. The dependence model is investigated at two levels. At the site level, joint maintenance of components at the same production site can save site-preparation cost because preparation cost is assumed that it is paid one time if components are maintained simultaneously. At the system level (GDPS level), to undertake joint maintenance of components at different production sites, maintenance team moves following an adequate maintenance itinerary, thus, transportation cost can be reduced due to cutback of travel distance compared to individual maintenance. The transportation cost saving is described as a geographical dependence.

To formulate the dependence model by grouping maintenance activities, firstly, tentatively individual plan of components need to be defined. After that, joint maintenance activities of components are performed to take advantages of economic and geographical dependencies. By that way, economic profit cost model is formulated and used as a basis for the development of our dependence model.

3.3.1 Tentative maintenance plan under individual optimization

The aim of this subsection is to establish a tentative plan of components by individual optimization. The tentative plan determines the optimal replacement date of component i based on age-based maintenance policy. To do that, the following assumptions are considered.

- ASSUMPTION 4: Failures rate of a component is described by Weibull distribution law.
- ASSUMPTION 5: The long-term average maintenance cost of a component is used as criterion to evaluate age-based maintenance policy.
- ASSUMPTION 6: The maintenance cost criterion depends on the following unitary costs:
 - A preventive maintenance cost ($C_i^p, i = 1, 2, \dots, n$) if a preventive maintenance is performed.
 - A corrective maintenance cost ($C_i^c, i = 1, 2, \dots, n$) if a failure occurs.
- ASSUMPTION 7: The corrective maintenance duration is minimized and can be neglected.
- ASSUMPTION 8: Each component is maintained at least one time on maintenance planning.

For the age-based maintenance policy, preventive maintenance cycle of a component (x_i^*) can be determined based on its lifetime distribution law. This law can be evaluated by many standard statistical methods of parametric, semi-parametric and non-parametric inference type [87, 175–177]. In the literature, several laws of probabilities are associated with the lifetime distribution of the components such as Weibull law, the normal law (Gaussian), the Gamma law, etc [178]. In our thesis, to facilitate mathematical comprehension and formulation, we assume that failures of components occur according to a **Weibull law**. This law is widely used in literature because of its versatility and simplicity [20, 179]. Remind that the Weibull distribution law is expressed by $r_i(t) = \frac{\beta_i}{\lambda_i} \left(\frac{x}{\lambda}\right)^{\beta_i-1}$, $i = 1, 2, \dots, n$ in where β_i and λ_i are shape and scale parameters respectively.

Assume that a component i is systematically replaced at the fixed age limit x_i which is determined by optimizing long-term average maintenance cost of the component. When component i breaks down between two periods of preventive maintenance, it is immediately restarted by a minimal repair. Note that in this case, the nominal preventive

maintenance cycle is equal to x_i^* . Applying the renewal theory, the long-term average maintenance cost of the component i , denoted $\phi_i(t_i)$, can be determined as follows:

$$\phi_i(x_i) = \lim_{t_i \rightarrow +\infty} \frac{C_i(t)}{t_i} \quad (3.6)$$

Where

t_i : the renewal cycle length of a component i

$C_i(t_i)$: the total maintenance cost of component i on a renewal cycle

Let $MC_i(x)$ be the total of corrective maintenance cost incurred in x time units since the last PM activity of component i is performed. According to the minimal repair policy, $MC_i(x)$ can be expressed as follows, [86]:

$$MC_i(x_i) = C_i^c \cdot \Lambda_i(0, x_i) = C_i^c \cdot \int_0^{x_i} r_i(t) dt \quad (3.7)$$

where $\Lambda_i(0, x_i) = \int_0^{x_i} r_i(t) dt$ is average number of failures of component i on interval $(0, x_i)$.

If a component i is preventively maintained when its age reaches limit x_i , the expected maintenance cost within $[0, x_i]$ is:

$$C_i(x_i) = C_i^p + MC_i(x_i) \quad (3.8)$$

From Equations (3.7) and (3.8), we obtain

$$C_i(x_i) = C_i^p + C_i^c \cdot \left(\frac{x}{\lambda_i}\right)^{\beta_i} \quad (3.9)$$

It is assumed that component i is preventively replaced at every x_i time units. From Equations (3.6) and (3.9), the long-term maintenance cost rate can be calculated as:

$$\phi_i(x_i) = \lim_{t \rightarrow +\infty} \frac{C_i(t)}{t} = \frac{C_i^p + C_i^c \cdot \int_0^{x_i} r_i(t) dt}{x_i + \omega_i} = \frac{C_i^p + C_i^c \cdot \left(\frac{x_i}{\lambda_i}\right)^{\beta_i}}{x_i + \omega_i}. \quad (3.10)$$

where ω_i is denoted the PM duration of component i and $t_i = x_i + \omega_i$

The optimal PM cycle of component i , denoted x_i^* , can be then determined by solving the following equation

$$x_i^* = \arg \min_{x_i} \phi_i(x_i) \implies \left. \frac{d\phi_i(x_i)}{dx_i} \right|_{x_i=x_i^*} = 0 \iff \quad (3.11)$$

$$C_i^c \cdot (\beta_i - 1) \cdot (x_i^*)^{\beta_i} + C_i^c \cdot \beta_i \cdot \omega_i \cdot (x_i^*)^{\beta_i-1} - C_i^p \cdot \lambda_i^{\beta_i} = 0$$

Let \tilde{x}_i^* be the optimal interval length for the preventive maintenance of component i when ignoring the maintenance duration ($\omega_i = 0$). It can be determined as following [20]:

$$\tilde{x}_i^* = \lambda_i \sqrt[\beta_i]{\frac{C_i^p}{C_i^c (\beta_i - 1)}} \quad (3.12)$$

Let $g(x) = C_i^c \cdot (\beta_i - 1) \cdot (x)^{\beta_i} + C_i^c \cdot \beta_i \cdot \omega_i \cdot (x)^{\beta_i - 1} - C_i^p \cdot \lambda_i^{\beta_i}$. It is easy to show that $g'(x) > 0, \forall \beta_i > 1, \forall x > 1$; $g(0) = C_i^p \cdot \lambda_i^{\beta_i} < 0$; and $g(\tilde{x}_i^*) = C_i^c \cdot \beta_i \cdot \omega_i \cdot (\tilde{x}_i^*)^{\beta_i - 1}$. Then Equation (3.11) has only one solution (x_i^*) in the interval $(0, \tilde{x}_i^*)$. Moreover, it is not difficult to show that $\phi''_i(x_i^*) > 0$. Therefore, we can deduce that (x_i^*) exists and it is unique, $x_i^* \in (0, \tilde{x}_i^*)$.

Let ϕ_i^* be the minimal long-term average maintenance cost of component i , one gets $\phi_i^* = \phi_i(x_i^*)$. The optimal interval length x_i^* , which can be numerically calculated using Equation (3.11), represents a nominal preventive maintenance frequency of component i (with $i = 1; \dots; N$).

From nominal preventive maintenance cycle of component i , the tentative maintenance plan is defined as follows:

- The first preventive maintenance date of component i is determined by

$$t_{i1} = x_i^* + T_{begin} - t_i^e + \omega_{i1}^{\Sigma} \quad (3.13)$$

Where

t_{i1} : is the first preventive maintenance date of component i .

x_i^* : is the preventive maintenance cycle of component i .

t_i^e : the total operational time of component i elapsed from the last replacement.

ω_{i1}^{Σ} : the cumulative downtime of component i at site j within interval $[T_{begin}, t_{i1}]$. The downtime may be resulted from the PM of other components that are located on the same site.

T_{begin} : The time is chosen by the planner.

- The z^{th} preventive maintenance date of component i ($z > 1$) is given as follows:

$$t_{iz} = t_{iz-1} + x_i^* + \omega_{iz}^{\Sigma} \quad (3.14)$$

Where

t_{iz-1} : the previous preventive maintenance date of component i .

x_i^* : is the preventive maintenance cycle of component i .

ω_{iz}^{Σ} : the cumulative downtime of component i at site j within interval $[t_{iz-1}, t_{iz}]$.

- Since each component is maintained at least one time on planning horizon, the end of date of the planning horizon is determined as follows

$$T_{end} = (t_{i_j^1} + \omega_{i_j}) \quad \text{with } t_{i_j^1} = \max_{i=1:n} t_i^1 \quad (3.15)$$

Where

$t_{i_j^1}$: the longest time in a set of tentative plan of the first maintenance activity of components.

ω_{i_j} : duration time of the component corresponding to $t_{i_j^1}$

As an example, individual PM dates of the tentative plan for a three-components system (at the same site) is shown in Figure 3.2. Over the planning horizon $PH = [T_{begin}, T_{end}]$, component 1 and 2 are preventively maintained only once time at t_{1^1} and t_{2^1} over the planning horizon. However, the component 3 is preventively maintained twice at t_{3^1} and t_{3^2} . As a result, the number of preventive maintenance operations over the planning horizon, denoted N, is equal to 4. In this example, the cumulative downtime of component i of z^{th} preventive maintenance is given as follows:

$$\omega_{i_j^z}^{\Sigma} = \begin{cases} \omega_{1_j^1}^{\Sigma} = \omega_2 + 2 \cdot \omega_3 \\ \omega_{2_j^1}^{\Sigma} = \omega_1 + \omega_3 \\ \omega_{3_j^1}^{\Sigma} = \omega_2 \\ \omega_{3_j^2}^{\Sigma} = \omega_1 \end{cases}$$

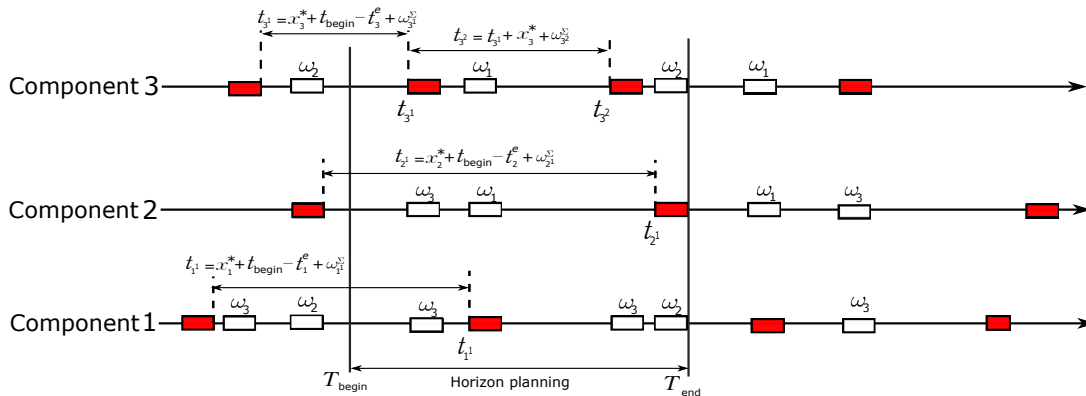


Figure 3.2: Tentatively individual maintenance plan of three considered components 1,2,3

3.3.2 Dependence modelling

The aim of this subsection is to formulate economic and geographical dependence-based cost model based on tentative maintenance plan presented in previous subsection. By grouping maintenance activities of components, economic profit model is defined and used as a base to formulate the cost model.

Considering a fixed group G_k of several components, which are tentatively maintained at their individual PM dates t_{iz} . To be jointly maintained, the individual PM dates have to be adjusted, and the components of G_k are actually preventively maintained at t'_{iz} instead of t_{iz} , with $i \in G_k$. When the components are jointly maintained, the maintenance team has to follow a specific itinerary (I_{G_k}) to maintain all the components of the group before go back to the maintenance center. The maintenance route prescribes the sequence of the sites that the maintenance team has to travel consecutively. There exists usually a large number of possible itineraries that across all the maintenance sites with different travel distances. Let t_{G_k} denote the time that the maintenance team leaves the maintenance center (departure time) to maintain group G_k , and $I_{G_k}(j) = v$ means that with respect to the route I_{G_k} , site j is visited by the maintenance team at the v^{th} order.

- If $I_{G_k}(j) = 1$, the maintenance team will visit site j at first after leaving the global maintenance center, the maintenance team will arrive at site j at $TAS_j = t_{G_k} + t_{0j}^{tr}$, where t_{0j}^{tr} is the travel time from the global maintenance center to site j . TAS_j is also the grouped PM dates of components of group G_k located at site j : $t'_{iz} = TAS_j$. The maintenance team will leave site j at time $TLS_j = TAS_j + \sum_{i \in G_k, i \in G_k} \omega_i$, and move to the next maintenance site.
- If $I_{G_k}(j) = v > 1$, the maintenance team will visit site j at the v^{th} order. The actual PM dates of components of group G_k located on site j are then $t'_{iz} = TLS_q + t_{qj}^{tr}$, where q is the site that the maintenance team has previously visited at the $(v-1)^{\text{th}}$ order.

Economic profit model thanks to geographical dependence: From the literature [1, 11], the economic dependence between the components indicates that the PM cost of the group ($C_{G_k}^p$) is not equal to the total PM cost of their components, i.e. $C_{G_k}^p \neq \sum_{i \in G_k} C_i^p$. Most of the grouping maintenance models consider the economic dependence related to the saving of the preparation cost ($\Delta S_{G_k}^0$) and the penalty cost (ΔH_{G_k}). The penalty cost occurs due to (i) the reduction of components useful life if the maintenance dates are advanced; (ii) the increase of component failure probability if the maintenance dates are postponed (see [20] for more details). Note that a number of existing works consider centralized multi-component systems and model the economic

dependence based on a single setup/preparation cost model. This model seems to be now not sufficient for the modeling of the economic dependence existing between the components of a GDPS. In a GDPS, the components are located in different production sites. The preparation tasks required for the maintenance of each site are not the same. They depend on the site characteristics. The preparation cost therefore should not be identical for all sites. For this reason, a multi-setup cost model needs to be developed for modeling the economic dependence between the components of GDPS by taking into account the characteristics of production sites. Moreover, as a typical characteristic of GDPS, the components of GDPS may be located far from each other. The maintenance execution date of a component impacting on penalty cost depends on travel time and the choice of maintenance itinerary. By these reasons, site-preparation cost saving and penalty cost should be modified in order to be adapted in GDPS context.

Site-preparation cost saving ($\Delta S_{G_k}^0$): Let $n_j^{G_k}$ be the number of components of group G_k at site j . Assumes that all components at site j have the same preparation cost (S_j^0) and joint maintenance of these components requires only one preparation cost. The total site preparation cost saving therefore is:

$$\Delta S_{G_k}^0 = \sum_{j \in G_k} \Delta S_j^{G_k} = \sum_{j \in G_k} (n_j^{G_k} - 1) \cdot S_j^0 \quad (3.16)$$

Where

$\Delta S_j^{G_k}$: site-preparation cost saving at site j of the group G_k .

$n_j^{G_k}$: the number of components located at site j of the group G_k .

S_j^0 : the site preparation cost of each component at site j .

Penalty cost (ΔH_{G_k}): Penalty cost is additional cost occurring when components are maintained earlier or later than their optimal replacement date [11](see Figure 3.3). The penalty cost of a component i maintained at z^{th} times can be determined by (see [20]):

$$h_i(\Delta t_{iz}) = C_i^c \cdot \left[\left(\frac{x_i^* + \Delta t_{iz}}{\lambda_i} \right)^{\beta_i} - \left(\frac{x_i^*}{\lambda_i} \right)^{\beta_i} \right] - \Delta t_{iz} \phi_i^* \quad (3.17)$$

Where

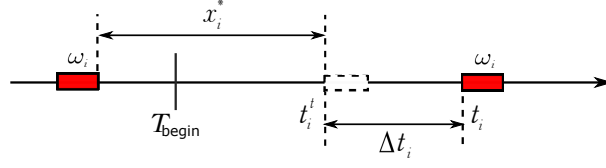
t'_{iz} : maintenance execution date of a component i at z^{th} times

t_{iz} : the tentative maintenance date of a component i at z^{th} times

Δt_{iz} : the difference between maintenance execution date and tentative maintenance date of component at z^{th} times i ($\Delta t_{iz} = t'_{iz} - t_{iz}$)

x_i^* : the optimal replacement cycle of component i

ϕ_i^* : the minimum long-term average maintenance cost rate of component i


 Figure 3.3: Illustration of change of maintenance execution date of component i

It should be noted that differing to centralized system, maintenance execution date of a component within GDPS is a function depending on maintenance itinerary (I_{G_k}). For more details, let us consider an example in Figure 3.4. A maintenance team is responsible for the maintenance of a group of components located in three production sites 1, 2 and 3. To do the PM of the group, the maintenance team can follow different maintenance routes: $MC \rightarrow 1 \rightarrow 3 \rightarrow 2 \rightarrow MC$ (Figure 3.4a), $MC \rightarrow 2 \rightarrow 3 \rightarrow 1 \rightarrow MC$ (Figure 3.4b), and $MC \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow MC$ (Figure 3.4c). It is clear that, with the same departure time from the maintenance center t_{G_k} , the arrival times at each site depend on the selected maintenance route (see Figures 3.4a and 3.4c). Note that, in figures 3.4a and 3.4b, two different maintenance routes with the same travel distance can lead to different arrival times, in other words, different PM dates.

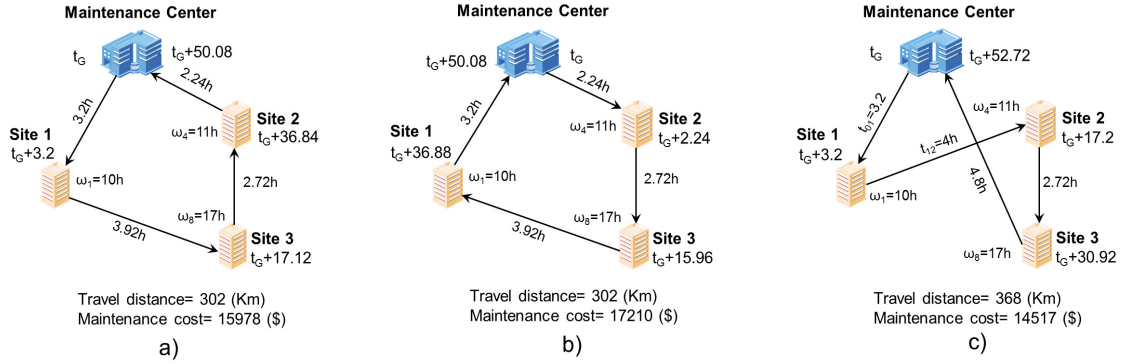


Figure 3.4: Impacts of maintenance routes on the PM dates and travel distance

From Equation (3.17), total penalty cost of group G_k is given as follows:

$$\Delta H_{G_k}(I_{G_k}) = \sum_{i \in G_k} h_i(\Delta t_{iz}) \quad (3.18)$$

Labor loss cost $\Delta C_{G_k}^{lb}$: In addition, when components are jointly maintained, technicians of the repair team have to be able to complete all the maintenance tasks associated with the group of components. Therefore, a polyvalent skills may be required. As a consequence,

the labor cost may be directly penalized as follows:

$$\Delta C_{G_k}^{lb} = R_{G_k}^{lb}(l_{G_k}) \cdot \omega_{G_k} - \sum_{i \in G_k} R_i^{lb}(l_i) \cdot \omega_i \quad (3.19)$$

Where

ω_{G_k} : the maintenance duration of group G_k . If only one maintenance team is considered, it is then reasonable to assume that $\omega_{G_k} = \sum_{i \in G_k} \omega_i$.

$R_{G_k}^{lb}(l_{G_k})$: labor cost rate respective to skill level l_{G_k} of group G_k . It should be noted that the highest skill level of repairman is requested for performing joint maintenance in order to ensure the success of all maintenance tasks. Therefore,

$$l_{G_k} = \max_{i \in G_k}(l_i).$$

Consequently, economic profit of group G_k yielded from economic dependence is given by:

$$EPE_{G_k} = \Delta S_{G_k}^0 - \Delta H_{G_k}(I_{G_k}) - \Delta C_{G_k}^{lb} \quad (3.20)$$

Economic profit model thanks to geographical dependence: In our joint dependence model, apart from the economic dependence, the geographical dependence is also considered. To do the PM on a group of several components, the maintenance team starts from the global maintenance center to sites of maintained components and replaces sequentially all of them in the group before going back to the global maintenance center. By that way, the travel distance and travel time are reduced when compared to an individual maintenance. The maintenance team has to travel from the global maintenance center to the production site where the maintained component is located on, and then come back to the maintenance center when the maintenance is completed. It should be noted that the reduction of travel distance lead to the saving of travel cost. Let I_{G_k} is a maintenance itinerary which maintenance team should follow and L_{G_k} is travel distance respective to this itinerary. Transportation cost saving of the group G_k (economic profit from geographical dependence) correspond to the maintenance itinerary I_{G_k} , denoted $\Delta S_{G_k}^{tr}(I_{G_k})$, and is calculated as follows:

$$\Delta S_{G_k}^{tr}(I_{G_k}) = R^{tr} \cdot \left(\sum_{j \in G_k} n_j^{G_k} \cdot (L_{0j} + L_{j0}) - L_{G_k} \right) \quad (3.21)$$

According to the above transportation cost saving function, total travel distance for performing separate maintenance is always greater than joint maintenance. It directly leads to transportation cost saving. It should be noted that the reduction of travel distance is very important since it is not only meaningful from the economic point of view, but

also sustainability one (reduce energy consumption, travel-related risks, environmental negative impacts). Therefore, it should be considered in maintenance strategies.

Economic profit model of joint consideration of economic and geographical dependence: From Equation (3.20) and (3.21), economic and geographical dependence-based profit cost model for a GDPS is proposed as follows:

$$EPG_{G_k}(t_{G_k}, I_{G_k}) = \Delta S_{G_k}^0 - \Delta H_{G_k}(t_{G_k}) - \Delta C_{G_k}^{lb} + \Delta S_{G_k}^{tr}(I_{G_k}) \quad (3.22)$$

Economic and geographical dependence-based cost model: From Equation (3.22), maintenance cost of group G_k is given as follows:

$$C_{G_k}^p = \sum_{i \in G_k} C_i^p - EPG_{G_k} = \sum_{i \in G_k} C_i^p - \Delta S_{G_k}^0 + \Delta H_{G_k}(I_{G_k}) + \Delta C_{G_k}^{lb} - \Delta S_{G_k}^{tr}(I_{G_k}) \quad (3.23)$$

3.4 Numerical application

The aim of this section is to validate the proposed dependence model for GDPS through a numerical example. According to maintenance architecture 2 (see Section 1.3), we consider a typical GDPS in Figure 3.5 containing 5 geographically dispersed sites and one maintenance center located far from these sites. Each site contains three components. The detailed distances among the sites and their global maintenance center are given in Table 3.1. It should be noticed that, in this study, all parameters are given in arbitrary units, e.g., arbitrary time unit (atu), arbitrary distance unit (adu) or arbitrary cost unit (acu).

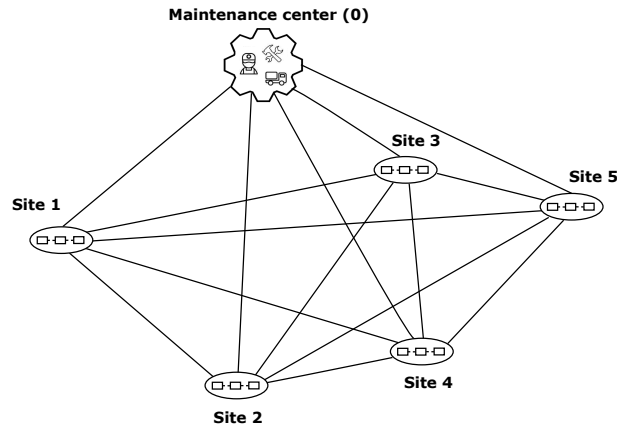


Figure 3.5: A typical GDPS containing 5 production sites

The average speed in moving the maintenance team is $AS = 25$ (adu)/(atu). Then, the travel time can be easily determined by dividing the travel distance by the average speed, i.e. $d_{ij} = L_{ij}/AS$. The transportation cost rate is considered to be the same for all components $R_i^{tr} = R^{tr}$, and is equal to 18 (acu).

Table 3.1: Distance matrix between sites

Site	0	1	2	3	4	5
0	-	80	56	120	131	152
1	80	-	100	98	87	250
2	56	100	-	68	103	154
3	120	98	68	-	54	161
4	131	87	103	54	-	209
5	152	250	154	161	209	-

The main characteristics of each site containing the main components, the down time cost rate (R_j^{dt}) and the preparation cost (S_j^{Site}) are given in Table 3.2.

Table 3.2: Given information related to the site level

Site	1	2	3	4	5
Component	1, 2, 3	4, 5, 6	7, 8, 9	10, 11, 12	13, 14, 15
R_j^{dt}	295	315	348	364	206
S_j^{Site}	200	160	120	80	160

Table 3.3: Components' data and individual maintenance optimization

Component	λ_i	β_i	C_i^{sp}	C_i^c	w_i	t_i^e	l_i	S_i^{tr}	x_i^*	ϕ_i^*	t_{i1}
1	2497	2.86	1745	568	10	1401	1	2880	5229.2	2.5727	3828.2
2	3258	2.76	2526	672	16	2730	2	2880	7868.4	2.6872	5169.4
3	2422	3.71	3250	632	21	782	3	2880	4613.7	5.5512	3841.7
4	2812	2.86	1845	676	9	2421	1	2016	5307.7	2.2411	2886.7
5	3507	2.73	2626	732	15	2656	2	2016	8110.5	2.4302	5485.5
6	2322	3.68	3407	625	22	1139	3	2016	4491.4	5.8042	3361.4
7	2649	2.81	1695	514	11	3278	1	4320	6387.2	2.6818	3109.2
8	3059	2.75	2325	552	17	3807	2	4320	8495.8	2.9651	4723.8
9	2623	3.55	3325	601	24	1041	3	4320	5637.8	5.7239	4607.8
10	2448	2.89	1645	449	10	2506	1	4716	5950.3	2.8403	3466.3
11	2962	2.73	2456	642	15	3004	2	4716	7808.9	3.1655	4836.9
12	2328	3.72	3325	685	22	1159	3	4716	4552.3	6.7836	3393.3
13	2697	2.86	1645	697	12	1556	1	5472	5680.5	2.9542	4141.5
14	3358	3.13	2426	612	17	3604	2	5472	7314.8	2.9951	3710.8
15	2482	3.64	3525	315	24	819	3	5472	6040.8	4.8354	5250.8

The data related to components' characteristics containing the shape and scale parameters of Weibull distribution, the spare part cost, the CM cost, PM time, the total operational time elapsed from the last replacement, the required level of repair team skill are all reported in Table 3.3. The labor cost rates R^{lb} are fixed at 100, 200, 300 (acu) for

required levels of repair team skills 1, 2, 3 respectively. Finally, from Equation 3.5, the maintenance cost of components are determined and shown Table 3.4.

Table 3.4: Preventive maintenance cost of components

Components	C_i^{sp}	$C_{i_j}^{dt}$	C_i^{lb}	$S_{i_j}^{sp}$	S_i^{tr}	C_i^p
1	1745	2950	1000	200	2880	8775
2	2526	4720	3200	200	2880	13526
3	3250	6195	6300	200	2880	18825
4	1845	2835	900	160	2016	7756
5	2626	4725	3000	160	2016	12527
6	3407	6930	6600	160	2016	19113
7	1695	3828	1100	120	4320	11063
8	2325	5916	3400	120	4320	16081
9	3325	8352	7200	120	4320	23317
10	1645	3640	1000	80	4716	11081
11	2456	5460	3000	80	4716	15712
12	3325	8008	6600	80	4716	22729
13	1645	2472	1200	160	5472	10949
14	2426	3502	3400	160	5472	14960
15	3525	4944	7200	160	5472	21301

3.4.1 Economic and geographical dependence and cost model

Assume that these 15 components are preventively maintained by the predetermined maintenance plan as given Table 3.5. According to this plan, these components are divided into three groups G_1 , G_2 , G_3 . The departure time (t_{G_k}) and maintenance itineraries of these groups are also shown in Table 3.5. Based on Equation from Section 3.2 and 3.3, the maintenance costs and cost savings are provided in the Table 3.6.

As shown in the Table 3.6, maintenance cost of these groups is less than individual maintenance of components of these groups thanks to economic profit yielded from economic and geographical dependence ($C_{G_k}^p < \sum C_i^p$). More precisely, for group G_1 , the four maintained components are located at different sites, so site-preparation cost saving is ignored. In addition, the maintenance execution dates of these components are to differ from their preventive maintenance cycle dates. It leads to occurrence of penalty cost ($\Delta H=1385.7$). As shown in Equation (3.20), because the total site-preparation cost saving is equal to 0, economic profit due to economic dependence is negative and its amplitude is equal to penalty cost. Obviously, economic profit from economic dependence is ineffective. However, joint maintenance of group G_1 save a big transportation cost. Consequently, economic profit of group G_1 based on economic and geographical depen-

dence model (see Equation (3.22)) is positive. It directly leads to reduction of 7.54 % maintenance cost.

The similar effectiveness is also expressed by group G_2 . Thanks to economic and geographical dependence modelling when components of this group is jointly performed, the economic profit in this case is approximately one fifth of maintenance cost and so the maintenance cost reduces of 16.55 %. Especially, a part of reduction of maintenance cost comes from the cost savings of site-preparation, without occurring in group G_1 . In addition, there are two components maintained at each site, however the site-preparation cost is only incurred on one component because execution of a group of activities requires only one preparation cost. It means that preparation cost can be saved to 50 %. The saving of the preparation cost in this case is really meaningful in reduction of maintenance cost.

For group G_3 , three components at site 5 are maintained simultaneously. By this way, the site-preparation cost is saved to 66.7 %. However, penalty cost and labor loss cost is too large, so economic profit from economic dependence is negative. In addition, transportation cost cuts up two-third because maintenance team only takes one time to move from global maintenance center to site 5 and turn back instead of three times if these components are performed separately. Consequently, economic profit of group G_3 provided by the proposed dependence model helps maintenance cost reduces 13.3 %.

Table 3.5: Maintenance plan of the GDPS

Groups	Departure time (t_{G_k})	Maintenance itineraries	$L_{G_k}^*$
$G_1 = \{3, 6, 9, 12\}$	3649.4	$0 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 0$	345
$G_2 = \{1, 2, 4, 5, 7, 8, 10, 11\}$	3972.0	$0 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 0$	345
$G_3 = \{13, 14, 15\}$	4585.6	$0 \rightarrow 5 \rightarrow 0$	304

Table 3.6: Maintenance cost provided by the predetermined maintenance plan

Groups	$\sum C_i^p$	ΔS^0	ΔH	ΔC_{lb}	EPE	ΔS^{tr}	EP	$C_{G_k}^p$
$G_1 = \{3, 6, 9, 12\}$	83984	0	1385.7	0	-1385.7	7722	6336.3	77647.7
$G_2 = \{1, 2, 4, 5, 7, 8, 10, 11\}$	96521	560	2235.9	4000	-5675.9	21654	15978.1	80542.9
$G_3 = \{13, 14, 15\}$	47210	320	886.2	4100	-4666.2	10944	6277.8	40932.2

3.4.2 Sensitivity analyses

As mentioned before, economic profit of the dependence model is to save the transportation costs. The dependence model then strongly depends on the transportation cost rate.

This subsection makes sensitive analyses of impacts of transportation cost rate. The analysis is carried out for G_2 identified in Subsection 3.4.1. The proposed dependence model is applied for different cases where the transportation cost rate is varied from 0 to 20 (acu), while the other given data remain unchanged.

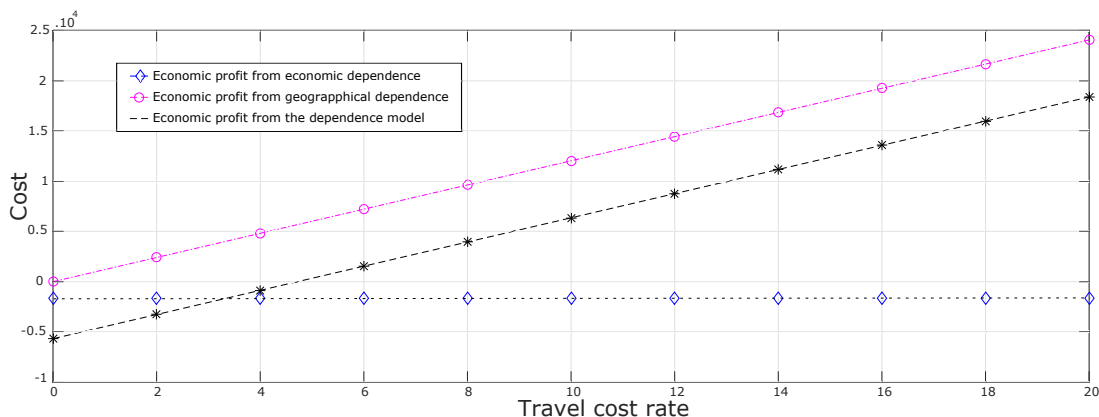


Figure 3.6: Sensitivity analysis of economic profit to transportation cost rate for the proposed dependence model

The evolution of economic profit when the transportation cost rate increases from 0 to 20 is plotted in Figure 3.6. In the Figure, when transportation cost rate is smaller than 4.8, economic profit of the dependence model is negative because positive economic profit from geographical dependence cannot compensate negative economic profit from geographical dependence. In this case, grouping maintenance of G_2 is ineffective. If transportation cost rate is greater than 4.8, economic profit of the dependence model is positive because positive economic profit from geographical is higher than negative economic profit from geographical dependence. In this case, grouping maintenance of G_2 is effective. In addition, from Figure 3.6, the bigger the transportation cost rate is, the higher the economic profit is obtained. The dependence model is therefore recommended for the GDPS with high transportation cost rates.

3.5 Conclusion

In this chapter, we formulate a dependence-based cost model for a GDPS with joint consideration of economic and geographical dependencies. In this model, economic and geographical dependencies are described by economic profit function with two influence factors being departure time (t_{G_k}) and maintenance itinerary (I_{G_k}). The dependence model is really meaningful because it can quantify economic profit when several components are jointly maintained. It directly supports to calculate maintenance cost for a group

of several components. In addition, the joint consideration of economic and geographical dependencies is better than separately consideration of them because interaction between these two kinds of dependencies is considered.

Due to impacts of economic and geographical dependencies on maintenance cost, a development of a dynamic grouping maintenance strategy for a GDPS taking into account economic and geographical dependencies is presented in next chapter.

Chapter 4

Dynamic grouping maintenance strategy for a GDPS

4.1 Introduction

This chapter describes our contribution with regards to the second scientific issue identified in Chapter 2: "How to build a grouping maintenance strategy for a GDPS with consideration of economic, geographical dependencies and impacts of dynamic contexts?". More precisely, we develop a dynamic grouping maintenance strategy for a GDPS including 4 phases. Phase 1 aims to find the optimal preventive maintenance cycles of components. Based on the maintenance cycles identified, phase 2 outlines a tentative maintenance plan of components on a planning horizon. This tentative maintenance plan is used as a basis for grouping maintenance optimization in phase 3. This phase aims to group maintenance activities so that grouping economic profit is maximum. Finally, phase 4 aims to update short-term information for the system when dynamic contexts occur. Based on the updated information, a new grouping maintenance plan can be outlined.

To construct this contribution in consistent way, Section 4.2 presents general assumptions. The key content of this chapter, developing a dynamic grouping maintenance strategy, is presented in Section 4.3. After that, a procedure for updating maintenance and routing plan in a dynamic context is investigated in Section 4.4.

4.2 General assumptions

We consider a GDPS with n components located at m sites. To perform preventive maintenance for such system, the maintenance architecture 2 (see Figure 1.4) is used. Remind that for this architecture, global maintenance center is responsible for the maintenance

actions. To replace an individual component, the maintenance team has to travel from the maintenance center to the maintenance site where the component is located on, and then come back to the maintenance center when the maintenance is completed. Otherwise, to do the preventive maintenance on a group of several components, the maintenance team replaces sequentially all components of the group and returns to the maintenance center only when the maintenance of all components in the group is completed.

The production of each site is supported by several machines (components) subjected to random failures. The failure rate of these components is assumed to be increasing over time by Weibull distribution law as presented in Section 3.3. The costs paid for maintenance on a component are described in Section 3.2.

In our work, assume that preventive maintenance is performed by global maintenance center while corrective maintenance is performed by local maintenance center. Therefore, two types of the maintenance are considered: corrective maintenance (CM) and preventive maintenance (PM). Minimal repair, a specific CM type, is herein applied to repair the failed components. The components are considered to be in the states that they had before their failures. The component is considered to be as good as new after the preventive maintenance (replacement action). To develop our dynamic grouping maintenance strategy of a GDPS, assumptions 1, 2, 3 identified in Chapter 1 and assumptions 4, 5, 6, 7, 8 identified in Chapter 3 are considered. In addition, the following additional assumptions are considered:

ASSUMPTION 9: Failure of a component leads the production site to stop.

ASSUMPTION 10: Interruption of a production site does not impact the normal operation of the others.

In addition, due to the geographic dispersion of the GDPS, the maintenance of such system faces a lot of difficulties related to the dynamic route and weather conditions, transportation capacity, etc.

1. *Change of route and weather conditions:* the maintenance routes and/or travel duration between different sites and maintenance center may be changed over time due to specific reasons such as failure of maintenance team's vehicles, bad weather conditions, or maintenance of specific routes [15, 16];
2. *Change of transportation capacity:* the transportation means may be changed due to economic and/or technical reasons, e.g., failure or replacement of vehicle with lower or higher capacity [15, 16].

These kinds of the above situations, referred to “dynamic contexts” in our study, may have significant impacts on the maintenance planning and routing. In the presence of a dynamic context, the current maintenance grouped plan and maintenance route may be

no longer optimal ones and need to be updated. The proposed maintenance grouping and routing approach should be a dynamic one which allows updating the optimal solution when a dynamic context occurs. In addition, according to different types of dynamic contexts, an appropriate updating processes needs to be developed.

4.3 Dynamic grouping maintenance strategy for a GDPS

The aim of this section is to develop a dynamic grouping maintenance strategy for a GDPS with consideration of economic, geographical dependencies and impacts of dynamic contexts. Due to economic and geographical dependencies related to maintenance routing and scheduling, the proposed strategy considers joint optimization of these processes to determine the optimal maintenance planning and routing. In addition, the strategy can update maintenance plan by taking into account short-term information (dynamic contexts). By that way, it ensures that the current maintenance plan is the best one when dynamic contexts occurs. The proposed strategy contains 4 phases as shown in Figure 4.1.

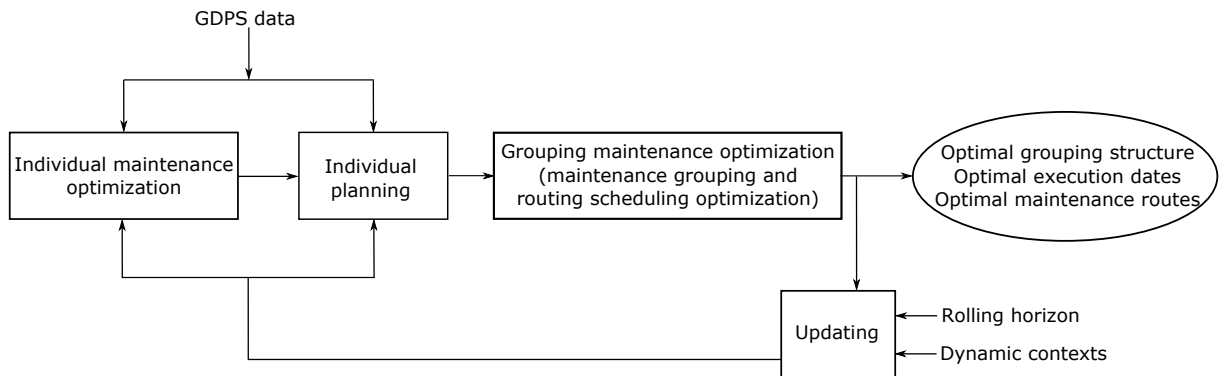


Figure 4.1: A model of the dynamic grouping maintenance strategy of a GDPS

Outline of this strategy: In the first phase, the PM cycle/interval of each component is determined by minimizing its long-term maintenance cost rate (see Section 4.3.1). This PM cycle is then used to determinate the individual PM date of each component in the planning horizon in phase 2 (see Section 4.3.2). In the third phase, the total economic profit of all groups (grouping structure) is firstly formulated based on the individual PM dates obtained in the previous phase. An optimization algorithm is then applied to find the best grouping structure GS^* (a set of exclusive groups), optimal PM dates of each group, and optimal maintenance itineraries of each group in GS^* . The best grouping structure is found by maximizing the total grouping economic profit in the considered

horizon (see Section 4.3.3). Finally, the last phase is devoted to update the maintenance planning and routing when (i) occurring a dynamic information (i.e. varying deterioration rate of components, change of maintenance routes, maintenance opportunities, etc.), or (ii) a new planning horizon is needed (see Section 4.3.4).

4.3.1 Phase 1: Individual maintenance optimization

The objective of this phase is to determine the optimal preventive maintenance cycle of each component. To do that, **we choose the age-based maintenance policy to optimize preventive maintenance cycle of individual component**. The age-based maintenance policy is based on life time distribution of components. This policy is widely applied in industries because it is relatively easy to implement and can only rely on the long-term statistical behavior of the degradation processes of components and personnel's experience [13].

For this policy, a component i is systematically replaced at the fixed age limit x_i which is determined by optimizing long-term average maintenance cost of the component. The nominal preventive maintenance cycle of component i , denoted x_i^* , leads to the minimal long-term average maintenance cost ($\phi_i(t_i)$). Note that when component i breaks down between successive preventive maintenance dates, it is immediately maintained by a minimal repair action. The steps formulating nominal preventive maintenance cycle and minimal long-term average maintenance cost of individual component are found in SubSection 3.3.1.

In summary, the main output of phase 1 is preventive maintenance cycles of all components and their minimal long-term average maintenance costs in a GDPS.

4.3.2 Phase 2: Individual planning

The aim of this phase is to build an individual maintenance plan in a finite planning horizon $PH = [T_{begin}, T_{end}]$. The individual maintenance plan for each component i is carried out at a certain time based on the individual maintenance rules of Phase 1. We determine when the z^{th} maintenance activity of component i should be performed. Under average operational conditions (that is, if the components are used as on average), this is x_i^* time units after that latest execution date of component i . However, because of choice of beginning time and dependence of activities of other components, this may be at another time. Based on preventive maintenance cycles identified in phase 1, the total operational time and the cumulative downtime of component i , the first preventive maintenance date of each component i in the planning horizon is calculated from Equation (3.13). From that, the execution date of the z^{th} PM of component i ($z > 1$) is determined

by Equation (3.14).

We now take a finite planning horizon and we consider the activities to be executed in this horizon. There are many possibilities to choose a planning horizon and the choice depends on the specific problem and the requirements of the maintenance manager. From the point of view that all components are taken into account in the maintenance decision [20], the planning horizon should be chosen in the way that each component is preventively carried out at least one time within the planning horizon. Therefore, the end of date of the planning horizon is determined by the Equation 3.15.

As an example, the planning horizon in Figure 3.3 can be determined as follows: $T_{begin} = 0$ and $T_{end} = (\max_i t_{i1} + \omega_{i1}) = t_{21} + \omega_{21}$.

4.3.3 Phase 3: Grouping maintenance optimization

The objective of this phase is to find the optimal way to group the individual PM dates identified in the previous phase, which maximizes the grouping economic profit in the planning horizon. This phase is extremely important because it directly gives maintenance decision-making based on system data. According to [180], this process includes two parts: (i) formulating mathematical optimization model, (ii) developing an optimization algorithm to solve this problem.

Mathematical optimization model: Remind that the works done by [55, 180, 181] usually assume that n maintenance activities are distributed into several groups to preventively maintain in a planning horizon $[T_{begin}, T_{end}]$. A group of activities is a nonempty subset of $\{1, \dots, N\}$. A partition of $\{1, \dots, N\}$ is a collection of m mutually exclusive groups G_1, \dots, G_m covering all activities, that is, $G_{k_1} \cap G_{k_2} = \emptyset \forall k_1 \neq k_2$, and $G_1 \cup G_2 \cup \dots \cup G_m = \{1, \dots, N\}$. A grouping structure (GS) is a partition of $\{1, \dots, N\}$ so that all PM operations of each group are executed at the same time. For each activity of component i we have its penalty cost function $h_i(\Delta t)$, expressing the expected costs of shifting the execution date of this activity.

For any group G_k , $\Delta H_{G_k}(G_k) = \sum_{i \in G_k} h_i(t_{G_k} - t_i)$ denotes the cumulative penalty function, expressing the additional expected costs of executing group G_k at time t_{G_k} , instead of executing each activity in G_k separately on its execution time t_i . The optimal execution time $t_{G_k}^*$ is the time for which $\Delta H_{G_k}(t_{G_k})$ is minimum. Let $\Delta H_{G_k}^*$ denote the minimal value of $\Delta H_{G_k}(t_{G_k}^*)$. Now we have $\Delta H_{G_k}^* = H_{G_k}^*(t_{G_k}^*)$. Each activity has the same set-up cost S , implying that grouping the execution of m activities yields a cost reduction of $(m - 1)S$. If for a group G_k , the setup cost saving is equal to $(n_{G_k} - 1) \cdot S$ in which n_{G_k} is the number of maintenance activities of group G_k . Thus, economic profit of a group G_k , denoted EPG_{G_k} , can be defined as $(n_{G_k} - 1) \cdot S - \Delta H_{G_k}^*$, i.e., the set-up cost

saving subtract the sum of the penalty costs. By that way, it shows that the grouping economic profit is originated from economic dependence between components.

For a grouping structure, its economic profit is sum of economic profit of its groups $EPS(GS) = \sum_{G_k \in SG} EPG_{G_k}$. For economic point of view, a grouping structure is optimal one (GS^*) if its economic profit is the highest among set of feasible grouping structures (SGS), $GS^* = \arg \max_{GS \in SGS} EPS(GS)$.

In the studies [55, 180, 181] this phase is devoted to formulate grouping maintenance model which aim to find optimal grouping structure. This model is completely appropriate to centralized production system, however it cannot be directly applied for a GDPS due to many difficulties:

1. For a GDPS, maintenance execution dates of components of a group cannot be the same because a maintenance team needs the time to travel among sites when maintaining components located at different sites. In other words, maintenance execution dates of components depend on travel time and maintenance itineraries as analyzed in Subsection 2.2.
2. In GDPS, there are not only existing economic dependence but also geographical dependence. It means that transportation cost of joint maintenance is less than total of transportation cost when performing separate maintenance. Therefore, we should consider the geographical dependence into optimization process.

Both these difficulties are related to maintenance routing problem for GDPS. Hence, to address these difficulties, joint optimization of maintenance routing and scheduling is considered in formulating mathematical optimization model. To formulate this optimization model, we give two concepts: grouping structure and grouping as follows:

Grouping structure concept: For a GDPS, a grouping structure can be illustrated as a matrix:

$$GS = \begin{pmatrix} y_{11} & \cdots & y_{1b} \\ \vdots & \ddots & \vdots \\ y_{a1} & \cdots & y_{ab} \end{pmatrix} \quad (4.1)$$

with

$$y_{ab} = \{m_z | z \in n_a\}$$

where a and b are index of site and component respectively. m_z is group index of z^{th} maintenance activity of component b and n_a is the number of maintenance activities of component b. $y_{24} = 1$ implies that component 4 located at site 2 lies in group 1.

From the matrix GS , a set of components of a group G_k can be determined as follows:

$$G_k = G_{y_{ab}} = \{b | y_{ab} = k \forall a\} \quad \text{with } 1 \leq k \leq \max GS \quad (4.2)$$

As an example, a grouping structure containing 4 components located at 2 sites is fully defined by the following matrix:

$$GS = \begin{bmatrix} \{1, 2\} & \{1\} & \emptyset & \emptyset \\ \emptyset & \emptyset & \{2\} & \{3\} \end{bmatrix}$$

It means that components $\{1, 2\}$, $\{3, 4\}$ are located at site 1 and site 2 respectively; grouping structure consists of 3 groups including $G_1 = \{1, 2\}$, $G_2 = \{1, 3\}$ and $G_3 = \{4\}$. Note that component 1 is performed two times in the planning horizon.

Grouping concept: Remind that to do preventive maintenance of a group G_k of several components which are tentatively maintained at their individual PM dates t_{iz} , the maintenance team has to leave global maintenance center at departure time (t_{G_k}) and then follow a specific itinerary (I_{G_k}) to maintain all the components of the group before going back to the maintenance center. The maintenance route prescribes the sequence of the sites that the maintenance team has to travel consecutively. The actual maintenance execution dates of components can be determined as expressed in Section 3.3. From this definition, each maintenance group G_k is characterized by the three following parameters: components of group, departure time of the maintenance team t_{G_k} , and maintenance itinerary I_{G_k} . Hence, for a specific group, *EPG* function depends on departure time of the maintenance team t_{G_k} , and maintenance itinerary I_{G_k} , denoted $EPG(t_{G_k}, I_{G_k})$.

In our study, the optimization model is formulated at two levels as shown in Figure 4.2. At group level, components of each group are maintained sequentially by specific maintenance itineraries so that *EPG* is maximum. Let $EPG_{G_k}^*(t_{G_k}^*, I_{G_k}^*)$ denote the maximal value of economic profit of a group G_k . Finding an optimal maintenance itinerary $I_{G_k}^*$ and optimal departure time $t_{G_k}^*$ for which *EPG* is maximal, is not simple due to interaction between economic and geographical dependence. As an example, we can understand that maintenance routing aims at finding the best itinerary with lowest travel distance/ travel time. It relates to geographical dependence. Whereas, related to economic dependence, maintenance scheduling aims at finding the best maintenance schedule of components in which grouping economic profit is maximum. Actually, the shortest maintenance itinerary can lead to a minimum transportation cost. However, this itinerary may be not optimal one because the penalty cost associated with this itinerary can be too large and it can lead to high maintenance cost. Remind that the penalty cost occurs when the execution dates of components are different to their tentative maintenance dates. To solve this problem, an optimization process should consider both maintenance routing and scheduling simultaneously. By that way, an economic profit model supporting this optimization process at group level is presented more specific in Chapter 5. This formulation is built based on the solving of maintenance routing and scheduling problem, in other words, maintenance routing scheduling problem. This problem is mentioned as a process finding an optimal

maintenance itinerary and optimal execution dates of components with aim of maximal economic profit of a group.

At grouping structure level, the economic profit model of a grouping structure can be simply calculated as:

$$EPS(GS, t_{G_k}, L_{G_k}) = \sum_{G_k \in GS} EPG(t_{G_k}, L_{G_k}) \quad (4.3)$$

$EPS(GS, t_{G_k}, L_{G_k})$ represents the performance of grouping structure GS . The grouping performance then depends on a grouping structure (GS), departure time of the maintenance team (t_{G_k}) and maintenance itinerary (I_{G_k}) to maintain each group G_k in GS . The best grouping performance is, the highest ESP is. The optimal grouping structure in a set of grouping structure SGS can be determined as follows:

$$(GS^*, t_{G_k}^*, I_{G_k}^*) = \arg \max_{GS \in SGS, t_{G_k}, I_{G_k}} \sum_{G_k \in GS} EPG_{G_k}(t_{G_k}, I_{G_k}) \quad (4.4)$$

Consequently, in this phase, the grouping economic profit model supporting to determine the optimal maintenance planning is formulated.

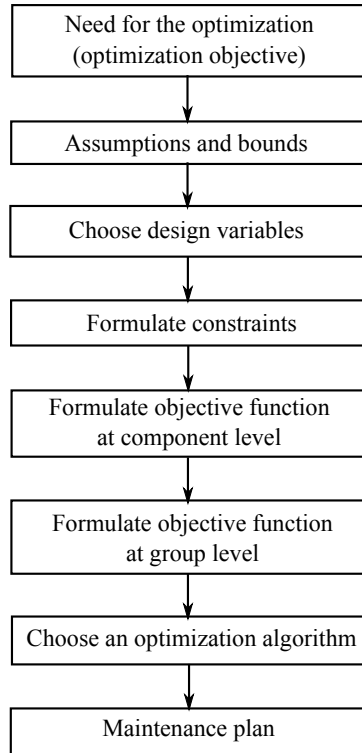


Figure 4.2: Flow chart of an optimization process [2]

Optimization algorithm: The aim of this step is to develop an optimization algorithm to find an optimal maintenance plan including an optimal grouping structure, an optimal

maintenance itinerary and optimal execution dates of components based on proposal mathematical optimization model. From works done by [20, 29], if we have N preventive maintenance activities in the considered horizon, we have $2^N - 1$ possible groups that we have to consider during the determination of GS^* . It shows clearly that the problem is NP-complete. To solve this problem, Genetic Algorithm (GA) is used as an intelligent search algorithm to find an optimal grouping structure (GS^*) [20, 29]. The GA, a robust method, is very suitable to find the best maintenance plan for large-scale system because it can integrate many constraints easily [155, 156]. However, applying the GA in GDPS context has to face difficulties related to geographical dispersion of a GDPS.

Indeed, remember that GA starts by randomly creating a set of possible grouping structures. At each GA's iteration, the grouping structures are compared each other based on their total economic profit (EPS). The good grouping structures with high economic profits will be saved and improved by applying genetic operations such as crossover, mutation, and elitism. GA is stopped when stopping criteria such as the maximum iteration number is reached. In the iteration process, the calculation of the total economic profit of a specific grouping structure is not evident. With the same grouping structure, the economic profit values may be varied depending on choice of departure times, and the choice of maintenance routes/itineraries that the maintenance team has to follow to perform the maintenance on the groups.

To solve this problem, we need to use a search algorithm that can find the optimal maintenance itinerary ($I_{G_k}^*$) and the optimal departure time ($t_{G_k}^*$) for specific groups of grouping structure GS so that economic profit values can be fixed and optimal. In other word, this algorithm addresses maintenance routing and scheduling optimization problem for groups of grouping structure GS . For a routing and scheduling optimization problem, Branch and Bound (BAB) method is effective solution [182]. It is one of exact methods to find the optimal maintenance itinerary that satisfies one or many objectives such as minimum travel cost, minimum maintenance cost, etc. Considering a specific group G_k of grouping structure GS , BAB method aims to find the optimal maintenance itinerary ($I_{G_k}^*$) and optimal departure time ($t_{G_k}^*$) with the highest economic profit.

After determining maximum economic profit of groups of a grouping structure by using BAB method, we can calculate the maximum grouping economic profit that this grouping structure can be achieved. Then, procedure of a GA can support to find the best grouping structure by its genetic operations. From this ideal, we develop an advanced algorithm based on GA and BAB method, named GAB, to find optimal maintenance plan for a GDPS. The details of this algorithm is presented in Chapter 6.

4.3.4 Phase 4: Update and rolling horizon

After the previous phases, we have an optimal grouped maintenance planning within the finite planning horizon $[T_{begin}, T_{end}]$. However, the current maintenance plan can be changed in next planning horizon due to the impacts of subjective or objective factors of dynamic contexts. The subjective factors can be mentioned such as change of production planning [109], change of system structure [55, 107]; change in maintenance costs (preventive and / or corrective) over time because of fluctuations in market prices [183]; change in availability of maintenance resources [135], etc. Whereas, the objective factors can be as change of the deterioration process of component due to unforeseen impacts of operational environment [72, 184]; specially change of maintenance routes, change of transportation capacity occurring within a GDPS frequently [15, 16], etc. In these cases, these changes of dynamic contexts should be integrated into the planning process to generate a new plan that is better than current one. By that way, the update and rolling horizon are carried out according to one of two following reasons:

1. *in presence of dynamic contexts:* As mentioned in Subsection 1.2.2, dynamic contexts related to change of maintenance routes, change of transportation capacity or change of components characteristics, etc may occur with time. In presence of such the dynamic contexts, the current grouping structure may be no longer the optimal one or even unusable. An adaptive maintenance planning is needed. To integrate these kinds of dynamic contexts, we need to go back to "Individual maintenance optimization" step and so on. As a typical example, an updating procedure related to type "change of maintenance routes" is detailed in next section.
2. *at the end of the current planning horizon:* A new maintenance planning for the next horizon is needed. New horizon can be constructed based on new required missions' interval with new maintenance constraints (availability and/or repairmen constraints). For this purpose, the rolling horizon procedure is used by returning to phase 2 of the optimization scheme to redefine all preventive maintenance activities in the new individual planning horizon and so on.

4.4 Procedure for updating maintenance and routing plan in a dynamic context

As mentioned in subsection 4.3.4, under impacts of the dynamic contexts, the current maintenance grouped plan may be no longer optimal one and need to be updated. According to different types of the dynamic contexts, change of maintenance routes is a

typical type of the dynamic contexts in GDPS, especially not exist in centralized system. From our best knowledge, an updating procedure considering this type of dynamic contexts has not been investigated yet. For this reason, in this section we develop an updating procedure with type of change of maintenance routes for the proposal strategy.

Assumes that a GDPS as shown in Figure 3.5 is preventively maintained according to a predetermined grouping maintenance plan corresponding to grouping structure GS_1 in planning horizon $[T_{begin}, T_{end}]$, and dynamic context "Change of maintenance routes" occurs at a moment $T_{dc} \in [T_{begin}, T_{end}]$. At this time, it is assumed that the direct road between the global maintenance center and site j is interrupted for a long period due to road maintenance activities. As a consequence, to go to site j from the maintenance center, the maintenance team has to travel on the other road with a longer distance. The travel distance of the new road from global maintenance center to site j is given by:

$$L'_{0j} = \min \{L_{0mj} | L_{0mj} = L_{0m} + L_{mj}; m \neq 0, j\} \quad (4.5)$$

where m is the site that maintenance team has to cross to come to site j .

Due to the appearance of this dynamic context, the current maintenance plan may be no longer optimal one and needs to be updated. An updating procedure is illustrated in Figure 4.3:

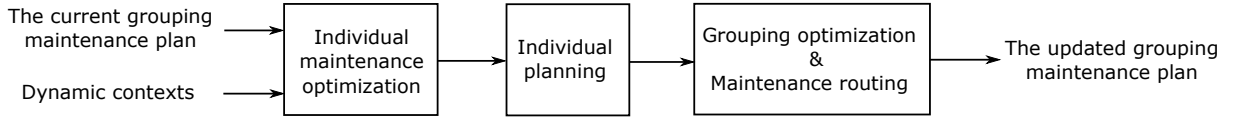


Figure 4.3: The updating procedure for a dynamic grouping maintenance approach

Phase 1: Individual maintenance optimization. Due to interruption of route from the global maintenance center to site j , the nominal optimal execution cycle x_i^* of components at site j is also changed. Thus, this phase is devoted to update the optimal preventive maintenance cycle of components at site j . Instead of going to site j in direct way, maintenance team has to take the route $0 \rightarrow m \rightarrow j$ (0 is the global maintenance center) and turn back when maintenance tasks are completed. It leads to the higher travel cost than previous one. Along with the increase of travel cost, preventive maintenance cost grows up also, and consequently the optimal PM cycle of these components is stretched as shown in Equation 3.11.

Phase 2: Individual planning. Based on input date of the previous phase, a tentative maintenance planning of individual components is established in new planning horizon $[T'_{begin}, T'_{end}]$, where the beginning date and the ending date are recalculated following

Equation 3.15.

Phase 3: Grouping maintenance optimization. In this phase, the optimization model is formulated as Subsection 4.3.3. It should be noted that the updated information in phase 1 and phase 2 is considered in optimization model of this phase. After that, the combination algorithm between Genetic Algorithm and Branch and Bound method is used to solve this optimization model and give a new maintenance plan including an optimal grouping structure, optimal execution dates and optimal maintenance itineraries on the new planning horizon $[T'_{begin}, T'_{end}]$.

4.5 Conclusion

In this chapter, we proposed a dynamic grouping maintenance strategy for a GDPS with consideration of economic, geographical dependencies and impacts of dynamic contexts. It is a very original contribution. For this type of system, the procedure to establish this strategy includes 4 phases. Phase 1 aims to find the optimal preventive maintenance cycles of components. To do that, an age-based policy, in which component's failure behavior is described by Weibull distribution and long-term average maintenance cost of the component is determined by the renewal theory, is conducted. Based on the maintenance cycles identified, phase 2 outlines a tentative maintenance plan of components on a planning horizon. This tentative maintenance plan is used as a basis for grouping maintenance activities. The grouping of maintenance activities in phase 3 yields the economic profit (see Equation 4.4) thanks to economic and geographical dependencies. This economic profit is used as a main evaluation criteria for the choice of maintenance plan. In our study, the best choice is a maintenance plan with the highest economic profit. Finally, phase 4 aims to update short-term information for the system when dynamic contexts occur. Based on the updated information, a new grouping maintenance plan can be outlined.

The maintenance strategy shows that there are both positive impacts (preparation cost saving and transportation cost saving) and negative impacts (penalty cost, labor loss cost) on the grouping of maintenance activities due to economic and geographical dependencies. In addition, the proposed strategy allows maintenance plan update when dynamic contexts occur. Therefore, our maintenance strategy can be well adapted to the dynamic contexts which frequently occurs in operation and maintenance of a GDPS.

In order to support maintenance optimization of the proposed strategy, mathematical models considering maintenance routing and scheduling are formulated in Chapter 5.

Chapter 5

Mathematical models for maintenance routing and scheduling problem

5.1 Introduction

This chapter describes our contribution with regards to the third scientific issue identified in Chapter 2: "How to formulate economic profit models of maintenance routing and scheduling?" More precisely, we formulate two economic profit models of maintenance routing and scheduling regarding to two different approaches: sequential maintenance routing and scheduling (SMaRS) and joint maintenance routing and scheduling (JMaRS). By SMaRS approach, the model is formulated by sequential steps of maintenance routing and scheduling. Whereas, maintenance routing and scheduling are jointly investigated in formulating the model with JMaRS approach.

To construct this contribution in consistent way, Section 5.2 presents a mathematical model of maintenance routing for a GDPS. Based on this model, Section 5.3 is devoted to formulate an economic profit models. By the different approaches, an economic profit model based on SMaRS approach is investigated in subsection 5.3.1, while an economic profit model based on SMaRS approach is formulated in subsection 5.3.2.

5.2 Mathematical modelling of maintenance routing

This section presents a mathematical model of maintenance routing used in the grouping maintenance strategy. It is as a basis to develop the economic profit models presented in section 5.3.

Traveling salesman problem (TSP) approach usually used to formulate mathematical model of maintenance routing are presenting in papers [25, 26, 30, 31]. Objective of the approach is to find an optimal itinerary with the shortest route or the lowest transportation cost. The TSP can be represented as the following graph-theoretic problem as Figure 5.1. Let $G = (V, A)$ be a complete graph where $V = \{0, 1, \dots, n_m\}$ is the vertex set $A = \{(j, m) | j, m \in V, j \neq m\}$ is the arc set. Vertices from 1 to n_m correspond to the production sites, while vertex 0 correspond to the global maintenance center. Each $arc(j, m)$ is associated with a distance L_{jm} . Objective is to construct a set of itinerary that satisfies the following constraints:

- Each itinerary starts and ends at a global maintenance center, represented as a sequence $I_{G_k} = (0 \dots j \dots m \dots 0)$.
- Each site j is only visited one time
- Travel distance of itinerary is minimum. It means that the travel cost/transportation cost is minimum because travel cost is proportional to travel distance.

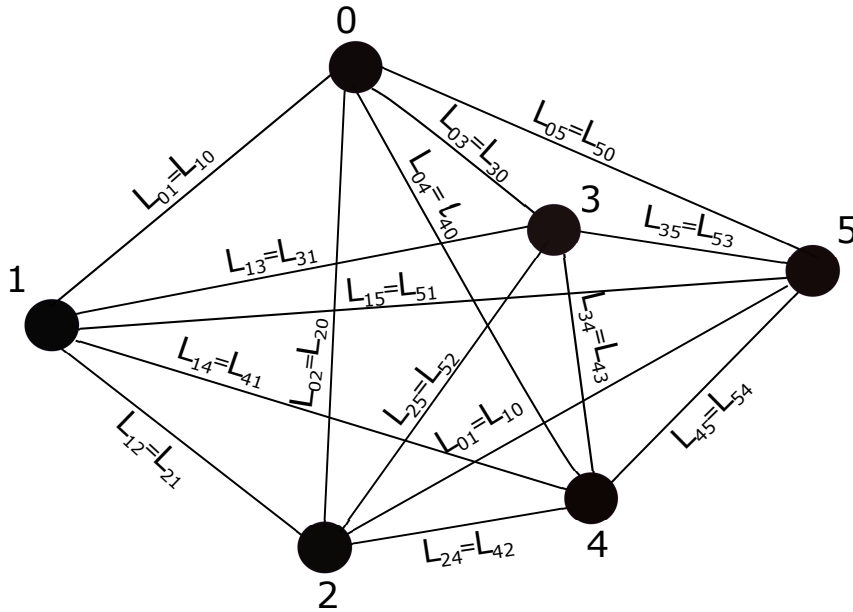


Figure 5.1: A Traveling Salesman Problem

Applying the TSP method to schedule maintenance itinerary for a group G_k consisting of n_{G_k} components located at m_{G_k} sites. Routing plan is represented by decision variable X_{jv} as follows:

$$X_{jv} = \begin{cases} 1, & \text{if site } j \text{ is the } v\text{th location visited} \\ 0, & \text{otherwise} \end{cases} \quad (5.1)$$

Hence, the routing plan is determined by the following $(m_s \times m_{G_k})$ matrix X with m_s being the number of all sites of a system and m_{G_k} being the number of sites in group G_k :

$$X = \begin{pmatrix} X_{11} & \cdots & X_{1m_{G_k}} \\ \vdots & \ddots & \vdots \\ X_{m_s1} & \cdots & X_{m_sm_{G_k}} \end{pmatrix} \quad (5.2)$$

With

$$\sum_{j=1}^{m_s} X_{jv} = 1, \forall v = [1, 2 \dots m_{G_k}]$$

$$\sum_{v=1}^{m_{G_k}} X_{jv} \leq 1, \forall j = [1, 2 \dots m_s]$$

As an example, maintenance itinerary crossing 5 sites is fully defined by the following matrix X :

$$X = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

It means that the maintenance team is implemented an itinerary as follow 0-2-5-3-1-0, where 0 is a representation of global maintenance center.

Note that maintenance itinerary can be transformed from matrix of routing plan to vector of routing plan. This vector, denoted I_{G_k} , includes global maintenance center and sites containing maintained components arranged in order of moving of maintenance team as shown in above.

From the matrix of routing plan (X), total distance of a maintenance itinerary of group G_k , denoted L_{G_k} , can be calculated as

$$L_{G_k} = L_{0v_1} + L_{v_{end}0} + \sum_{j=1}^{m_s} \sum_{v=2}^{m_{G_k}} \sum_{m=1, m \neq j}^{m_s} X_{jv} \cdot X_{m(v-1)} \cdot L_{mj} \quad (5.3)$$

Where

- L_{0v_1} : distance between global maintenance center and the first site of itinerary.
- $L_{0v_{end}}$: distance between global maintenance center and the last site of itinerary.
- L_{mj} : distance from site m to site j .

Corresponding to the predetermined maintenance itinerary, transportation cost of a group G_k , denoted $S_{G_k}^{tr}$, can be calculated as follows:

$$S_{G_k}^{tr} = R^{tr} \cdot \left(L_{0v_1} + L_{v_{end}0} + \sum_{j=1}^{m_s} \sum_{v=2}^{m_{G_k}} \sum_{m=1, m \neq j}^{m_s} X_{jv} \cdot X_{m(v-1)} \cdot L_{mj} \right) \quad (5.4)$$

Where

R^{tr} : travel cost rate.

Consequently, transportation cost saving when performing joint maintenance of a group G_k is given as follows:

$$\Delta S_{G_k}^{tr} = \sum_{i \in G_k} S_i^{tr} - S_{G_k}^{tr} \quad (5.5)$$

The optimal maintenance itinerary based on minimum travel cost criterion is yielded as follows:

$$(I_{G_k}^*) = \arg \max_{t_{G_k}, I_{G_k}} \Delta S_{G_k}^{tr} \quad (5.6)$$

By using TSP method, the optimal maintenance itinerary ($I_{G_k}^*$) with the lowest travel cost is determined in advance. Based on this itinerary, a maintenance schedule is built for components of group G_k .

5.3 Mathematical modelling of maintenance routing and scheduling

This section is devoted to formulate economic profit models based on two approaches: sequential maintenance routing and scheduling (SMaRS) and joint maintenance routing and scheduling (JMaRS). By using the SMaRS approach, economic profit model is formulated by sequential steps of maintenance routing and scheduling. Whereas, using the JMaRS approach, maintenance routing and scheduling is jointly investigated in formulating economic profit model.

5.3.1 Sequential consideration of maintenance routing and scheduling

In this subsection, we formulate an economic profit model based on SMaRS approach. By that way, the procedure is illustrated in Figure 5.2. First step, a mathematical modelling

of maintenance routing is done. After that, a mathematical modelling of maintenance scheduling is considered to generate an economic profit model of maintenance routing and scheduling.

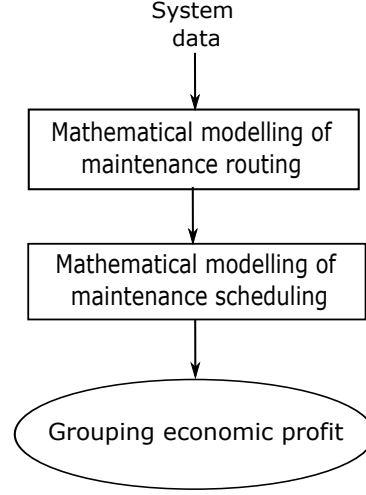


Figure 5.2: The procedure formulating economic profit model by the SMaRS approach

More precisely, considering joint maintenance of several components of a group G_k within a GDPS, the mathematical modelling of maintenance routing is derived from Section 5.2. By that way, the maintenance itinerary (I_{G_k}) is determined based on matrix of routing plan identified in Equation (5.2) and optimal maintenance itinerary $I_{G_k}^*$ is determined as Equation (5.6). Let t_{G_k} be departure time of a group G_k in optimal maintenance itinerary. Based on Equation (3.20) in Chapter 3, the economic profit yielded through mathematical modelling of maintenance scheduling can be calculated as:

$$EPE_{G_k}(t_{G_k}, I_{G_k}^*) = \sum_{j \in G_k} (n_j^{G_k} - 1) \cdot S_j^0 - \sum_{i \in G_k} h_i [\Delta t_i(t_{G_k}, I_{G_k}^*)] - \Delta C_{G_k}^{lb} \quad (5.7)$$

From Equation 5.7 and 5.6, total economic profit of group G_k is expressed as:

$$EPG_{G_k}(t_{G_k}, I_{G_k}^*) = \sum_{j \in G_k} (n_j^{G_k} - 1) \cdot S_j^0 - \sum_{i \in G_k} h_i [\Delta t_i(t_{G_k}, I_{G_k}^*)] - \Delta C_{G_k}^{lb} + \max \Delta S_{G_k}^{tr}(G_k) \quad (5.8)$$

As a consequence, the optimal departure time of group G_k is determined as follows:

$$(t_{G_k}^*) = \arg \max_{t_{G_k}=0 \rightarrow \infty} EPG_{G_k}(t_{G_k}, I_{G_k}^*) \quad (5.9)$$

The economic profit model is represented by total economic profit of group G_k as shown in Equation (5.8).

5.3.2 Joint consideration of maintenance routing and scheduling

As presented in above, SMaRS is a fragmented approach in which optimization of maintenance routing and scheduling is implemented sequentially. The advantage of SMaRS is that its implementation procedure is slightly simple. Specially, SMaRS is appropriate to GDPS whose production sites are located very far from each other. In this case, the penalty cost has a very small impact on the maintenance cost saving compared to transportation cost saving. However, due to the fragmented approach, maintenance plan provided by SMaRS is a local optimization solution. The optimal maintenance schedule is provided based on the shortest maintenance itineraries. Actually, in several cases, this itinerary may not be optimal because the penalty cost associated with this itinerary can be too large and it can lead to a high maintenance cost.

To address this problem, an economic profit model with joint consideration of maintenance routing and scheduling (JMaRS) is studied and formulated in this section. By using JMaRS approach, a global optimization solution with the highest economic profit is always provided. Note that interaction between maintenance routing and scheduling is also investigated by JMaRS approach. The stage to formulate this economic profit is illustrated in Figure 5.3. More precisely, considering a group G_k containing n_{G_k} components located at m_{G_k} different sites, the maintenance team has to follow a maintenance itinerary to replace these components sequentially. The maintenance itinerary is described by matrix of routing plan as Equation (5.2). By that way, the maintenance costs of a group G_k are defined as follows:

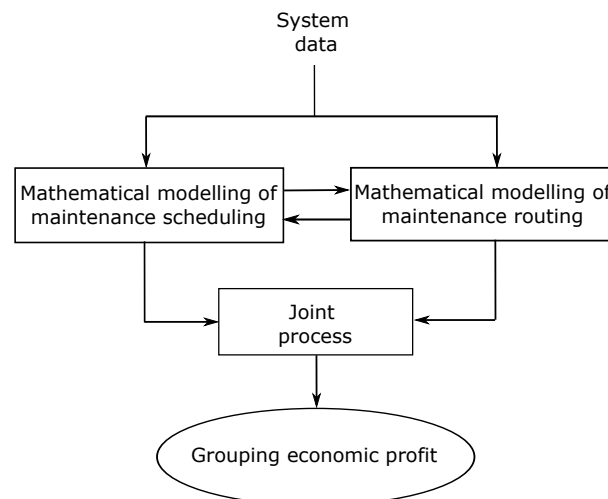


Figure 5.3: The procedure formulating economic profit model by the JMaRS approach

- Spare part cost of a group G_k

$$C_{G_k}^{sp} = \sum_{i \in G_k} C_i^{sp} \quad (5.10)$$

- Downtime cost of a group G_k

$$C_{G_k}^{dt} = \sum_{j \in G_k} (R_{jG_k}^{dt} \cdot \sum_{i \in G_k, i \in j} \omega_i) \quad (5.11)$$

where $R_{jG_k}^{dt}$ and ω_i are the downtime cost rate and the maintenance duration of component i of G_k at site j .

- Labor cost of a group G_k

$$C_{G_k}^{lb} = R_{G_k}^{lb}(l_{G_k}) \cdot w_{G_k} = R_{G_k}^{lb}(l_{G_k}) \sum_{i \in G_k} \omega_i \quad (5.12)$$

- Site preparation cost of a group G_k

$$S_{G_k}^0 = \sum_{j=1}^{m_s} \sum_{v=1}^{m_{G_k}} X_{jv} \cdot S_j^{sp} \quad (5.13)$$

where S_j^{sp} is site preparation cost at site j . This cost has to be paid once time when once component of the site is preventively maintained.

- Travel cost $S_{G_k}^{tr}$ of a group G_k is determined as Equation 5.4.

Consequently, total maintenance cost of G_k is given by

$$\begin{aligned} C_{G_k}^p &= C_{G_k}^{sp} + C_{G_k}^{dt} + C_{G_k}^{lb} + S_{G_k}^0 + S_{G_k}^{tr} \\ &= \sum_{i \in G_k} C_i^{sp} + \sum_{j \in G_k} (R_{jG_k}^{dt} \cdot \sum_{i \in G_k, i \in j} \omega_i) + R_{G_k}^{lb} \cdot w_{G_k} + \sum_{j=1}^{n_s} \sum_{v=1}^{m_s} X_{jv} \cdot S_j^{sp} \\ &\quad + R^{tr} \cdot \left(L_{0v_1} + L_{v_{end}0} + \sum_{j=1}^{n_s} \sum_{v=2}^{m_s} \sum_{m=1, m \neq j} X_{jv} \cdot X_{m(v-1)} \cdot L_{mj} \right) \end{aligned} \quad (5.14)$$

Compared to individual maintenance, the economic profit when these components are jointly maintained is calculated as follows:

$$\begin{aligned} EPG_{G_k}(t_{G_k}, L_{G_k}) &= \sum_{i \in G_k} C_i^p - C_{G_k}^p + \Delta H_{G_k}(t_{G_k}, L_{G_k}) \\ &= \left(\sum_{i, j \in G_k} S_{ij}^{sp} - S_{G_k}^0 \right) + \left(\sum_{i \in G_k} S_i^{tr} - S_{G_k}^{tr} \right) - \left(C_{G_k}^{lb} - \sum_{i \in G_k} R_i^{lb} \cdot \omega_i \right) - \Delta H(t_{G_k}, L_{G_k}) \\ &= \Delta S_{G_k}^{sp} + \Delta S_{G_k}^{tr}(L_{G_k}) - \Delta C_{G_k}^{lb} - \Delta H(t_{G_k}, L_{G_k}) \end{aligned} \quad (5.15)$$

Where

- $\Delta S_{G_k}^{sp}$ is site-preparation cost saving due to reduction preparation cost of and be calculated as follows:

$$\Delta S_{G_k}^{sp} = \sum_{i,j \in G_k} S_{i_j}^{sp} - \sum_{j=1}^{m_s} \sum_{v=1}^{m_{G_k}} X_{jv} \cdot S_j^{sp} \quad (5.16)$$

- $\Delta S_{G_k}^{tr}(L_{G_k})$ is transportation cost saving due to reduction of travel distance and is determined by:

$$\Delta S_{G_k}^{tr}(L_{G_k}) = R^{tr} \cdot \left[\sum_{j \in G_k} n_j^{G_k} \cdot (L_{0j} + L_{j0}) - \left(L_{0v_1} + L_{v_{end}0} + \sum_{j=1}^{m_s} \sum_{v=2}^{m_{G_k}} \sum_{m=1, m \neq j}^{m_s} X_{jv} \cdot X_{m(v-1)} \cdot L_{mj} \right) \right] \quad (5.17)$$

- $\Delta C_{G_k}^{lb}$ is the labor loss cost and is calculated as Equation (3.19)

$$\Delta C_{G_k}^{lb} = R_{G_k}^{lb} \omega_{G_k} - \sum_{i \in G_k} R_i^{lb} \cdot \omega_i \quad (5.18)$$

- $\Delta H(t_{G_k}, L_{G_k})$ is the incurred penalty cost when components are jointly maintained. As analyzed above, the penalty cost of a group G_k is a function that depends on both the maintenance dates of the group (t_{G_k}) and maintenance itinerary (I_{G_k}). Thus, penalty cost is different with each maintenance itinerary. The reason is that execution dates of components correspond to these itineraries are different. To help for determining execution dates of components and penalty cost of the group, we give a definition of maintenance order of a group. For a maintenance itinerary I_{G_k} , this order is defined as follows:

$$J_v = \sum_{j=1}^{m_s} j \cdot X_{jv} \quad \text{with } m_{G_k} \geq v \geq 1 \quad (5.19)$$

It means that the visited order of site J is v th. Thus, the execution dates of all components at site j is:

$$\begin{aligned} t_v(J_v) &= t_{v-1}(J_{v-1}) + \sum_{i \in I_{v-1}, i \in G_k} w_i + t_{J_{v-1}J}^{tr} \\ &= t_{v-1}(J_{v-1}) + \sum_{j=1}^{n_s} \left(X_{j(v-1)} \cdot \sum_{i \in J_{v-1}, i \in G_k} w_i \right) + t_{J_{v-1}J}^{tr} \end{aligned} \quad (5.20)$$

where $t_{J_{v-1}J}^{tr}$ is travel time from site J_{v-1} to J_v . Note that v is equal to 0 representing the global maintenance center. We define:

$$\begin{cases} J_0 = 0 & \text{departure at maintenance center} \\ t_0(J_0) = t_{G_k} & \text{is departure time at maintenance center} \end{cases}$$

In other words, the execution date of a component i of a group G_k at site J is calculated as follows:

$$t'_i = t_v(J_v) \quad \text{with } i \in J_v \quad (5.21)$$

The penalty cost $\Delta H_{G_k}(t)$ of a group G_k is rewritten as follows:

$$\Delta H(t_{G_k}, I_{G_k}) = \sum_{J_v \in G_k} \sum_{i \in G_k; i \in J_v} h_i(t_v(I_v) - t_i) \quad (5.22)$$

From Equation (5.15), the optimal maintenance date ($t_{G_k}^*$) and itinerary ($I_{G_k}^*$) can be determined as

$$(t_{G_k}^*, I_{G_k}^*) = \arg \max_{t_{G_k}, I_{G_k}} EPG_{G_k}(t_{G_k}, I_{G_k}) \quad (5.23)$$

In summary, the economic profit model is represented by total economic profit of group G_k as show at Equation (5.15).

5.4 Conclusion

In this chapter, we formulate two economic profit models based on SMaRS and JMaRS approaches respectively. From manners to formulate models, we see that the SMaRS approach, as a fragmented approach, is more easily implementable than the JMaRS. Unfortunately, because the lack of interaction between maintenance routing and scheduling, this approach can lead to significant inefficiencies on maintenance planning. Whereas, the JMaRS is a better choice because interactions between maintenance routing and scheduling are considered in formulation process. Hence, the economic profit model based on the JMaRS approach should be considered in calculation of economic profit of the grouping maintenance in GDPS context.

Chapter 6

Development of optimization algorithms for dynamic grouping maintenance strategy

6.1 Introduction

This chapter describes our contribution with regards to the fourth scientific issue identified in Chapter 2: "How to develop an advanced algorithm to support maintenance optimization for GDPS in considering maintenance planning and routing?". For a GDPS, due to geographical dispersed production, optimization of the grouping maintenance strategy not only depends maintenance planning but also maintenance routing. From the state of the art in Chapter 2, to determine the optimal maintenance planning, Genetic Algorithm (GA) is usually considered due to its effectiveness in addressing optimization problem for large scale system (multi-component, multi-site, multi-constraint). Whereas, Branch and Bound method (BAB) is usually used for routing optimization problem because it can reduce computational time compared to exhaustive search thanks to trying to rule out parts of the search space that cannot contain the best solution. Based on these ideas, we develop an advanced algorithm based on GA and BAB, named GAB, to determine the optimal maintenance planning and routing.

To construct this contribution in consistent way, in Section 6.2, we develop optimization algorithms based on Branch and Bound method for optimization of maintenance routing. Then, Section 6.3 presents a GAB for joint optimization of maintenance planning and routing. Noted that the proposed algorithms are develop on Matlab platform.

6.2 At group level

In this section, we develop two optimization algorithms using Branch and Bound method to optimize maintenance planning and routing at group level. These algorithms are simulated based on two approaches identified in Section 5.3 : SMaRS and JMaRS approaches. By the SMaRS approach, an optimization algorithm, named sBAB, is formulated. Whereas, by the JMaRS approach, an optimization algorithm, named jBAB, is formulated. It should be noted that simulation of these algorithms is supported by Nelder-Mead method supplied by Matlab platform. Nelder-Mead method is a famous method used for nonlinear optimization problem. Assume that we have a nonlinear function $y = f(x)$. The Nelder-Mead method aims to find the x value in order that function is maximum or minimum.

6.2.1 Optimization algorithm for SMaRS approach

In this subsection, the objective is to develop sBAB algorithm to find an optimal maintenance plan at group level with maximizing economic profit of the model identified in Section 5.3.1. By SMaRS approach, in search process, optimization of maintenance routing and maintenance scheduling are sequentially implemented by sBAB algorithm as illustrated in Figure 6.1. Firstly, the proposed method has to optimize maintenance routing to find an optimal maintenance itinerary with the lowest transportation cost. After that, the maintenance scheduling is optimized based on this itinerary. Obviously, the core of issue is to find the shortest route/cheapest route that maintenance team can follow to replace components sequentially. The sBAB algorithm is used to find this optimal route in this case.

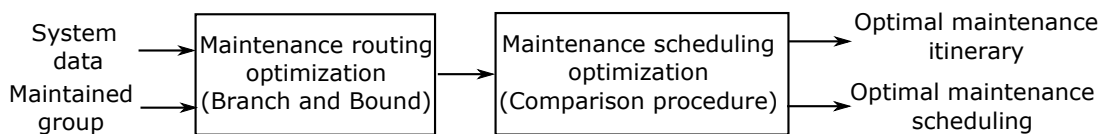
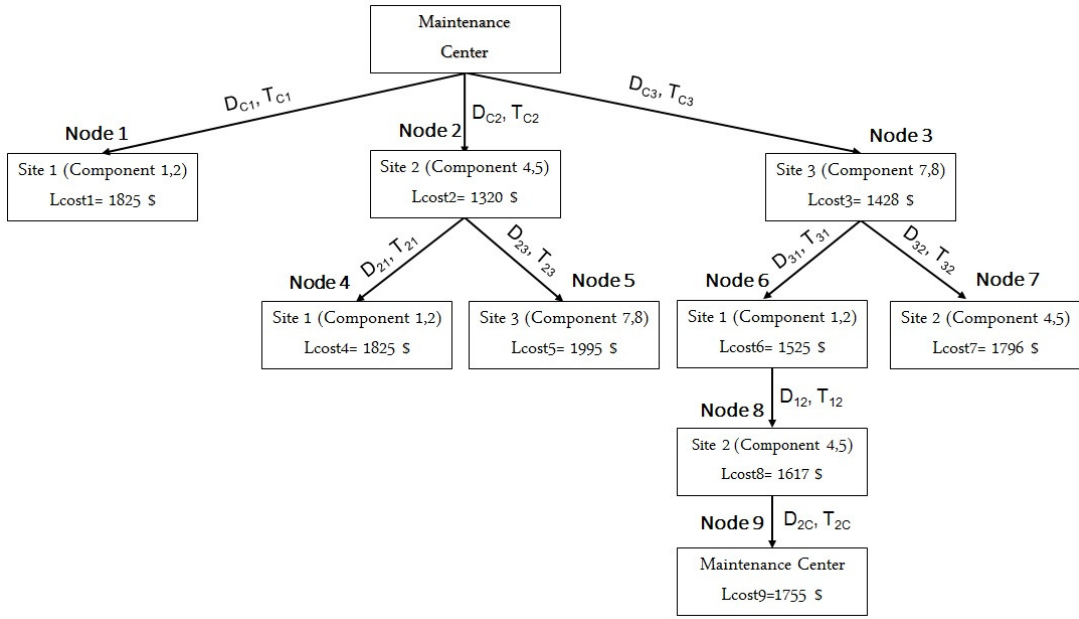


Figure 6.1: Optimization procedure based on SMaRS

Remember that BAB technique is a critical enumeration of the search space. It enumerates, but constantly tries to rule out parts of the search space that cannot contain the best solution, by using lower estimated bounds of the quantity being optimized. At each visited location (node), a minimum travel distance/ transportation cost, called lower bound, is estimated as follows:

$$LB_q = r_q + e_q \quad (6.1)$$

Figure 6.2: Search tree for the group $G_k = \{1, 2, 4, 5, 7, 8\}$

Since r_q , fixed value, is the travel distance/transportation cost from the starting point (root) to node q (corresponding to site j), and e_q is the estimated distance/transportation cost from q to the goal. Thus, f_q estimates the total travel distance/transportation cost at node q . At each step, a node with the lowest f_q value is chosen for expansion. The expanded node is called parent node and the generated nodes are child nodes. After expansion, lower bounds of all child nodes are recalculated from Equation (6.1). The solution space, consisting of all unexpanded nodes of previous set and all child nodes, is updated when each child node is generated. The work is iterated until returning starting point. The optimal maintenance itinerary is taken out from the set of solution space if its distance/transportation cost is minimum.

To facilitate the understanding, let us go to an example as in Figure 6.2. In the Figure, the root node (node 0) at the top of the tree represents the global maintenance center, the nodes at level one represent all the sites that could be visited first (node 1, node 2, and node 3), the nodes at level two represent all the sites that could be visited second (node 4, node 5, node 6, and node 7), etc. Generally, the horizontal set of all nodes at level l is denoted by HN_l . Otherwise, the vertical set of nodes, denoted $VN_{a \rightarrow b}$, represents an entire route ($a \equiv b \equiv 0$) or a part of route from node a to node b . For example, in Figure 6.2, $VN_{0 \rightarrow 8}$ denotes the part of route where the maintenance team travels from the global maintenance center to node 3, node 6, and node 8 consecutively. The BAB algorithm iteratively solves the maintenance routing problem by considering first level at a time starting from the top of the search tree (level 0) to the last level (level $ns_k + 1$).

In Figure 6.2, we consider the maintenance routing of group G_k containing components 1, 2, 4, 5, 7, and 8 located in three different sites 1, 2 and 3. The BAB will be done from the maintenance center (level 0) to the last level (level 4).

At a considered level l , the following steps are realized:

1. Estimate lower bound value of each node $q \in HN_l$. The lower bound value of node q , denoted $LB(q)$, indicates the minimum logistic cost (minimum travel distance), that we can obtain if we decide to travel across the node q .
2. Select a node for expansion. Let EHN_l be the set containing all nodes of level v (HN_v) and all unexpanded nodes of the previous levels. The node with the lowest value of the lower bound among all nodes in EHN_l (the most promising node) will be selected for the expansion.
3. Expand the selected node. The node expansion is to identify all possible nodes that the maintenance team can directly travel to from the selected node. The expanded node is called parent node, and the generated nodes are child ones. The BAB process then jumps to the level of the child nodes.

The only one problem now is how to estimate the lower bound value. Firstly, let L_{jm} denote the distance between two sites j and m . $L_{jm} = +\infty$ if there is no direct route connecting the two sites. The lower bound of transportation cost which represents the smallest transportation cost, that the routes traveling across node q can be obtained, is calculated as

$$LBTC(q) = R^{tr} \cdot (L_{0 \rightarrow q} + \hat{L}_{q \rightarrow 0}) \quad (6.2)$$

- $L_{0 \rightarrow q}$ is the total travel distance of the planned part of the routes from the maintenance center to node q . Consider node 2 in Figure 6.2, we have $L_{0 \rightarrow 2} = L_{02}$.
- $\hat{L}_{q \rightarrow 0}$ is the expected total travel distance of the unplanned part of the routes from node q to the maintenance center. Since the route from node q to global maintenance center is still unknown, the calculation of its total distance has to be done approximately. Consider a site m that the maintenance team has not yet visited $m \notin VN_{0 \rightarrow q}$, it is clear that the shortest distance to go to site m is $L_m^{min} = \min_{j \in SJ} L_{jm}$. SJ is the set of sites that the maintenance team could be in before visiting site m . Consequently, we have

$$\hat{L}_{q \rightarrow 0} = \sum_{m \notin VN_{0 \rightarrow q}} L_m^{min} \quad (6.3)$$

For example, turning back node 2 as shown in Figure 6.2, the maintenance team has already visited site 2. The expected travel distance of the unplanned part is

$$\hat{L}_{2 \rightarrow 0} = \min(L_{10}, L_{30}) + \min(L_{21}, L_{31}) + \min(L_{23}, L_{13}) \quad (6.4)$$

Based on above principle, an algorithm simulating the function of lower bound of transportation cost (*LBTC*) is given by Algorithm 1. From that, the procedure to find the cheapest maintenance itinerary implemented by sBAB is demonstrated in Algorithm 2.

Algorithm 1 Calculating lower bound of transportation cost when expanded at node q corresponding to j

- 1: **function** LBTC=LBTCFUNCTION($L, VN_{0 \rightarrow q}, Route, SJ$) \triangleright Where L - Distance matrix, $VN_{0 \rightarrow q}$ - vertical set of visited nodes, $Route$ - route that maintenance team travel from $MC(0)$ to node q , SJ - the set of sites that the maintenance team could be in before visiting site.
 - 2: $CD = L_{Route}$ \triangleright CD (current distance) - total transportation cost from MC to node q
 - 3: **for** $m \notin VN_{0 \rightarrow q}$ **do**
 - 4: $L_m^{\min} = \min \{L_{jm} | j \in SJ\}$
 - 5: $ED = sum \{L_m^{\min} | m \notin VN_{0 \rightarrow q}\}$ \triangleright ED - expected total travel distance from node q to MC
 - 6: $LBTC = R^{tr}.sum \{CD, ED\}$ \triangleright lower bound of transportation cost
 - 7: **end function**
-

After using sBAB, a set of maintenance itineraries with the lowest transportation cost for a specific group is provided. In this set, maintenance cost according to these itineraries can be different due to the impact of penalty cost. As an example, in figure 3.4, two different maintenance routes in a and b have the same travel distance/transportation cost. However arrival time/execution dates of components at the same site may be different due to different moving directions of maintenance itineraries. This reason leads to difference of penalty cost, in other words, difference of total maintenance cost. To determine a maintenance itinerary with the lowest maintenance cost (the highest economic profit) in this set, a comparison procedure of economic profit between these itineraries is formulated as shown in Algorithm 3. In this procedure, the higher the economic profit is, the better the itinerary is. The total economic profit and the optimal departure time of group G_k is described by Equation (5.8) and (5.9) respectively. It should be noted that the optimal departure time is determined based on the Nelder–Mead algorithm referred in Matlab platform.

Algorithm 2 Using Brand and Bound method to find the shortest route

```

1: procedure OPTIMAL ROUTE WITH MINIMUM COST
2:    $L = \{L_{jm}\}$  ▷ Distance matrix
3:    $Route = \{0\}$  ▷ Maintenance itinerary is started at global maintenance center (0)
4:    $SoS = \{0, 1, 2, \dots, n\}$  ▷ Set of all visited sites
5:    $CSS = \{S_0\}$  ▷ Complete solution set; there is one element at beginning position
6:    $St = 1$  ▷ Declare condition to stop; algorithm stop when St=2
7:    $q = 0$  ▷ Root node
8:   while  $St < 2$  do
9:     for  $m = SoS - (Route \cap SoS)$  do
10:       $q = q + 1$ 
11:       $VN_{0 \rightarrow q} = \{j | j \in Route\}$  ▷ Vertical set of visited nodes
12:       $SJ = SoS - Route\{1, \dots, (end - 1)\} - \{m\}$  ▷ The set of sites that the
maintenance team could be in before visiting site
13:       $LBTC_q = LBTC_{Function}(L, VN_{0 \rightarrow q}, Route, SJ)$  ▷ Call function of lower
bound of transportation cost
14:       $RouteS_q = \{Route, m\}$ 
15:       $[Index, \min Cost] = \min(LBTC)$  ▷ Position and value get minimum cost
16:       $CSS = \{CSS, S_{Index}\}$  ▷ Update the complete solution set
17:       $Route = RouteS_q$  ▷ Update the route
18:      if  $length(Route) = n + 1$  then
19:         $Route_{final} = \{Route, 0\}$ 
20:         $LBTC_{final} = LBTC_{index}$ 
21:         $St = St + 1$ 
22: end procedure

```

Algorithm 3 Comparison procedure

```

1: procedure OPTIMIZING MAINTENANCE SCHEDULING
2:    $Route1 = Route_{final}$ 
3:    $ETC1 = \{ETC1_i | i \in Route1\}$       ▷ Maintenance execution time of components
      corresponding to Route1
4:    $H_{R1} = sum\{f(ETC1_i)\}$       ▷ Total penalty cost of components corresponding to
      Route1
5:    $Route2 = flipfr(Route_{final})$       ▷ Flipping maintenance itinerary
6:    $ETC2 = \{ETC2_i | i \in Route2\}$       ▷ Maintenance execution time of components
      corresponding to Route2
7:    $H_{R2} = sum\{f(ETC2_i)\}$       ▷ Total penalty cost of components corresponding to
      Route2
8:   if  $H_{R1} \leq H_{R2}$  then
9:      $Route_{optimal} = Route1$           ▷ The optimal maintenance itinerary
10:     $Schedule_{optimal} = ETC1$         ▷ The optimal maintenance schedule
11:  else
12:     $Route_{optimal} = Route2$           ▷ The optimal maintenance itinerary
13:     $Schedule_{optimal} = ETC2$         ▷ The optimal maintenance schedule
14: end procedure

```

6.2.2 Optimization algorithm for JMaRS approach

In this subsection, the objective is to develop jBAB algorithm to find an optimal maintenance plan at group level with maximizing economic profit of the model identified in Section 5.3.2. In search process of this method, optimization of maintenance routing and maintenance scheduling are implemented simultaneously. By that way, interactions between two processes are investigated, so this method can lead to global optimization of maintenance routing and scheduling. More precisely, to simulate jBAB, the lower bound identified in Equation (6.1) is modified as follows:

$$LBC_q(I_{G_k}, t_{G_k}) = LBTC_q(I_{G_k}) + LBPC_q(I_{G_k}, t_{G_k}) \quad (6.5)$$

Where

$LBTC_q(I_{G_k})$: the lower bound of transportation cost of the routes containing node q .
 $LBPC_q(I_{G_k}, t_{G_k})$: the lower bound of penalty cost of the routes containing node q .

The problem is how to calculate the lower bound cost of Equation (6.5). The difficulty is that the lower bound cost consisting of both transportation cost and penalty cost not only depends on travel distance but also execution dates of components. The lower bound of transportation cost only depends on travel distance and can be calculated by Equation (6.2). Whereas, the lower bound of penalty cost depends on travel time, and calculating this lower bound is more complex because determining execution dates of components in a group to optimize penalty cost is an extreme difficult work. The reason is that execution dates depend on undetermined factors such as departure time and travel itinerary, analyzed in subsection 5.3.2. To calculate this part, the lower bound of penalty cost of the routes containing node q is proposed as follows:

$$LBPC_q(I_{G_k}, t_{G_k}) = H_{0 \rightarrow q} + \hat{H}_{q \rightarrow 0} \quad (6.6)$$

- $H_{0 \rightarrow q}$ is the total penalty cost related to the planned part of the routes from the maintenance center to node q . Note that with the given planned part, the arrival time of the maintenance team at each site can be calculated as $t'_{i_s} = f(t_{G_k}, VN_{0 \rightarrow q})$ if the departure time at maintenance center, denoted t_{G_k} , is determined. Because a part of itinerary from root node to node q is defined, the execution dates of components at visited sites can be determined based on Equations (5.20) and (5.21). Let CP_q denote the set of all components that have been visited by the maintenance team within the planned part of the routes, $H_{0 \rightarrow q}$ can be calculated as

$$H_{0 \rightarrow q} = \sum_{i \in CP_q} h_i(t'_{i_s}, t_{i_s}) \quad (6.7)$$

Consider the example, we have

$$H_{0 \rightarrow 2} = h_4(t'_{4_s}, t_{4_s}) + h_5(t'_{5_s}, t_{5_s}) \quad (6.8)$$

Note that $t'_{4_s} = t'_{5_s} = T A S_2$.

- $\hat{H}_{q \rightarrow 0}$ is the expected total penalty costs related to the unplanned part of the routes. Given the part of the routes has not planned yet, the determination of t'_{i_s} of component i located on site m has to be done approximately. m is a site that the maintenance team has not visited yet. t'_{i_s} will be smallest if the maintenance team directly go to site m after leaving node q . We have

$$t'_{i_s}{}^{min} = T L S_w + \frac{L_{wm}}{V} \quad (6.9)$$

where, w is the site corresponding to node q , $T L S_w$ is the time when the maintenance team leaves node q . V is average moving speed.

On the contrary, t'_{i_s} will be biggest if $L_{w \rightarrow m}$ is maximal. Let W denote the set contains all sites that the maintenance team has not visited yet and site w , the maximum of t'_{i_s} can be determined as

$$t'_{i_s}{}^{max} = T L S_w + \frac{\sum_{y \neq w, y \in W} \left(\max_{j \neq u, j \in W} L_{jy} \right)}{V} \quad (6.10)$$

Based on the maximum and minimum values of t'_{i_s} , the minimum value of $h_i(t'_{i_s}, t_{i_s})$ is

$$h_i^{min}(t'_{i_s}, t_{i_s}) = \begin{cases} h_i(t'_{i_s}{}^{min}, t_{i_s}) & \text{if } t_{i_s} \leq t'_{i_s}{}^{min} \\ 0 & \text{if } t'_{i_s}{}^{min} < t_{i_s} < t'_{i_s}{}^{max} \\ h_i(t'_{i_s}{}^{max}, t_{i_s}) & \text{if } t_{i_s} \geq t'_{i_s}{}^{max} \end{cases} \quad (6.11)$$

Let CUP_q denote the set of all components that have not been visited by the maintenance team, $\hat{H}_{q \rightarrow 0}$ is expressed as

$$\hat{H}_{q \rightarrow 0} = \sum_{i \in CUP_q} h_i^{min}(t'_{i_s}, t_{i_s}) \quad (6.12)$$

Consider the example of node 2, we have

$$\hat{H}_{2 \rightarrow 0} = h_1^{min}(t'_{1_s}, t_{1_s}) + h_2^{min}(t'_{2_s}, t_{2_s}) + h_7^{min}(t'_{7_s}, t_{7_s}) + h_8^{min}(t'_{8_s}, t_{8_s}) \quad (6.13)$$

Consequently, lowest bound cost at node q is determined based on Equations 6.5. It should be noted that, both departure time at global maintenance center and maintenance itinerary are not predetermined. Assume that maintenance team and maintenance resource are available any time. It means that maintenance team can start whenever they

want in order to get the lowest penalty cost. Thus, optimal departure time and optimal maintenance itinerary of group G_k , denoted $t_{G_k}^*$ and $I_{G_k}^*$ respectively, are given as follows:

$$LBC_q^{\min}(I_{G_k}^*, t_{G_k}^*) = \min_{\substack{t_{G_k}=0 \rightarrow \infty \\ I_{G_k} \in SI}} LBC_q(I_{G_k}, t_{G_k}) \quad (6.14)$$

Based on above principle, an algorithm simulating the function of lower bound considering

Algorithm 4 Calculate lower bound cost at node q corresponding to site w

- 1: **function** LBC=LBCFUNCTION($LBTC, VN_{0 \rightarrow q}, SJ, ETC, L, VN_{0 \rightarrow q}, Route, TLS_w, q, w, t_i$)
 \triangleright Where $LBTC$ - lower bound of travel cost, $VN_{0 \rightarrow q}$ - vertical set of visited nodes, SJ - the set of sites that the maintenance team could be in before visiting site, ETC - execution time of components in $VN_{0 \rightarrow q}$, L - distance matrix, TLS_w - time that maintenance team leaves site w , q - current node, w - current site, t_i - tentative dates of components.
 - 2: **if** $i \in VN_{0 \rightarrow q}$ **then**
 - 3: $H_{0 \rightarrow q} = \text{sum}(f(ETC_i))$ \triangleright Total penalty cost of all components contained in itinerary from root node (0) to node q
 - 4: **else**
 - 5: $t'_{i_s}{}^{\min} = TLS_w + \text{MinTravelTime}_{wm}$ \triangleright The shortest time that a component i located outside the route from MC to site w is maintained
 - 6: $t'_{i_s}{}^{\max} = TLS_w + \text{MaxTravelTime}_{wm}$ \triangleright The longest time that a component i located outside the route from MC to site w is maintained
 - 7: **if** $t_i < t'_{i_s}{}^{\min}$ **then**
 - 8: $h_i = f(t'_{i_s}{}^{\min})$
 - 9: **else if** $t_i > t'_{i_s}{}^{\max}$ **then**
 - 10: $h_i = f(T = t'_{i_s}{}^{\max})$
 - 11: **else**
 - 12: $h_i = 0$
 - 13: $\hat{H}_{q \rightarrow 0} = \text{sum}(h_i)$
 - 14: $LBPC_q = H_{0 \rightarrow q} + \hat{H}_{q \rightarrow 0}$ \triangleright Lower bound of penalty cost (see in Algorithm 1)
 - 15: $LBTC_q = \text{LBTCFunction}(L, VN_{0 \rightarrow q}, Route, SJ)$ \triangleright Call function of lower bound of transportation cost
 - 16: $LBC = LBPC_q + LBTC_q$ \triangleright Lower bound cost of at node q corresponding to w
 - 17: **end function**
-

both transportation cost and penalty cost is shown in Algorithm 4. From that, the procedure to find the cheapest maintenance itinerary implemented by jBAB is demonstrated

Algorithm 5 Using Brand and Bound method to find the best itinerary with highest economic profit

```

1: procedure OPTIMAL ITINERARY WITH HIGHEST ECONOMIC PROFIT
2:    $L = \{L_{jm}\}$  ▷ Distance matrix
3:    $Route = \{0\}$  ▷ Maintenance itinerary is started at global maintenance center (0)
4:    $SoS = \{0, 1, 2, \dots, n\}$  ▷ Set of all visited sites
5:    $CSS = \{S_0\}$  ▷ Complete solution set; there is one element at beginning position
6:    $St = 1$  ▷ Declare condition to stop; algorithm stop when  $St=2$ 
7:    $q = 0$  ▷ Root node
8:   while  $St < 2$  do
9:     for  $m = SoS - (Route \cap SoS)$  do
10:       $q = q + 1$ 
11:       $VN_{0 \rightarrow q} = \{j | j \in Route\}$  ▷ Vertical set of visited nodes
12:       $SJ = SoS - Route\{1, \dots, (end - 1)\} - \{m\}$  ▷ The set of sites that the
maintenance team could be in before visiting site
13:       $ETC = \{t'_{i_s} | i \in j \& j \in VN_{0 \rightarrow q}\}$  ▷ Execution time of components in  $VN_{0 \rightarrow q}$ 
14:       $w = m$  ▷ Current site
15:       $TLS_w = TAS_w + sum(\omega_{i_s})$  ▷ Time that maintenance team leaves site  $w$ 
16:       $LBC = LBCFunction(LBTC, VN_{0 \rightarrow q}, SJ, ETC, L, Route, TLS_w, q, w, t_i)$  ▷
Call function of lower bound of transportation cost
17:       $RouteS_q = \{Route, m\}$ 
18:       $[Index, \min Cost] = \min(LBTC)$  ▷ Position and value get minimum cost
19:       $CSS = \{CSS, S_{Index}\}$  ▷ Update the complete solution set
20:       $Route = RouteS_q$  ▷ Update the route
21:      if  $length(Route) = n + 1$  then
22:         $Route_{final} = \{Route, 0\}$ 
23:         $LBTC_{final} = LBTC_{index}$ 
24:         $St = St + 1$ 
25: end procedure

```

in Algorithm 5. In the jBAB algorithm, the optimal departure time $t_{G_k}^*$ is determined based on the Nelder–Mead algorithm referred in Matlab platform.

Note that both sBAB and jBAB only address optimization of maintenance grouping and routing at group level. In other words, optimization is only perform for each specific group. To optimize maintenance grouping at grouping structure level, we develop an advanced algorithm which considering joint optimization of maintenance planning and routing. The detail is presented in next section.

6.3 At grouping structure level

The purpose of this section is to develop an advanced algorithm based on GA and BAB method, named GAB, to optimize maintenance planning and routing for the proposed strategy. In fact, GA is an effective method in addressing optimization problem of maintenance planning for production systems, especially large scale system with multi-component, multi-site and multi-constraint [1, 51, 55]. Normally, a procedure of traditional GA includes the following steps. Initially, GA starts by randomly creating a set of possible grouping structures. At each GA's iteration, the grouping structures are compared based on their total economic profit (EPS), also called fitness/objective function. The good grouping structures with higher economic profit will be saved and improved by applying genetic operations such as crossover, mutation, and elitism. GA is stopped when stopping criteria such as the maximum iteration number is reached. To GA more adapted for a GDPS for which routing optimization is an extremely part in establishing maintenance strategy, a BAB algorithm is integrated into a procedure of traditional GA as illustrated in Figure 6.3. The principle of this algorithm is described as follows:

- *Step 1: Coding.* This step is aimed at defining the way to introduce a grouping structure in GAB. A grouping structure is here represented by an array GS in which elements of GS , denoted $EGS_p(i^z)$, is defined: $EGS_p(i^z) = k$ if z_{th} maintenance activity of component i is in group k . For instance, The coding of a grouping structure containing 3 groups $G_1 = \{1^1, 2^1\}$, $G_2 = \{3^1, 1^2\}$, $G_3 = \{4^1\}$ is shown in Figure 6.4.
- *Step 2: Generating a population of grouping structures.* GAB creates randomly an initial population of grouping structures. It should be noted that the maximum number of groups in a grouping structure is equal to length of array GS (denoted $length(GS)$). To generate a grouping structure, the number of groups is randomly chosen in $[1, length(GS)]$. Next, all PM activities are randomly put into the chosen

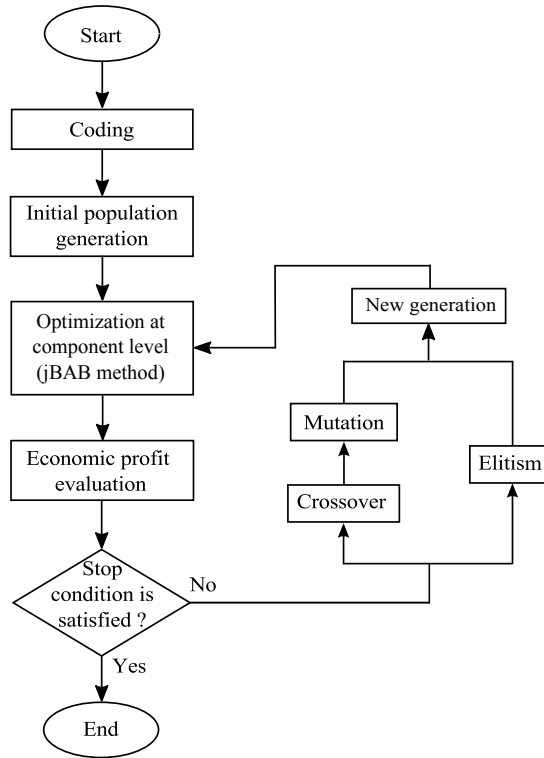


Figure 6.3: The principle of GAB for grouping maintenance and routing optimization problem

$$GS = \begin{array}{|c|c|c|c|c|} \hline 1 & 1 & 2 & 3 & 2 \\ \hline \end{array}$$

PM activities 1^1 2^1 3^1 4^1 1^2

Figure 6.4: Encoding for a grouping structure

groups in which two maintenance activities of a component do not lie in the same group. Coming back above example, $GS(1^1)$ has to differ $GS(1^2)$.

- *Step 3: Optimization at group level.* The outstanding of our proposal algorithm than traditional genetic algorithm is that we integrate an optimization process at group level into classical genetic algorithm. Before evaluating economic profit of grouping structure EPS , economic profit of its each group at group level EPG should be determined. To do this, for a group G_k , the jBAB method is applied to find the optimal departure time ($t_{G_k}^*$) and optimal maintenance itinerary ($I_{G_k}^*$) with the highest grouping economic profit. Based on selected maintenance itinerary and departure time, the performance of a grouping structure can be evaluated at next step.
- *Step 4: Evaluating the performance of grouping structure by fitness function.* The

performance of a grouping structure in the population is assessed by its total profit economic EPS . Based on the grouping structure as well as all optimal itineraries and departure times of its groups, the grouping economic profit can be evaluated as follows:

$$EPS(GS) = \sum_{G_k \in GS} EPG(I_{G_k}^*, t_{G_k}^*) \quad (6.15)$$

- *Step 5: Elitism.* The two best grouping structures of the current population are directly copied to the next generation in order to protect them from the high level of disruption.
- *Step 6: Crossover.* Crossover is performed to combine a pair of parent grouping structures to generate better grouping structures. To do this, two PM activities are firstly randomly chosen as the crossover points. And then, the elements between these points of the selected parent grouping structures are exchanged (see Figure 6.5A). The probability that the crossover is done for a pair of grouping structures is around 80%.

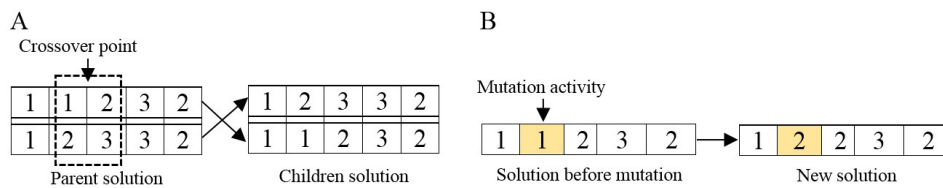


Figure 6.5: Example of crossover and mutation operators.

- *Step 7: Mutation.* Mutation helps to prevent GAB from capturing local optima. For each selected grouping structure, a maintenance activity of a group is randomly selected and then moved to another group (see Figure 6.5B). Mutation probability should be small to prevent GA from random search. It is usually chosen from 1% to 5%.
- *Step 8: New generation.* After implementing the steps 4,5,6, a new population including the best grouping structure of previous population and new grouping structure due to elitism, crossover and mutation is generated. The new generation is evaluated in the next iteration until stop criteria is triggered.
- *Step 9: Stopping.* GAB will be stopped when the maximum number of generations is reached.

Based on above principle, the GAB is simulated based on Algorithm 6.

Algorithm 6 Using combination algorithm (GAB) to find the best maintenance plan

```

1: procedure GAB ALGORITHM
2:    $sp = \text{SizeofPopulation}$ 
3:   for  $g=1 \rightarrow sp$  do
4:      $GS_g = \{EGS(i^z) | EGS(i^z) = k\}$  ▷ Coding
5:    $P = \{GS_g\}$  ▷ Generating initial population
6:    $iter = 1$ 
7:    $Stop = \text{NumberofIteration}$ 
8:   while  $iter < stop$  do  $iter = iter + 1$ ;
9:     for  $g = 1 \rightarrow sp$  do
10:      for  $k = 1 \rightarrow \max\{GS_g\}$  do
11:         $G_k = \{GS(i_z) = k\}$ 
12:         $(t_{G_k}^*, I_{G_k}^*) = \arg \min_{\substack{t_{G_k} = 0 \rightarrow \infty \\ I_{G_k} \in SI}} EPG_{G_k}(t_{G_k}, I_{G_k})$  ▷ Optimization at group level
13:         $EPG_k^{max} = EPG_k(t_{G_k}^*, I_{G_k}^*)$ 
14:         $EPS_g = \sum_{k=1}^{\max\{GS_g\}} EPG_k^{max}$ 
15:         $g^* = \arg \max_{g=0 \rightarrow sp} \{EPS_g | g = 0 \rightarrow sp\}$ 
16:         $EPS_g^{max} = EPS_{g^*}$  ▷ Economic profit evaluation
17:      if  $iter = stop$  then ▷ Stop condition
18:         $Display(GS_{g^*}, I_{G_k}^*, t_{G_k}^*)$ 
19:      else
20:         $GS_1 = GS_{g^*}$  ▷ Elitism
21:      for  $g = 2 \rightarrow sp$  do ▷ Crossover
22:         $Parent1 = \text{random}\{GS_q | q = 2 \rightarrow sp\}$ 
23:         $Parent2 = \text{random}\{GS_q | q = 2 \rightarrow sp\}$ 
24:         $ChildrenGS = \text{crossover}(Parent1, Parent2)$ 
25:         $GS_g = ChildrenGS$ 
26:      for  $mg = 1 \rightarrow \text{round}(sp/20)$  do ▷ Mutation
27:         $g = \text{random}(3 \rightarrow \text{length}(P))$ 
28:         $p = \text{random}(1 \rightarrow \text{length}(GS_g))$ 
29:         $EGS_p(i^z) = \text{random}(1 \rightarrow \max(GS_g))$ 
30:         $NGS = \{GS_g | g = 1 \rightarrow sp\}$  ▷ New generation
31: end procedure

```

6.4 Conclusion

In this chapter, we developed an advanced algorithm based on Genetic Algorithm (GA) and Branch and Bound (BAB) method, named GAB, to solve optimization problem for a GDPS. BAB is integrated into the procedure of a traditional GA to supports to determine the maximum grouping economic profit of objective function. The proposed algorithm can totally solve difficulties of the grouping maintenance optimization problem for a GDPS. Indeed, in this algorithm, optimization of maintenance routing is determined by the BAB method. Whereas, by joint consideration of GA and BAB method, the GAB algorithm can determine the optimal maintenance planning and routing for the dynamic grouping maintenance strategy of a GDPS. In addition, using the GA can make the proposed algorithm more flexible (computational time can be adjusted by changing iterations or the special parameters such as crossover rate, mutation rate,etc) and apply for large-scale GDPS including muti-components and multi-constraints.

Chapter 7

Numerical study for the proposed dynamic grouping maintenance strategy

7.1 Introduction

To study the performance and evaluate the proposed dynamic grouping maintenance strategy, a numerical study is conducted in this chapter. More precisely, validation of the dynamic grouping maintenance strategy is done through assessment of the grouping performance and performance of economic profit at group level and grouping structure level. In addition, an illustration of updating maintenance plan is done to evaluate ability to update the maintenance plan when dynamic contexts occur. Finally, a sensitivity analysis of two parameters (travel cost rate R^{tr} and site-preparation cost S_j^0) is done to illustrate sensitivity level of the proposed strategy under changes of these parameters.

To illustrate globally the results obtained, Section 7.2 presents the system data used to establish our maintenance strategy. From these data, the optimal preventive maintenance cycle and the tentative maintenance execution dates of all components are determined as presented in Chapter 4. The key content of this chapter, performance studies of the dynamic grouping maintenance strategy at group level and grouping structure level are investigated in Section 7.3 and 7.4 respectively. Section 7.5 presents a sensitivity analysis of the proposed strategy.

7.2 Given data of a typical GDPS

In this study, the proposed maintenance strategy is applied for a GDPS system which is shown in Figure 7.1. All parameters are given in arbitrary units, e.g., arbitrary time unit (atu), arbitrary distance unit (adu) or arbitrary cost unit (acu). Based on the GDPS in Figure 7.1, the connections between production sites and global maintenance center represent the possible routes to be followed by the maintenance team and distances between them. The distances are given in Table 7.1. Moreover, due to dispersion of production sites, it takes time in order that maintenance team moves among production sites and their global maintenance center. The average speed in moving the maintenance team is $V = 30$ (adu)/(atu). Then, the travel time can be easily determined by dividing the travel distance by the average speed, i.e. $d_{ij} = L_{ij}/V$. From that, a matrix time representing the travel time is shown in Table 7.2. The transportation cost rate is considered to be the same for all components $R_i^{tr} = R^{tr}$, and is equal to 18 (acu).

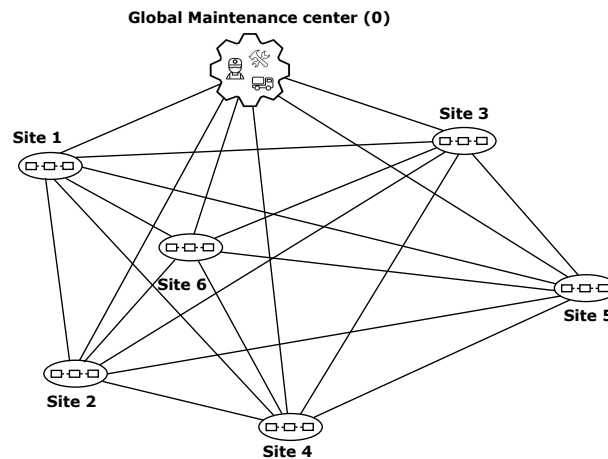


Figure 7.1: A typical GDPS containing 6 production sites

Table 7.1: Travel distances among sites and their global maintenance center

Sites	0	1	2	3	4	5	6
0	-	160	225	240	262	298	150
1	160	-	200	196	174	500	120
2	225	200	-	136	206	308	320
3	240	196	136	-	108	322	180
4	262	174	206	108	-	418	202
5	298	500	308	322	418	-	500
6	150	120	320	180	202	250	-

The main characteristics related to the components site, the down time cost rate (R_j^{dt}) and the preparation cost (S_j^{Site}) are given in Table 7.3.

Table 7.2: Travel times among sites and their maintenance center

Sites	0	1	2	3	4	5	6
0	-	5.3	7.5	8	8.7	9.9	5
1	5.3	-	6.7	6.5	5.8	16.7	4
2	7.5	6.7	-	4.5	6.9	10.3	10.7
3	8	6.5	4.5	-	3.6	10.7	6
4	8.7	5.8	6.9	3.6	-	13.9	6.7
5	9.9	16.7	10.3	10.7	13.9	-	8.3
6	5	4	10.7	6	6.7	8.3	-

Table 7.3: Components, downtime cost rate and site-preparation cost of each production site

Sites	1	2	3	4	5	6
Components	1, 2, 3	4, 5, 6	7, 8, 9	10, 11, 12	13, 14, 15	16, 17, 18
R_j^{dt}	294	316	349	365	207	294
S_j^0	210	170	120	190	140	200

The data related to components' characteristics containing the shape and scale parameters of Weibull distribution, the spare part cost, the CM cost, PM time, the age at t_{begin} , the required level of repair team skill are reported in Table 7.4.

Finally, the labor cost rates R^{lb} are fixed at 100, 170, 240 for required levels of repair team skills 1, 2, 3 respectively.

Based on the above given data, an individual maintenance planning is established and is shown in Figure 7.2. According to this planning, components are preventively maintained only one time in the horizon planning ($T = 8993.5$ unit of time)

7.3 Performance study for SMarS and JMarS approaches at group level

This section is aiming to assess the performance of the dynamic grouping maintenance strategy at group level by means of the economic profit models proposed in Chapter 5. It is assumed that 8 components $\{3,6,9,12,13,14,15,18\}$ of a group G_k need to be jointly maintained. It should be noted that these 8 components are located at 6 different sites, hence, there are $6!$ feasible itineraries that maintenance team can follow. For each maintenance itinerary, maintenance cost is very different due to differences of transportation cost and penalty cost. By applying the SMarS and JMarS approach identified in Section 5.3, the obtained results are shown in Table 7.5 and 7.6. In addition, performance of

Table 7.4: Components' data and individual maintenance optimization results

Unit	λ_i	β_i	C_i^{sp}	C_i^c	w_i	t_i^e	sl_i	S_i^{tr}	x_i^*	ϕ_i^*	t_i^1
1	2499	2.85	1757	561	30	1398	1	5760	6984.1	4.2833	5649.1
2	3257	2.77	2546	669	48	2729	2	5760	10532.4	4.5423	7896.4
3	2423	3.72	3651	628	63	781	3	5760	5753.4	10.132	4972.4
4	2815	2.87	1874	665	27	2336	1	8100	7569.3	4.3106	5299.3
5	3505	2.74	2676	722	45	2649	2	8100	11504.5	4.4643	8948.5
6	2327	3.69	3397	619	66	1142	3	8100	5773.8	11.313	4631.8
7	2645	2.82	1704	517	33	3281	1	8640	8478.5	4.5924	5197.5
8	3057	2.76	2341	547	51	3799	2	8640	11502.1	5.0869	7808.1
9	2624	3.54	3313	611	72	1035	3	8640	7141.6	10.485	6139.6
10	2446	2.88	1656	445	30	2498	1	9432	7966.3	4.8235	5534.3
11	2963	2.74	2449	628	45	2999	2	9432	10598.7	5.3347	7695.8
12	2327	3.73	3332	690	66	1105	3	9432	5665.6	12.554	4560.6
13	2698	2.84	1659	689	36	1546	1	10728	7532.2	4.7964	6109.2
14	3359	3.16	2432	609	51	3598	2	10728	9246.6	5.1051	5720.6
15	2483	3.65	3532	314	72	1819	3	10728	7452.9	8.4961	5633.9
16	2501	2.84	1757	561	30	1798	1	5400	6981.3	4.2119	5246.3
17	3262	2.76	2546	669	48	2929	2	5400	10568.9	4.4814	7732.9
18	2398	3.71	3651	628	63	981	3	5400	5699.6	10.149	4718.6

individual maintenance optimization (IMO) approach is also shown in Table 7.6.

Table 7.5: Maintenance routes and departure times provided by SMaRS and JMaRS approaches

Approaches	Departure times	Maintenance itineraries	Travel distances
JMaRS	4856.4	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow MC$	1294
SMaRS	4831	$MC \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow 6 \rightarrow MC$	1286

Table 7.6: Maintenance costs provided by SMaRS, JMaRS and individual maintenance optimization (IMO) approaches

Approaches	$C_{G_k}^{sp}$	$C_{G_k}^{dt}$	$C_{G_k}^{lb}$	$S_{G_k}^p$	$S_{G_k}^{tr}$	ΔH_{G_k}	$\Delta^t r_{G_k}$	EPG_{G_k}	$C_{G_k}^p$
JMaRS	24967	140031	117360	1030	23292	4096.1	46254	42157.9	310776.1
SMaRS	24967	140031	117360	1030	23148	5066.8	46368	41301.2	311602.8
IMO	24967	140031	108750	1310	69516	0	0	0	344574

According to obtained results from Table 7.6, total maintenance cost from IMO approach ($C_{G_k}^p$) is higher than other approaches. In other words, the economic profit models

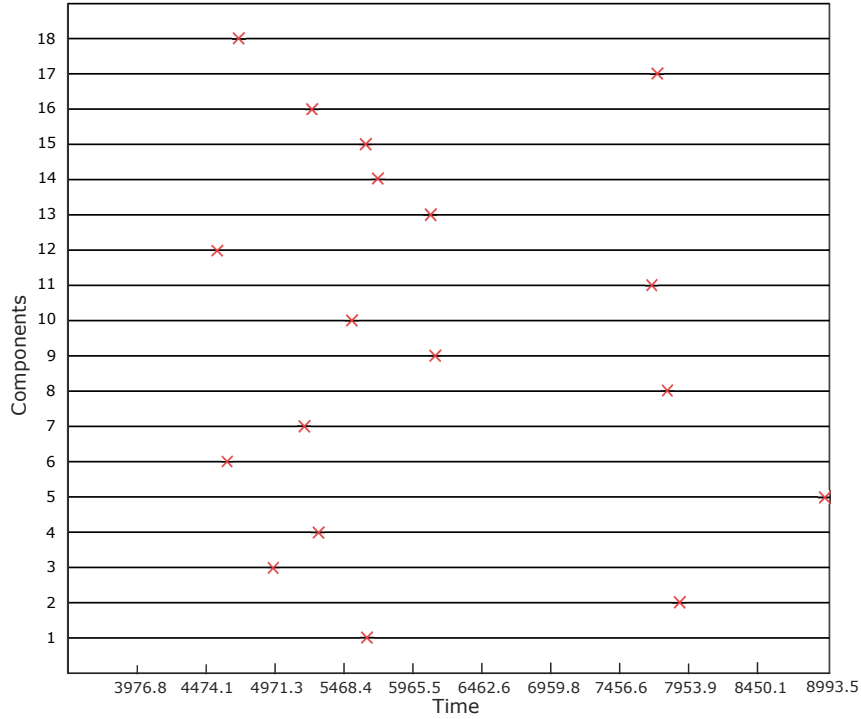


Figure 7.2: Tentative execution dates of components provided by individual maintenance planning

are higher performance than individual maintenance in terms of economic profit. In addition, obtained results in Table 7.5 show that using different approaches (JMaRS or SMaRS) leads to different maintenance itineraries and their optimal departure times are also different too. Due to the difference of maintenance itineraries, the travel distance and preventive maintenance cost corresponding to these approaches are different. This directly leads to differences of transportation cost and penalty cost between the two approaches as shown in Table 7.6. By SMaRS approach, transportation cost as well as total travel distance are the lowest. It means that transportation cost saving is the highest. However, penalty cost is slightly high because maintenance routing process finding the optimal maintenance itinerary is independent with maintenance scheduling process. In the contrast, by JMaRS approach, penalty cost reduces considerable although transportation cost increases a little. It leads to that economic profit of the considered group provided by JMaRS is higher than provided by SMaRS because the spare part cost, the down time cost, the labor cost and the preparation-site cost are unchanged due to their independence with maintenance itinerary. It means that performance provided by JMaRS approach is more effective than provided by SMaRS approach in terms of economic profit. The JMaRS should be considered in development of dynamic grouping maintenance strategy for a GDPS.

7.4 Optimal maintenance and routing plan

The aim of this section is to assess performance of the dynamic grouping maintenance strategy at grouping structure in terms of the grouping performance and economic profit performance. Performance study is investigated by three different approaches: JMaRS and JMaRS identified in Section 5.3 and IMO approach.

7.4.1 Optimization of maintenance and routing plan based on JMaRS approach

The aim of section is to illustrate performance of the dynamic grouping maintenance strategy based on JMaRS approach. Then, the performance provided by JMaRS approach is evaluated by comparing to the performance provided by IMO approach.

Individual maintenance optimization. The preventive maintenance is assumed to be carried out separately for each component of the GDPS. The maintenance team has to go to the maintained site and go back each time whenever a component of the site is preventively maintained. The transportation cost (S_i^{tr}), the optimal PM cycle (x_i^*) and the minimum maintenance cost rate (ϕ_i^*) of each component are calculated and shown in Table 7.4. Based on the obtained PM cycle and given values of t_i^e , all tentative PM dates are identified and reported in the same table 7.4 and Figure 7.2.

In this example, each component is maintained only once within planning horizon $PH = [0, t_{5^1} + \omega_5] = [0, 8993.5]$. The use of this individual maintenance plan will lead to an average maintenance cost of the system, which is equal to

$$\phi_{sys}^{individual} = \sum_{i=1}^{15} \phi_i^* = 119.16 \quad (7.1)$$

It should be noted that the transportation and setup costs respectively take 13.52% and 13.81% of the above cost. The reduction of the two costs is then crucial from the economic point of view. The grouping maintenance is a promising solution to solve this problem.

Grouping maintenance. In order to reduce the transportation cost, the proposed grouping optimization approach is applied. The adapted GA and the BAB with taking into account the grouping penalties during the finding of the optimal route are implemented for the considered system. The obtained results are shown in Table 7.7 and Figure 7.3.

According to the Table 7.7, the best grouping structure contains three groups. The components in each group are optimally selected to satisfy a number of factors such as the

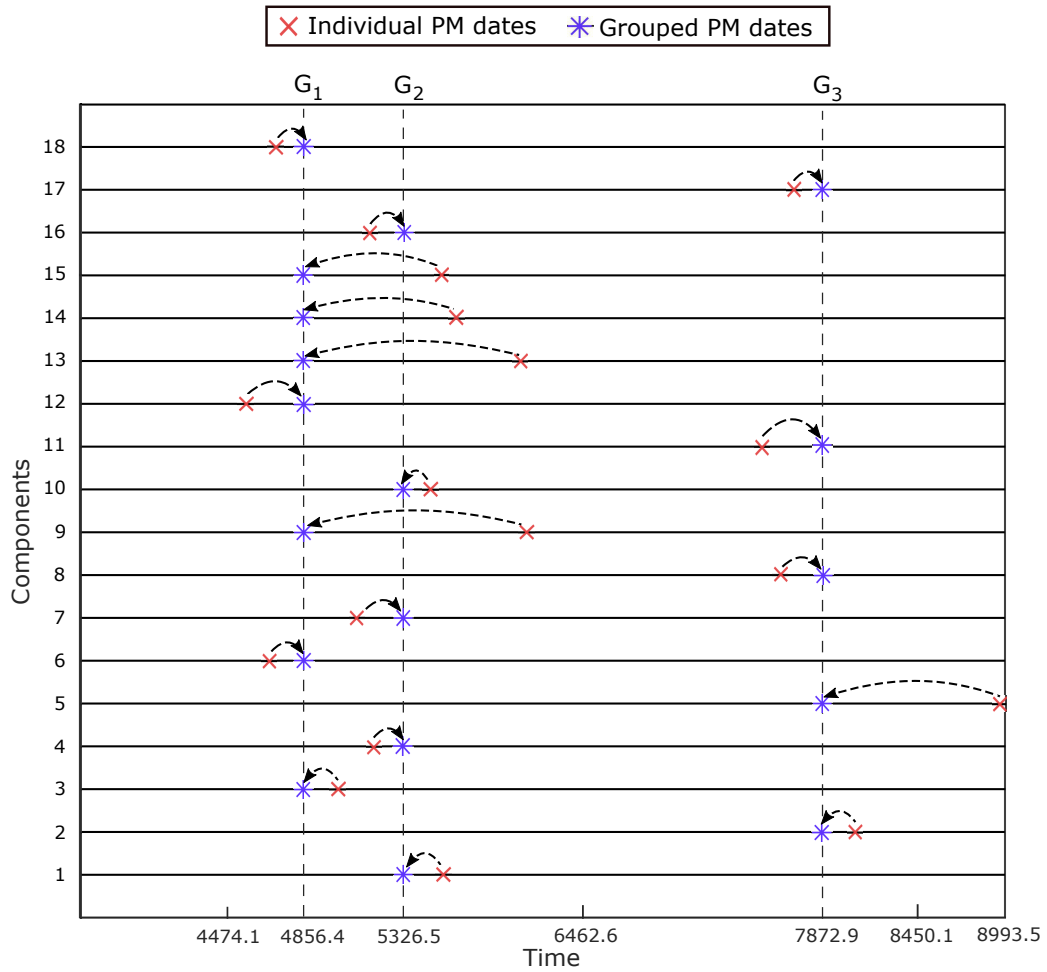


Figure 7.3: Optimal grouped maintenance plan

Table 7.7: Optimal grouping structure and maintenance costs provided by JMaRS

Optimal grouping structure	$\Delta S_{G_k}^{tr}$	$\Delta S_{G_k}^0$	$\Delta C_{G_k}^{lb}$	ΔH_{G_k}	EPG_{G_k}	EPS
$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$	46224	280	8610	4096.1	33797.9	75215.3
$G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$	20898	0	0	68.7	20829.3	
$G_3 = \{2^1, 5^1, 8^1, 11^1\}$	20898	0	0	309.9	20588.1	

saving of transportation cost, the penalties related to the shift of execution date and the labor costs. Among these factors, the transportation cost saving takes the most important part (the biggest value), and has the strongest impact on the composition of the groups. Indeed, even if the PM dates of components 13, 14, 15 of site 5 (the farthest site from the maintenance center) are not closed, they are still grouped in group G_1 , because the grouping of these components can significantly reduce the transportation cost. For this reason, the tentative PM dates of components of the optimal groups are not necessary to

be closed to each other as underlined by the other existing works dealing with centralized multi-component systems.

The joint optimization of dynamic grouping and routing scheduling helps to reduce 61.05% of travel distance of the maintenance team as well as the transportation cost, and save up to 9.06% of preparation cost when comparing to the individual maintenance. The reduction of travel distance is very important since it is not only meaningful from economic point of view, but also sustainable one (i.e. reduce energy consumption, travel-related risks, environmental negative impacts). Along with the above advantages, the grouping maintenance also leads to some disadvantages and penalties. Indeed, the labor cost increases 5.25% and penalty cost reaches to 4474.7 (acu). In summary, the grouping maintenance helps to save up to 7.05% of total maintenance cost when compare to the individual one. The average maintenance cost of the system when the maintenance activities of components is grouped is:

$$\phi_{sys}^{grouping} = \phi_{sys}^{individual} - \frac{EPS}{t_{end}} = 110.75 \quad (7.2)$$

Maintenance routing. To guarantee the above performances of the grouping maintenance plan, the maintenance team has to respect the optimal maintenance itineraries and the optimal departure times from the maintenance center, which are specified in Table 7.8.

Table 7.8: Optimal maintenance routes and optimal departure times provided by JMaRS

Groups	Departure times	Maintenance routes	Travel distances
$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$	4856.4	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow MC$	1294
$G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$	5326.5	$MC \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 6 \rightarrow MC$	913
$G_3 = \{2^1, 5^1, 8^1, 11^1, 17^1\}$	7872.9	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow MC$	913

According to obtained results shown in Table 7.8, to do the PM of group G_1 , the maintenance team has to start from the maintenance center at 4856.4 (atu), travel across the sites 6, 1, 4, 3, 2 and 5 respectively, and return to the maintenance center. The total travel distance of the round trip is equal to 1294 (adu). When compared to the individual maintenance, the total travel distance is saved up to 66.5%. The same as the group G_1 , to do the maintenance of group G_2 , the maintenance team has to start from the maintenance center at 5073.2 (arbitrary time unit), and travel across sites 2, 3, 4, 1 and 6 consequently and return to the maintenance center. The total travel distance of the round trip is equal to 913 (adu) and this trip saves 76.35% in relation to individual maintenance. Note that to do the PM of group G_2 , the visiting of site 5 is not necessary. Finally, maintenance journey of group G_3 starts from maintenance center at time 7872.9 (atu), then travels across the sites 6, 1, 4, 3 and 2 respectively, and returns to the maintenance center. The

total travel distance of the round trip and saving travel distance is similar as G_2 . Another reason that maintenance team has to follow these itineraries is that penalty cost due to the shift of execution dates of components is minimum in these cases. As an example, G_2 and G_3 have the same travel distance, however moving direction of maintenance team is different in two cases. The reason is that their penalty cost reach to minimum value respective to their direction.

As a consequence, performance of the proposed strategy is better than individual optimization strategy in terms of economic profit. The proposed strategy can make penalty cost and labor cost go up, however cost-savings from transportation cost and setup cost is too great and can compensate for the losses caused by grouping maintenance.

7.4.2 Optimization of maintenance and routing plan based on SMaRS approach

The aim of this section is to illustrate performance of the dynamic grouping maintenance strategy based on SMaRS approach. Then, this performance is assessed by comparing to the performance provided by JMaRS approach. It is assumed that the GDPS remains as Section 7.4.1, the obtained results when establishing maintenance strategy based on the JMaRS approach are shown in Tables 7.9 and 7.10.

Table 7.9: Optimal grouping structure and maintenance costs provided by SMaRS

Optimal grouping structure	$\Delta S_{G_k}^{str}$	$\Delta S_{G_k}^0$	$\Delta C_{G_k}^{lb}$	ΔH_{G_k}	EPG_{G_k}	EPS
$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$	46368	280	8610	5066.8	32971.2	74388.6
$G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$	20898	0	0	68.7	20829.3	
$G_3 = \{2^1, 5^1, 8^1, 11^1\}$	20898	0	0	309.9	20588.1	

Table 7.10: Optimal maintenance routes and optimal departure times provided by SMaRS

Groups	Departure times	Maintenance routes	Travel distances
$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$	4831	$MC \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow 6 \rightarrow MC$	1286
$G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$	5326.5	$MC \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 6 \rightarrow MC$	913
$G_3 = \{2^1, 5^1, 8^1, 11^1, 17^1\}$	7872.9	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow MC$	913

By comparing the obtained results shown in Tables 7.8 and 7.10, we can see that both JMaRS and SMaRS have the identical grouping structure, however, the optimal route and departure time of group G_1 provided by the two approaches are different. The differences of maintenance itinerary and departure time provided by these two approaches lead to

differences of penalty cost and transportation cost saving of group G_1 (see Tables 7.7 and 7.9). It should be noted that the site-preparation cost saving and labor loss cost of group G_1 provided by the two approaches are equal because these costs do not depend with maintenance itinerary and departure time of this group.

From the Tables 7.7 and 7.9, transportation cost saving provided by JMaRS is slightly lower than SMaRS approach. However penalty cost provided by JMaRS is too lower than SMaRS approach. Consequently, economic profit of group G_1 provided by JMaRS is higher than SMaRS approach. In addition, economic profit of G_2 and G_3 provided by the two approach are identical, so total economic profit of the grouping structure (EPS) provided by JMaRS approach is higher than SMaRS approach. It means that performance provided by JMaRS is always better than SMaRS in terms of economic profit.

7.4.3 Updating of maintenance and routing plan in dynamic context

The objective of this subsection is to present how the grouping maintenance plan can be updated when dynamic contexts occur. For this purpose, a dynamic context $n^o 1$ "Change of maintenance routes" (see again Section 4.4) was considered.

Assume that the optimal grouping solution presented in Table 7.7 and 7.8 is used. After the maintenance of group G_1 , at 5056.4 (atu), the direct road between the maintenance center and site 6 is interrupted for a long period due to road maintenance activities. As a consequence, to go to site 6 from the maintenance center, the maintenance team has to travel on the other road via site 1 with a longer distance. The travel distance of the new road is $L'_{60} = L'_{06} = L_{01} + L_{16} = 280$ (adu). This means that a new logistic dependence between sites 1 and 6 occurs. In the presence of this situation, the current grouped maintenance planning and routing may be no longer optimal and need to be updated as soon as possible. To do this, the proposed grouping strategy is re-executed. The optimization process starts from the "Individual maintenance optimization" step to update optimal maintenance schedule of components located at site 6. After that, next step "Individual planning" gives a new horizon, namely H2, begun from $t_{begin_H2} = 5056.4$ (atu) (see Figure 7.4). As shown in this figure, after the components 3, 6, 9, 12, 13, 14, 15, 18 are maintained at first time in horizon 1. Their next replacements are performed in horizon 2. The tentative planning of components 16, 17 located at site 6 is stretched because maintenance team travels a longer distance to accept site 6. Whereas, the rest of components still remain their tentative planning because they are not affected by this interruption.

At the end of the process, new optimal grouped maintenance planning is provided and

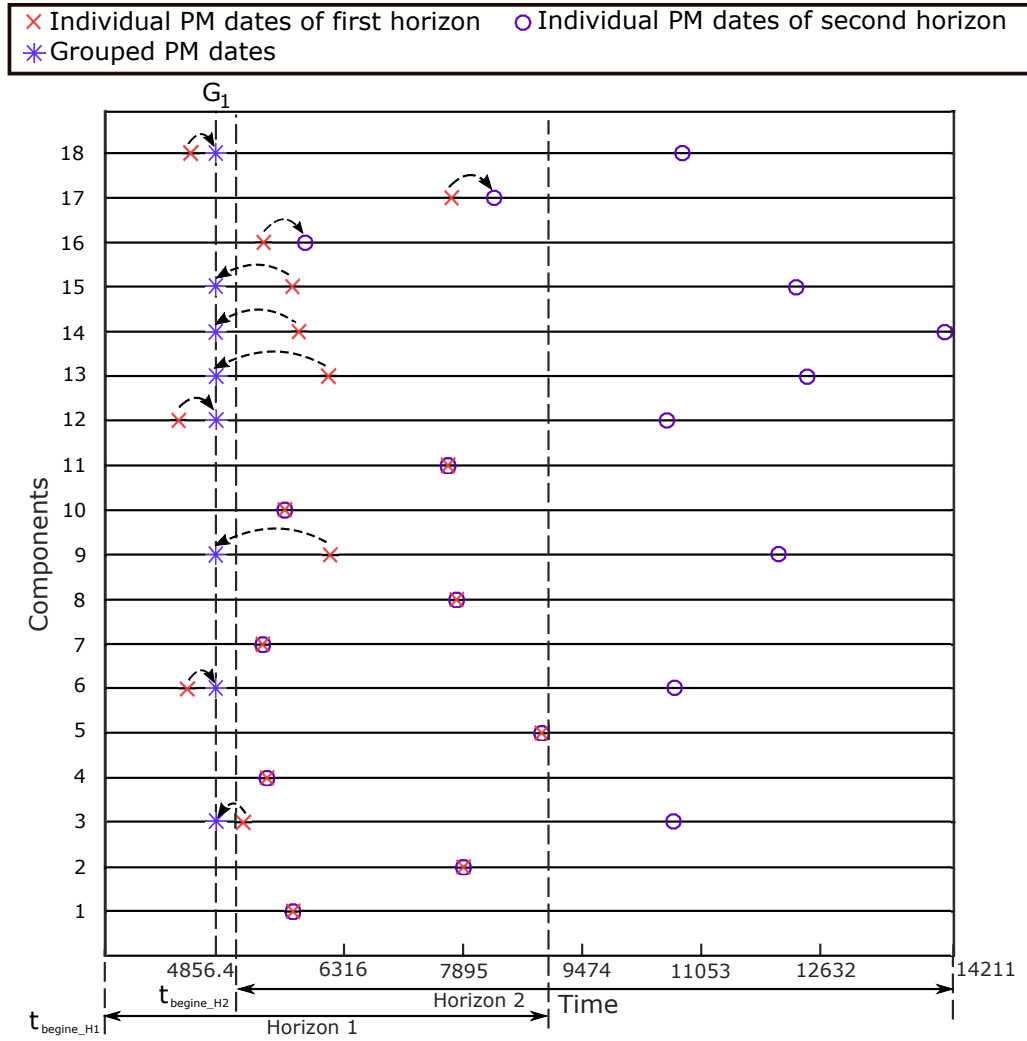


Figure 7.4: Updating tentative individual planning

sketched in Figure 7.5. G_i^{Hj} indicates the group i of the horizon j . The maintenance routing results are shown in Table 7.11.

Table 7.11: Optimal maintenance itineraries after updating

G_k^{H2} of GS^*	$t_{G_k}^*$	$I_{G_k}^*$	$L_{G_k}^*$
$G_1^{H2} = \{1^1, 2^1, 4^1, 5^1, 7^1, 8^1, 10^1, 11^1, 16^1, 17^1\}$	6273.6	$MC \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 6 \rightarrow 1 \rightarrow MC$	951
$G_2^{H2} = \{3^2, 6^2, 9^2, 12^2, 18^2\}$	10730	$MC \rightarrow 1 \rightarrow 6 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow MC$	951
$G_3^{H2} = \{13^2, 14^2, 15^2\}$	12711	$MC \rightarrow 5 \rightarrow MC$	596

The obtained results show that taking into account the dynamic context leads to the new grouping and routing solutions (Table 7.11). Indeed, components 2, 5, 8, 11, and 17 are maintained sooner than before, while the maintenance of components 1, 4, 7, 10 and 16 are postponed. These components are grouped to group G_{H2}^1 at 6273.6 (atu). From

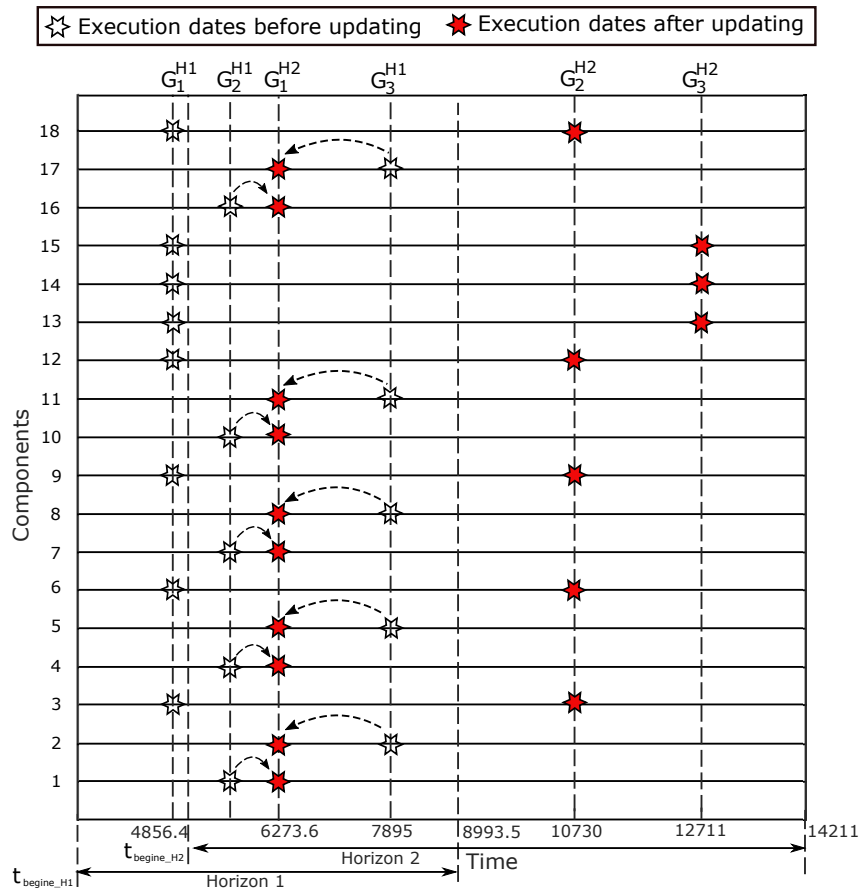


Figure 7.5: Updating the grouping maintenance planning in the presence of a road interruption

the logistic point view, the new configuration of the group is reasonable. In fact, given the interruption of the direct road between the global maintenance center and site 6, the maintenance team now starts from the maintenance center and then directly goes to site 1 instead of site 6. The solution with the direct connection between the maintenance center and site 6 no longer exists in the new grouping and routing solutions.

7.5 Sensitivity analysis

As mentioned before, the main intent of grouping maintenance is to save the transportation and setup costs. The grouping performance then strongly depends on the transportation cost rate and site-preparation cost. It is the reason of this sensitivity analysis.

7.5.1 Sensitivity analysis on the transportation cost rate

The aim of the subsection is to assess the impact of transportation cost rate (R^{tr}) on grouping optimization process. To do this, the proposed grouping strategy is applied for different cases where the transportation cost rate is varied from 5 to 95 (acu), while the other given data remain unchanged. The case where $R^{tr} = 0$ is not considered because it rarely occurs in the real life.

Table 7.12: Sensitivity analysis of grouping structure to transportation cost rate

R^{tr}	GS^*	Distance saving
[5, 9]	$G_1 = \{3^1, 6^1, 12^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 13^1, 16^1\}$ $G_3 = \{9^1, 14^1, 15^1\}$ $G_4 = \{2^1, 5^1, 8^1, 11^1, 17^1\}$	4076
(9, 18]	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$ $G_3 = \{13^1, 14^1, 15^1\}$	4890
(18, 50]	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 2^1, 4^1, 5^1, 7^1, 8^1, 10^1, 11^1, 16^1, 17^1\}$	5803
(50, 95]	$G_1 = \{1^1, 2^1, 3^1, 4^1, 5^1, 6^1, 7^1, 8^1, 9^1, 10^1, 11^1, 12^1, 13^1, 14^1, 15^1, 16^1, 17^1, 18^1\}$	6716

The evolution of grouping economic profit when the transportation cost rate increases from 5 to 95 is plotted in Figure 7.6. In the figure, the bigger the transportation cost rate is, the higher the grouping economic profit is obtained. The grouping maintenance is therefore recommended for the GDPS with high transportation cost rates.

Not only the grouping performance, but also the optimal grouping structure are studied and reported for different values of transportation cost rate in Table 7.12. From the table, we can observe that when the transportation cost rate increases, the optimal grouping structure is configured such that the saving of the travel distance is maximal.

7.5.2 Sensitivity analysis on the site-preparation cost

The same study was carried out by varying the site-preparation cost. Note that in this study, the site-preparation cost is adjusted by a parameter k . The recommended site-preparation cost, denoted S^{site} , is calculated by $S^{site} = k.S_0^{site}$ (where S_0^{site} is site-preparation cost given in section 7.2). The proposed grouping strategy was applied for each value of the site-preparation cost. The obtained results are presented in Table 7.13 and Figure 7.7.

The same conclusion as in the case of the transportation cost rate can be deduced from the obtained results. The bigger the site-preparation cost is, the higher the group-

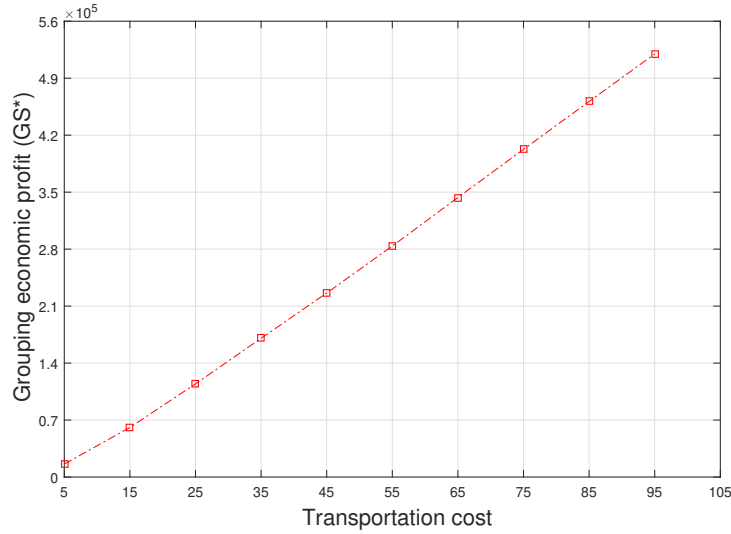


Figure 7.6: Sensitivity analysis of grouping economic profit to transportation cost rate

Table 7.13: Sensitivity analysis of grouping structure to site-preparation cost

K	GS^*	Site-preparation cost saving
[0, 1.2]	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$ $G^3 = \{2^1, 5^1, 8^1, 11^1, 17^1\}$	$2.k.S_5^0$
(1.2, 25]	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 2^1, 4^1, 5^1, 7^1, 8^1, 10^1, 11^1, 16^1, 17^1\}$	$2.k.S_5^0 + \sum_{j=1, y \neq 5}^6 S_j^0$
(25, ∞)	$G_1 = \{1^1, 2^1, 3^1, 4^1, 5^1, 6^1, 7^1, 8^1, 9^1, 10^1, 11^1, 12^1, 13^1, 14^1, 15^1, 16^1, 17^1, 18^1\}$	$2.k. \sum_{j=1}^6 S_j^0$

ing performance is. The grouping maintenance is therefore a powerful solution for the maintenance planning of a GDPS with high transportation or setup costs.

7.6 Performance study of the proposed GAB algorithm

The aim of this section is to illustrate performance of the proposed algorithm. Then, this performance is assessed by comparing to the performance provided by GAaES algorithm simulated based on Genetic Algorithm and Exhaustive Search method. The GAaES process is the same as GAB, except that the Exhaustive Search method (ES) is applied to search the optimal itinerary instead of Branch and Bound method. The Exhaustive Search method aiming to find the optimal itinerary is referred in [185]. The algorithms are simulated by Matlab R2016a running on Windows 7 and the used computer has

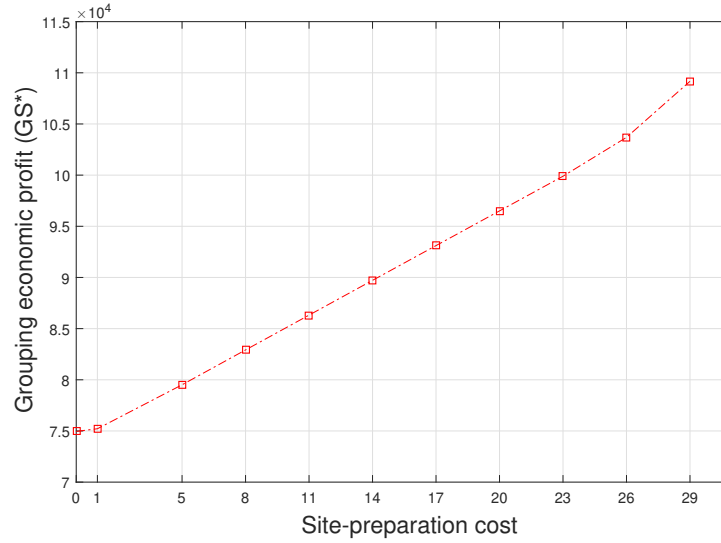


Figure 7.7: Sensitivity analysis of grouping economic profit to site-preparation cost

the following configurations: Chip (Intel (R) Core(TM) i5-4590) and Ram (4G). The computational time of simulation is accounted by time computer's time unit(ctu). It also assumes that the algorithms are executed for the proposed maintenance strategy in which the GDPS remains as Section 7.4.1.

7.6.1 At group level

The objective of this subsection is to assess performance of jBAB and ES when they are used to find an optimal maintenance plan at group level. The jBAB and the ES is executed for there different groups as shown in Table 7.14. According to Table 7.14, jBAB and ES give the identical results in terms of economic profit and optimal itinerary, however the number of search itineraries and search time are different. Indeed, the exhaustive search method give an optimal solution by considering all feasible solutions in search space, while jBAB try to rule out parts of the search space that cannot contain the best solution by using lower or upper bound. Therefore, the number of search itineraries of jBAB is less than ES. More precisely, with 8 components of group 1 located at 6 different sites, ES considers 720 feasible maintenance itineraries to find an optimal itinerary while the number of search itineraries of jBAB is 318. It explains why search time of ES is greater than jBAB. In this case, using jBAB saves approximate 30 percent time compared to ES. However, when the number of sites reduce, the search time by these methods is approximately identical. The reason is that jBAB take the amount of time to calculate lower/upper bound. Thus, in some cases, this loss time can be larger than time saving thanks to reduction of the number of itineraries. It can be seen obviously through search results of

G_2 and G_3 where only 5 sites is considered. Although the number of searching itineraries of jBAB is less than GA, time search by both methods is approximately identical.

Table 7.14: Comparison of search time between the jBAB and ES

Optimal grouping structures	Methods	Economic profit	Optimal itineraries	The number of search itineraries	Search time (ctu)
$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$	jBAB	33797.9	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow MC$	318	4.65
	ES	33797.9	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 5 \rightarrow MC$	720	6.67
$G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$	jBAB	20829.3	$MC \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 6 \rightarrow MC$	74	3.14
	ES	20829.3	$MC \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 1 \rightarrow 6 \rightarrow MC$	120	3.94
$G_3 = \{2^1, 5^1, 8^1, 11^1\}$	jBAB	20588.1	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow MC$	72	3.15
	ES	20588.1	$MC \rightarrow 6 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow MC$	120	3.97

Table 7.15: A population of GA

Individuals	Grouping structures
1	$G_1 = \{1^1, 2^1, 3^1, 4^1, 5^1, 6^1, 7^1, 8^1, 9^1, 10^1, 11^1, 12^1, 13^1, 14^1, 15^1, 16^1, 17^1, 18^1\}$
2	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$ $G_3 = \{13^1, 14^1, 15^1\}$
3	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 2^1, 4^1, 5^1, 7^1, 8^1, 10^1, 11^1, 16^1, 17^1\}$
4	$G_1 = \{3^1, 6^1, 12^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 13^1, 16^1\}$ $G_3 = \{9^1, 14^1, 15^1\}$ $G_4 = \{2^1, 5^1, 8^1, 11^1, 17^1\}$
5	$G_1 = \{3^1, 6^1, 9^1, 12^1, 15^1, 18^1\}$ $G_2 = \{1^1, 2^1, 4^1, 5^1, 7^1, 8^1, 10^1, 11^1, 13^1, 14^1, 16^1, 17^1\}$
6	$G_1 = \{3^1, 6^1, 9^1, 12^1, 15^1, 18^1\}$ $G_2 = \{1^1, 5^1, 8^1, 10^1, 13^1, 17^1\}$ $G_3 = \{2^1, 4^1, 7^1, 11^1, 14^1, 16^1\}$
7	$G_1 = \{1^1, 3^1, 4^1, 6^1, 7^1, 9^1, 10^1, 12^1, 13^1, 15^1, 16^1, 18^1\}$ $G_2=G_3 = \{2^1, 5^1, 8^1, 11^1, 14^1, 17^1\}$
8	$G_1 = \{1^1, 6^1, 9^1, 12^1, 15^1, 18^1\}$ $G_2 = \{2^1, 5^1, 8^1, 11^1, 14^1, 17^1\}$ $G_3 = \{3^1, 4^1, 7^1, 10^1, 13^1, 16^1\}$
9	$G_1 = \{2^1, 6^1, 9^1, 12^1, 15^1, 17^1\}$ $G_2 = \{1^1, 5^1, 8^1, 11^1, 14^1, 16^1\}$ $G_3 = \{3^1, 4^1, 7^1, 10^1, 13^1, 18^1\}$
10	$G_1 = \{2^1, 4^1, 8^1, 11^1, 13^1, 15^1, 17^1\}$ $G_2 = \{3^1, 7^1, 10^1, 14^1, 18^1\}$ $G_3 = \{1^1, 5^1, 6^1, 9^1, 12^1, 16^1\}$

7.6.2 At grouping structure level

The objective of this subsection is to assess performance of GAB and GAaES when they are used to find an optimal maintenance plan at grouping structure. This work is very difficult because after each iteration, next generation provided by GAB and GAsES is different because of the random of crossover and mutation. The comparison between two algorithms only can carry out when after each iteration, next generation provided by GAB and GAsES is identical. For this reason, we do an adjustment procedure in order that next generation provided by GAB and GAsES can be identical. Assume that initial population of two algorithm is identical and shown in Table 7.15. Considering execution of GAB and GAsES in 10 iterations, the search time is shown in Table 7.16. Obviously, the search time provided by GAB go down by 54.5 % compared to GAaES.

Table 7.16: Search time of GAB and GAaES

Algorithms	The best solution	EPS	Search time
GAB	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$ $G_3 = \{13^1, 14^1, 15^1\}$	75215.3	28.89
GAaES	$G_1 = \{3^1, 6^1, 9^1, 12^1, 13^1, 14^1, 15^1, 18^1\}$ $G_2 = \{1^1, 4^1, 7^1, 10^1, 16^1\}$ $G_3 = \{13^1, 14^1, 15^1\}$	75215.3	41.68

7.7 Conclusion

This chapter has tackled the performance analysis and evaluation of the proposed strategy. Based on performance study of the proposed strategy at group level, we see that JMaRS approach is better than SMaRS approach since the interaction between maintenance routing and scheduling is jointly investigated. Therefore, considering the JMaRS approach in establishing dynamic grouping maintenance strategy for a GDPS is very useful. Indeed, performance study of the proposed maintenance strategy at grouping structure level illustrates that performance of economic profit provided by JMaRS approach is better than individual maintenance approach and SMaRS approach. In addition, the obtained results highlight that the proposed maintenance strategy obviously has ability to update the grouping maintenance plan when a dynamic context such as the interruption of the direct road connected between the maintenance center and site 6 occurs. Finally, the sensitivity analysis of two parameters (travel cost rate R^{tr} and site-preparation cost S_{ij}^0) shows that the maintenance plan is re-newed due to changes of these parameters. It ensures that the

proposed strategy always find an optimal maintenance plan when these parameters are changed (of course in the frame of the assumption made).

General conclusion

Developing maintenance strategies for a GDPS is a real challenge for maintenance planner because a GDPS is a large-scale system with many parameters and constraints, especially it has many other characteristics than a centralized system. So, in the framework of maintenance planning and optimization for a GDPS, the main challenge addressed by this PhD work is "How to extend existing maintenance strategies for GDPSs in considering its features in terms of multi-components, multi-sites, operating contexts and routing". To attack this challenge of a GDPS, we promote "A dynamic grouping maintenance strategy for a GDPS". For this purpose, a scientific problem statement on maintenance for a GDPS is developed with regards to dependence modelling, grouping maintenance strategies, mathematical optimization modelling of maintenance routing and scheduling problem, and finally maintenance optimization methods/algorithms. From the state of the art, four scientific issues are deduced:

- How to formulate a dependence model for a GDPS in which economic and geographical dependence are jointly considered? (*scientific issue 1*)
- How to develop a dynamic grouping maintenance strategy for GDPS with consideration of the economic, geographical dependencies and the impacts of dynamic contexts? (*scientific issue 2*)
- How to formulate economic profit models of maintenance routing and scheduling in GDPS context? (*scientific issue 3*).
- How to develop an hybrid algorithm to support maintenance optimization for GDPS in considering maintenance planning and routing? (*scientific issue 4*)

Addressing these scientific issues in establishing maintenance strategy for GDPS leads to our contributions in the frame of the PhD as follows:

- Firstly, we formulated a dependence model for a GDPS in which economic and geographical dependencies are jointly considered. The dependence model is really meaningful because it can quantify economic profit when several components are

jointly maintained. In addition, the joint consideration of economic and geographical dependencies results in greater efficiency than separately consideration of them.

- Secondly, the main contribution of our study is to develop a dynamic grouping maintenance strategy for a GDPS with consideration of economic, geographical dependence and impacts of dynamic contexts. Our proposal is reliable when: (i) economic profits from economic and geographical dependencies are taken into account; (ii) the maintenance plan can be updated when dynamic contexts occur. It makes the proposed maintenance strategy more flexible for real applications.
- Thirdly, another contribution is to formulate economic profit models of maintenance scheduling and routing that support for optimization of maintenance strategies in GDPS context. The economic profit models are formulated following two different approaches: sequential maintenance routing and scheduling (SMaRS) and joint maintenance routing and scheduling (JMaRS). By using the SMaRS approach, economic profit model is formulated by sequential steps of maintenance routing and scheduling. Whereas, using the JMaRS approach, maintenance routing and scheduling is jointly investigated in formulating economic profit mode. The model provided by JMaRS approach is the better choice because interactions between maintenance routing and scheduling are considered in mathematical modelling. Hence, using this model for maintenance optimization of the dynamic grouping maintenance strategy in GDPS context is more effective.
- Last but not least, our thesis developed a optimization algorithm to support maintenance optimization for grouping maintenance strategy of a GDPS. This algorithm is a hybrid between Genetic Algorithm (GA) and Branch and Bound (BAB) method, named GAB. In that way, at group level, BAB method is responsible to optimize maintenance plan. At grouping structure level, the GAB algorithm is used to find an optimal grouping structure containing groups with their optimal maintenance plans.

According to these contributions, the main originality of our works is to develop a dynamic grouping maintenance strategy for a GDPS. From our best knowledge, this is first time that the dynamic grouping maintenance strategy is develop for a GDPS. In frame of our study, the maintenance strategy can address most of difficulties due to geographical dispersion of a GDPS on maintenance planning. Indeed, the strategy not only considers optimization of maintenance planning but also optimization of maintenance routing. Remind that optimization of maintenance routing is a problem appearing due to geographical dispersion of a GDPS. In addition, the strategy allows maintenance plan

update when dynamic contexts occur. Therefore, the strategy can be well adapted to the dynamic contexts which frequently occurs in operation and maintenance of a GDPS. It makes the proposal strategy more appropriate for real applications.

With regards to our current contributions, several limits exist:

- Our strategy is limited for GDPSs whose production sites are operation independently. It means that interruption of a production site does not impact the normal operation of the others.
- Optimizing allocation of maintenance resource (spare part, repairman, etc.) is not considered in our strategy.
- The age-based maintenance policy cannot exactly determine the preventive maintenance cycle date of a component because the policy is based on the operating time and failure time distribution of a component without considering the real state of components.

Perspectives

The limits, we have analyzed, allow us to give short-term and long-term perspectives concerning the development of maintenance strategies for a GDPS.

For the short-term, we interest to extend a dynamic grouping maintenance strategy for a GDPS when interactions/ dependencies between sites are considered. As an example, in hydro power plant network where each plant is located far apart each other, when a plant is failed or splits from the network to maintain, others have to run in overload state to compensate for the shortage capacity caused by the stopped plant. If the power demand is higher than the allowed threshold, the grid can be disconnected on whole system and lead to stop of all other plants. Therefore, considering interaction between other different production sites is a research direction in our future studies.

For long-term, we consider to develop dynamic grouping maintenance strategies for a GDPS taking into account issues related to resource allocation (spare parts, repairman, etc.).

In addition, we interest to build a dynamic grouping maintenance strategies for GDPSs using condition-based maintenance policy.

The proposed strategy is to adapt well for GDPSs in framework of our study. However, in order that the proposed strategy becomes more realistic and adapts well to other different GDPS systems, the works below should be considered in the future.

Condition-based maintenance estimates the maintenance execution dates of components based on information collected through system condition monitoring. By that way,

General conclusion

the maintenance execution dates of components are determined more exactly than age-based maintenance policy. It helps maintenance decision more effective.

Publication of the author

Journal papers:

- H.S.H. Nguyen, P. Do, H.C. Vu, and B. Iung. Dynamic maintenance grouping and routing for geographically dispersed production systems. *Reliability Engineering & System Safety*, 185:392–404, 2019.

Conference papers:

- H.S.H. Nguyen, P. Do, B. Iung, and H.C. Vu. A dynamic grouping maintenance strategy for geographically dispersed production systems. *In 10th International Conference on Mathematical Methods in Reliability*, MMR, 2017.
- H.S.H. Nguyen, P. Do, H.C. Vu, and B. Iung. Joint maintenance scheduling and routing optimization for geographically dispersed production systems. *In 10th IMA International Conference on Modelling in Industrial Maintenance and Reliability*, MIMAR, pages 1–6, 2018.
- H.S.H. Nguyen, P. Do, H.C. Vu, and B. Iung. Developing a dynamic grouping maintenance strategy for geographically dispersed production systems. *In Application of Artificial Intelligence in Manufacturing 4.0 Workshop*, AIPL, Faculty of Sciences and Technologies, pages 68–72, 2019.

Bibliography

- [1] Hai Canh Vu. *Stratégies de regroupement pour la maintenance des systèmes à composants multiples avec structure complexe*. PhD thesis, Troyes, 2015.
- [2] Abdullah Omar Alrabghi. Simulation-based optimisation of complex maintenance systems. 2015.
- [3] Bram de Jonge. *Maintenance Optimization based on Mathematical Modeling*. 2017.
- [4] Enrico Zio and Michele Compare. Evaluating maintenance policies by quantitative modeling and analysis. *Reliability Engineering & System Safety*, 109:53–65, 2013.
- [5] Maurizio Bevilacqua and Marcello Braglia. The analytic hierarchy process applied to maintenance strategy selection. *Reliability Engineering & System Safety*, 70(1):71–83, 2000.
- [6] R Keith Mobley. *An introduction to predictive maintenance*. Elsevier, 2002.
- [7] JM Van Noortwijk. A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, 94(1):2–21, 2009.
- [8] Charles J Latino. Hidden treasure: Eliminating chronic failures can cut maintenance costs up to 60%. *Plant Engineering*, 50(12):166–167, 1996.
- [9] Geert Waeyenbergh and Liliane Pintelon. A framework for maintenance concept development. *International journal of production economics*, 77(3):299–313, 2002.
- [10] Roberto Cigolini, Lorenzo Fedele, Marco Garetti, and Marco Macchi. Recent advances in maintenance and facility management. *Production Planning & Control*, 19(4):279–286, 2008.
- [11] Robin P Nicolai and Rommert Dekker. Optimal maintenance of multi-component systems: a review. In *Complex system maintenance handbook*, pages 263–286. Springer, 2008.

- [12] Anne Barros. *Maintenance des systèmes multicomposants sous surveillance imparfaite: modélisation stochastique et optimisation*. PhD thesis, Troyes, 2003.
- [13] Hongzhou Wang. A survey of maintenance policies of deteriorating systems. *European journal of operational research*, 139(3):469–489, 2002.
- [14] Dominik T Matt, Erwin Rauch, and Patrick Dallasega. Trends towards distributed manufacturing systems and modern forms for their design. *Procedia CIRP*, 33:185–190, 2015.
- [15] CP Bajaj. Some constrained shortest-route problems. *Unternehmensforschung*, 15(1):287–301, 1971.
- [16] Hans C Joksch. The shortest route problem with constraints. *Journal of Mathematical analysis and applications*, 14(2):191–197, 1966.
- [17] Erwin Rauch and Patrick Dallasega. Sustainability in manufacturing and supply chains through distributed manufacturing systems and networks. Elsevier, 2017.
- [18] A Windsperger, S Steinlechner, M Fischer, U Seebacher, B Lackner, B Hammerl, and I Kaltenecker. Integriertes nutzungsmodell zum effizienteren rohstoffeinsatz im wirtschaftsbereich (integrated usage model for more efficient use of raw materials in economics). bmvit 19/2006, federal ministry for transport. *Innovation and Technology, Vienna*, 2006.
- [19] Jagjit Singh Srari, Mukesh Kumar, Gary Graham, Wendy Phillips, James Tooze, Simon Ford, Paul Beecher, Baldev Raj, Mike Gregory, Manoj Kumar Tiwari, et al. Distributed manufacturing: scope, challenges and opportunities. *International Journal of Production Research*, 54(23):6917–6935, 2016.
- [20] Ralph Edwin Wildeman, Rommert Dekker, and ACJM Smit. A dynamic policy for grouping maintenance activities. *European Journal of Operational Research*, 99(3):530–551, 1997.
- [21] Minou CA Olde Keizer, Simme Douwe P Flapper, and Ruud H Teunter. Condition-based maintenance policies for systems with multiple dependent components: A review. *European Journal of Operational Research*, 261(2):405–420, 2017.
- [22] Zafar Hameed and Jørn Vatn. Reliability of offshore wind turbines by grouping suitable inspection regimes. In *Proceedings of the EWEA Conference*, 2011.

-
- [23] Zafar Hameed and Kesheng Wang. Development of optimal maintenance strategies for offshore wind turbine by using artificial neural network. *Wind Engineering*, 36(3):353–364, 2012.
- [24] Shawki A. Abouel-seoud and Mohamed I. Khalil. Cost optimization of maintenance scheduling for wind turbine gearbox. *World Journal Control Science and Engineering*, 1(1):25–34, 2013.
- [25] Asvin Goel and Frank Meisel. Workforce routing and scheduling for electricity network maintenance with downtime minimization. *European Journal of Operational Research*, 231(1):210–228, 2013.
- [26] Fatih Camci. Maintenance scheduling of geographically distributed assets with prognostics information. *European Journal of Operational Research*, 245(2):506–516, 2015.
- [27] Eduyn López-Santana, Raha Akhavan-Tabatabaei, Laurence Dieulle, Nacima Labadie, and Andrés L Medaglia. On the combined maintenance and routing optimization problem. *Reliability Engineering & System Safety*, 145:199–214, 2016.
- [28] LC Thomas. A survey of maintenance and replacement models for maintainability and reliability of multi-item systems. *Reliability Engineering*, 16(4):297–309, 1986.
- [29] Hai Canh Vu, Phuc Do, Anne Barros, and Christophe Bérenguer. Maintenance grouping strategy for multi-component systems with dynamic contexts. *Reliability Engineering & System Safety*, 132:233–249, 2014.
- [30] Jenny Díaz-Ramírez, José Ignacio Huertas, and Federico Trigos. Aircraft maintenance, routing, and crew scheduling planning for airlines with a single fleet and a single maintenance and crew base. *Computers & Industrial Engineering*, 75:68–78, 2014.
- [31] Nayla Ahmad Al-Thani, Mohamed Ben Ahmed, and Mohamed Haouari. A model and optimization-based heuristic for the operational aircraft maintenance routing problem. *Transportation Research Part C: Emerging Technologies*, 72:29–44, 2016.
- [32] Kamran S Moghaddam. *Preventive maintenance and replacement scheduling: models and algorithms*. PhD thesis, University of Louisville, 2008.
- [33] Keren Wang et al. *Integrated decision-making framework for preventive maintenance scheduling and spare part logistic planning*. PhD thesis, 2018.

- [34] AWJ Chisholm. Nomenclature and definitions for manufacturing systems. *CIRP annals*, 39(2):735–742, 1990.
- [35] Monica Bellgran and Eva Kristina Säfsten. *Production development: design and operation of production systems*. Springer Science & Business Media, 2009.
- [36] Jagjit Singh Srail, Mukesh Kumar, Gary Graham, Wendy Phillips, James Tooze, Simon Ford, Paul Beecher, Baldev Raj, Mike Gregory, Manoj Kumar Tiwari, et al. Distributed manufacturing: scope, challenges and opportunities. *International Journal of Production Research*, 54(23):6917–6935, 2016.
- [37] Andrew S Tanenbaum and Maarten Van Steen. *Distributed systems: principles and paradigms*. Prentice-Hall, 2007.
- [38] Ralf Reichwald, Christof M Stotko, and Frank T Piller. Distributed mini-factory networks as a form of real-time enterprise: concept, flexibility potential and case studies. In *The Practical Real-Time Enterprise*, pages 403–434. Springer, 2005.
- [39] Rommert Dekker, Ralph E Wildeman, and Frank A Van der Duyn Schouten. A review of multi-component maintenance models with economic dependence. *Mathematical Methods of Operations Research*, 45(3):411–435, 1997.
- [40] R Wildeman. *The art of grouping maintenance*. PhD thesis, Erasmus University. PhD thesis, Erasmus University Rotterdam, Netherlands, 1996.
- [41] Fernanda Menezes, Oscar Porto, Marcelo L Reis, Lorenza Moreno, Marcus Poggi de Aragão, Eduardo Uchoa, Hernán Abeledo, and Nelci Carvalho do Nascimento. Optimizing helicopter transport of oil rig crews at petrobras. *Interfaces*, 40(5):408–416, 2010.
- [42] Ho Si Hung Nguyen, Phuc Do Van, Benoît Iung, and Hai Canh Vu. A dynamic grouping maintenance strategy for geographically dispersed production systems. In *10th International Conference on Mathematical Methods in Reliability, MMR 2017*, 2017.
- [43] Halima Benaicha. *Analyse des stratégies de maintenance des systèmes de production industrielle*. PhD thesis, University of sciences and technology in Oran, 2015.
- [44] Chandra Ade Irawan, Djamila Ouelhadj, Dylan Jones, Magnus Stålhane, and Iver Bakken Sperstad. Optimisation of maintenance routing and scheduling for offshore wind farms. *European Journal of Operational Research*, 256(1):76–89, 2017.

-
- [45] Norme AFNOR. Terminologie de la maintenance. *NF-EN*, 13306:X60–319, 2001.
- [46] Adolfo Crespo Márquez. *The maintenance management framework: models and methods for complex systems maintenance*. Springer Science & Business Media, 2007.
- [47] Adriaan Van Horenbeek and Liliane Pintelon. A dynamic predictive maintenance policy for complex multi-component systems. *Reliability Engineering & System Safety*, 120:39–50, 2013.
- [48] Albert H Schrottenboer, Michiel AJ uit het Broek, Bolor Jargalsaikhan, and Kees Jan Roodbergen. Coordinating technician allocation and maintenance routing for off-shore wind farms. *Computers & Operations Research*, 98:185–197, 2018.
- [49] Ho Si Hung Nguyen, Phuc Do, Hai-Canh Vu, and Benoit Iung. Dynamic maintenance grouping and routing for geographically dispersed production systems. *Reliability Engineering & System Safety*, 185:392–404, 2019.
- [50] Qianmei Feng, Koosha Rafiee, Elias Keedy, Ali Arab, David W Coit, and Sanling Song. Reliability and condition-based maintenance for multi-stent systems with stochastic-dependent competing risk processes. *The International Journal of Advanced Manufacturing Technology*, 80(9-12):2027–2040, 2015.
- [51] Hai Canh Vu, Phuc Do, and Anne Barros. A stationary grouping maintenance strategy using mean residual life and the birnbaum importance measure for complex structures. *IEEE Transactions on reliability*, 65(1):217–234, 2016.
- [52] Robin Pieter Nicolai. *Maintenance models for systems subject to measurable deterioration*. Number 420. Rozenberg Publishers, 2008.
- [53] Gabriella Budai, Dennis Huisman, and Rommert Dekker. Scheduling preventive railway maintenance activities. *Journal of the Operational Research Society*, 57(9):1035–1044, 2006.
- [54] B. Castanier, A. Grall, and C. Bérenguer. A condition-based maintenance policy with non-periodic inspections for a two-unit series system. *Reliability Engineering & System Safety*, 87(1):109–120, 2005.
- [55] Phuc Do Van, Anne Barros, Christophe Bérenguer, Keomany Bouvard, and Florent Brissaud. Dynamic grouping maintenance with time limited opportunities. *Reliability Engineering & System Safety*, 120:51–59, 2013.

- [56] Gerhard van Dijkhuizen. Maintenance grouping in multi-step multi-component production systems. In *Maintenance, modeling and optimization*, pages 283–306. Springer, 2000.
- [57] WMJ Geraerds. The cost of downtime for maintenance: preliminary considerations. *EUT-BDK report. Dept. of Industrial Engineering and Management Science*, 11, 1984.
- [58] Shey-Huei Sheu and Jhy-Ping Jhang. A generalized group maintenance policy. *European Journal of Operational Research*, 96(2):232–247, 1997.
- [59] C Sriskandarajah, AKS Jardine, and CK Chan. Maintenance scheduling of rolling stock using a genetic algorithm. *Journal of the Operational Research Society*, 49(11):1130–1145, 1998.
- [60] Sarat Chandra Vegunta and Jovica V Milanovic. Estimation of cost of downtime of industrial process due to voltage sags. *IEEE Transactions on power Delivery*, 26(2):576–587, 2011.
- [61] Emre Berk and Kamran Moinzadeh. Analysis of maintenance policies for m machines with deteriorating performance. *Iie Transactions*, 32(5):433–444, 2000.
- [62] Guillaume Goffaux, A Vande Wouwer, and Olivier Bernard. Improving continuous–discrete interval observers with application to microalgae-based bioprocesses. *Journal of Process Control*, 19(7):1182–1190, 2009.
- [63] Ülkü Gürler and Alev Kaya. A maintenance policy for a system with multi-state components: an approximate solution. *Reliability Engineering & System Safety*, 76(2):117–127, 2002.
- [64] A Higgins. Scheduling of railway track maintenance activities and crews. *Journal of the Operational Research Society*, 49(10):1026–1033, 1998.
- [65] Kim-Anh Nguyen, Phuc Do, and Antoine Grall. A joint predictive maintenance and spare parts provisioning policy for multi-component systems using rul prediction and importance measure. In *2nd European Conference of the Prognostics and Health Management Society, PHME*, volume 5, pages 500–511, 2014.
- [66] Kim Anh Nguyen. *Développement de stratégies de maintenance prévisionnelle de systèmes multi-composants avec structure complexe*. PhD thesis, Troyes, 2015.
- [67] D. Stengos and L.C. Thomas. The blast furnaces problem. *European Journal of Operational Research*, 4(5):330–336, 1980.

-
- [68] W B Langdon and P C Treleaven. Scheduling maintenance of electrical power transmission networks using genetic programming. Technical report, 1997.
- [69] SL Albin and Seng Chao. Preventive replacement in systems with dependent components. *IEEE Transactions on Reliability*, 41(2):230–238, 1992.
- [70] Terje Aven and Bo Bergman. Optimal replacement times—a general set-up. *Journal of Applied Probability*, 23(2):432–442, 1986.
- [71] David Assaf and J George Shanthikumar. Optimal group maintenance policies with continuous and periodic inspections. *Management Science*, 33(11):1440–1452, 1987.
- [72] Keomany Bouvard, Samuel Artus, Christophe Bérenguer, and Vincent Cocquempot. Condition-based dynamic maintenance operations planning & grouping. application to commercial heavy vehicles. *Reliability Engineering & System Safety*, 96(6):601–610, 2011.
- [73] Rommert Dekker and Ingrid FK Roelvink. Marginal cost criteria for group replacement. *European Journal of Operational Research*, pages 467–480, 1995.
- [74] Nasser Fard and Xitong Zheng. An approximate method for non-repairable systems based on opportunistic replacement policy. *Reliability Engineering & System Safety*, 33(2):277–288, 1991.
- [75] Zhigang Tian, Youmin Zhang, and Jialin Cheng. Condition based maintenance optimization for multi-component systems. In *Annual Conference of the Prognostics and Health Management Society*, 2011.
- [76] Zhisheng Zhang, Yifan Zhou, Yong Sun, and Lin Ma. Condition-based maintenance optimisation without a predetermined strategy structure for a two-component series system. *Eksplloatacja i Niezawodnosc–Maintenance and Reliability*, 14(2):120–129, 2012.
- [77] Davinder PS Sethi. Opportunistic replacement policies. In *The Theory and Applications of Reliability with Emphasis on Bayesian and Nonparametric Methods*, pages 433–447. Elsevier, 1977.
- [78] Roger C Vergin and Michael Scriabin. Maintenance scheduling for multicomponent equipment. *AIIE Transactions*, 9(3):297–305, 1977.
- [79] IB Gertsbakh. Optimal group preventive maintenance of a system with observable state parameter. *Advances in Applied Probability*, 16(4):923–925, 1984.

- [80] Mamoru Ohashi. Group replacement policy for a maintained coherent system. *Journal of the Operations Research Society of Japan*, 25(3):228–237, 1982.
- [81] Mamoru Ohashi. Replacement policy for components in a markovian deteriorating system with minimal repair. *Journal of the Operations Research Society of Japan*, 29(4):249–265, 1986.
- [82] K Okumoto and EA Elsayed. An optimum group maintenance policy. *Naval Research Logistics Quarterly*, 30(4):667–674, 1983.
- [83] Eunshin Byon, Lewis Ntaimo, and Yu Ding. Optimal maintenance strategies for wind turbine systems under stochastic weather conditions. *IEEE Transactions on Reliability*, 59(2):393–404, 2010.
- [84] Ho Si Hung Nguyen, Phuc Do Van, Hai-Canh Vu, and Benoît Iung. Joint maintenance scheduling and routing optimization for geographically dispersed production systems. In *10th IMA International Conference on Modelling in Industrial Maintenance and Reliability, MIMAR 2018*, pages 1–6, 2018.
- [85] Ho Si Hung Nguyen. Developing a dynamic grouping maintenance strategy for geographically dispersed production systems. In *In Application of Artificial Intelligence in Manufacturing 4.0, Workshop 2019*.
- [86] Smit Adriaan Dekkert Rommert and Losekoot Jerosen. Combining maintenance activities in an operational planning phase: a set-partitioning approach. *IMA Journal of Management Mathematics*, 3(4):315–331, 1991.
- [87] DF Redmond, AH Christer, SR Rigden, E Burley, A Tajelli, and A Abu-Tair. Or modelling of the deterioration and maintenance of concrete structures. *European Journal of Operational Research*, 99(3):619–631, 1997.
- [88] SK Goyal and MI Kusy. Determining economic maintenance frequency for a family of machines. *Journal of the Operational Research Society*, 36(12):1125–1128, 1985.
- [89] Suresh K Goyal and A Gunasekaran. Determining economic maintenance frequency of a transport fleet. *International Journal of Systems Science*, 23(4):655–659, 1992.
- [90] Rommert Dekker, Hans Frenk, and Ralph E Wildeman. How to determine maintenance frequencies for multi-component systems? a general approach. In *Reliability and maintenance of complex systems*, pages 239–280. Springer, 1996.

-
- [91] Rommert Dekker, RE Wildeman, JBG Frenk, and R Van Egmond. A general approach for the coordination of maintenance frequencies in cases with a single set-up. In *Maintenance, Modeling and Optimization*, pages 245–282. Springer, 2000.
- [92] Jia-Yen Huang. New search algorithm for solving the maintenance scheduling problem for a family of machines. *Optimisation Methods and Software*, 21(3):461–477, 2006.
- [93] Radouane Laggoune, Alaa Chateaneuf, and Djamil Aissani. Preventive maintenance scheduling for a multi-component system with non-negligible replacement time. *International Journal of Systems Science*, 41(7):747–761, 2010.
- [94] Dileep R Sule and Bryan Harmon. Determination of coordinated maintenance scheduling frequencies for a group of machines. *AIIE Transactions*, 11(1):48–53, 1979.
- [95] Moncer Hariga. Coordinated overhaul scheduling of production units. *Naval Research Logistics (NRL)*, 41(4):565–577, 1994.
- [96] Moncer Hariga. A deterministic maintenance-scheduling problem for a group of non-identical machines. *International Journal of Operations & Production Management*, 14(7):27–36, 1994.
- [97] SO Duffuaa and M Ben-Daya. An extended model for the joint overhaul scheduling problem. *International Journal of Operations & Production Management*, 14(7):37–43, 1994.
- [98] Peter Ritchken and John G Wilson. (m, t) group maintenance policies. *Management Science*, 36(5):632–639, 1990.
- [99] Shey-Huei Sheu. A generalized block replacement policy with minimal repair and general random repair costs for a multi-unit system. *Journal of the Operational Research Society*, 42(4):331–341, 1991.
- [100] YW Archibald and Rommert Dekker. Modified block-replacement for multiple-component systems. *IEEE transactions on reliability*, 45(1):75–83, 1996.
- [101] Menachem Berg and Benjamin Epstein. A modified block replacement policy. *Naval Research Logistics Quarterly*, 23(1):15–24, 1976.
- [102] Menachem Berg. General trigger-off replacement procedures for two-unit systems. *Naval Research Logistics Quarterly*, 25(1):15–29, 1978.

- [103] X. Zheng and N. Fard. A maintenance policy for repairable systems based on opportunistic failure-rate tolerance. *IEEE Transactions on Reliability*, 40(2):237–244, 1991.
- [104] Fangfang Ding and Zhigang Tian. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. *Renewable Energy*, 45:175–182, 2012.
- [105] Jinqiu Hu and Laibin Zhang. Risk based opportunistic maintenance model for complex mechanical systems. *Expert Systems with Applications*, 41(6):3105–3115, 2014.
- [106] Jinqiu Hu, Laibin Zhang, and Wei Liang. Opportunistic predictive maintenance for complex multi-component systems based on dbn-hazop model. *Process Safety and Environmental Protection*, 90(5):376–388, 2012.
- [107] Radouane Laggoune, Alaa Chateaneuf, and Djamil Aissani. Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units. *Computers & Chemical Engineering*, 33(9):1499–1510, 2009.
- [108] Tangbin Xia, Xiaoning Jin, Lifeng Xi, and Jun Ni. Production-driven opportunistic maintenance for batch production based on mam–apb scheduling. *European Journal of Operational Research*, 240(3):781–790, 2015.
- [109] W. Zhou, H.P. Hong, and S. Zhang. Impact of dependent stochastic defect growth on system reliability of corroding pipelines. *International Journal of Pressure Vessels and Piping*, 96-97:68–77, 2012.
- [110] S Mizutani, T Nakagawa, and M Chen. Extended maintenance and inspection models for a parallel system. In *2009 IEEE International Conference on Industrial Engineering and Engineering Management*, pages 248–251. IEEE, 2009.
- [111] Toshio Nakagawa. Optimal number of units for a parallel system. *Journal of Applied Probability*, 21(02):431–436, 1984.
- [112] Elmira Popova and John G Wilson. Group replacement policies for parallel systems whose components have phase distributed failure times. *Annals of operations research*, 91:163–189, 1999.
- [113] K. Yasui, T. Nakagawa, and S. Osaki. A summary of optimum replacement policies for a parallel redundant system. *Microelectronics Reliability*, 28(4):635–641, 1988.

-
- [114] C.-S. Chung and J. Flynn. Optimal replacement policies for k-out-of-n systems. *IEEE Transactions on Reliability*, 38(4):462–467, 1989.
- [115] Minjae Park and Hoang Pham. A generalized block replacement policy for a k-out-of-n system with respect to threshold number of failed components and risk costs. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 42(2):453–463, 2012.
- [116] T. Nakagawa and S. Mizutani. A summary of maintenance policies for a finite interval. *Reliability Engineering & System Safety*, 94(1):89–96, 2009.
- [117] Jun Wu, Tsan Sheng Adam Ng, Min Xie, and Hong-Zhong Huang. Analysis of maintenance policies for finite life-cycle multi-state systems. *Computers & Industrial Engineering*, 59(4):638–646, 2010.
- [118] J.M. Worm and A. van Harten. Model based decision support for planning of road maintenance. *Reliability Engineering & System Safety*, 51(3):305–316, 1996.
- [119] K.G. Papakonstantinou and M. Shinozuka. Optimum inspection and maintenance policies for corroded structures using partially observable markov decision processes and stochastic, physically based models. *Probabilistic Engineering Mechanics*, 37:93–108, 2014.
- [120] Gabriella Budai-Balke. *Operations research models for scheduling railway infrastructure maintenance*. Thela Thesis, 2009.
- [121] Tangbin Xia, Lifeng Xi, Xiaojun Zhou, and Jay Lee. Dynamic maintenance decision-making for series-parallel manufacturing system based on mam-mtw methodology. *European Journal of Operational Research*, 221(1):231–240, 2012.
- [122] Ralph E. Wildeman and Rommert Dekker. Dynamic influences in multi-component maintenance. *Quality and Reliability Engineering International*, 13(4):199–207, 1997.
- [123] Phuc Do Van, Hai Canh Vu, Anne Barros, and Christophe Berenguer. Grouping maintenance strategy with availability constraint under limited repairmen. *IFAC Proceedings Volumes*, 45(20):486–491, 2012.
- [124] Salih O Duffuaa. Mathematical models in maintenance planning and scheduling. In *Maintenance, modeling and optimization*, pages 39–53. Springer, 2000.

- [125] Lijuan Dai, Sören Ehlers, Marvin Rausand, and Ingrid Bouwer Utne. Risk of collision between service vessels and offshore wind turbines. *Reliability Engineering & System Safety*, 109:18–31, 2013.
- [126] Magnus Stålhane, Hanne Vefsnmo, Elin E. Halvorsen-Weare, Lars Magnus Hvattum, and Lars Magne Nonås. Vessel fleet optimization for maintenance operations at offshore wind farms under uncertainty. *Energy Procedia*, 94:357–366, 2016.
- [127] Dzung T Phan and Yada Zhu. Multi-stage optimization for periodic inspection planning of geo-distributed infrastructure systems. *European Journal of Operational Research*, 245(3):797–804, 2015.
- [128] Amine Dhahri, Kamel Zidi, and Khaled Ghedira. A variable neighborhood search for the vehicle routing problem with time windows and preventive maintenance activities. *Electronic Notes in Discrete Mathematics*, 47:229–236, 2015.
- [129] Hao Tang, Elise Miller-Hooks, and Robert Tomastik. Scheduling technicians for planned maintenance of geographically distributed equipment. *Transportation Research Part E: Logistics and Transportation Review*, 43(5):591–609, 2007.
- [130] Eduyn López-Santana, Raha Akhavan-Tabatabaei, Laurence Dieulle, Nacima Labadie, and Andrés L. Medaglia. On the combined maintenance and routing optimization problem. *Reliability Engineering & System Safety*, 145:199–214, 2016.
- [131] Nora Raknes, Katrine Ødeskaug, Magnus Stålhane, Lars Hvattum, Nora Tangen Raknes, Katrine Ødeskaug, Magnus Stålhane, and Lars Magnus Hvattum. Scheduling of maintenance tasks and routing of a joint vessel fleet for multiple offshore wind farms. *Journal of Marine Science and Engineering*, 5(1):11, 2017.
- [132] Philip A Scarf. On the application of mathematical models in maintenance. *European Journal of operational research*, 99(3):493–506, 1997.
- [133] Abouel-seoud Shawki and Khalil Mohamed. Cost optimization of maintenance scheduling for wind turbine gearbox components with assured reliability. *World Journal Control Science and Engineering*, 1:25–34, 2013.
- [134] Phuc Do, Hai Canh Vu, Anne Barros, and Christophe Bérenguer. Maintenance grouping for multi-component systems with availability constraints and limited maintenance teams. *Reliability Engineering & System Safety*, 142:56–67, 2015.
- [135] Mahmood Shafiee and Stefanka Chukova. Maintenance models in warranty: A literature review. *European Journal of Operational Research*, 229(3):561–572, 2013.

-
- [136] Seyed MR Iravani and Vijayalakshmi Krishnamurthy. Workforce agility in repair and maintenance environments. *Manufacturing & Service Operations Management*, 9(2):168–184, 2007.
- [137] Lie-Fern Hsu. Optimal preventive maintenance policies in a serial production system. *The International Journal of Production Research*, 29(12):2543–2555, 1991.
- [138] Danijela Đorić, Abdessamad Ait El Cadi, Saïd Hanafi, Nenad Mladenović, and Abdelhakim Artiba. Clustering approach in maintenance of capillary railway network. *Electronic Notes in Discrete Mathematics*, 58:239–246, 2017.
- [139] Xiaodong Yao, Michael Fu, Steven I Marcus, and Emmanuel Fernandez-Gaucherand. Optimization of preventive maintenance scheduling for semiconductor manufacturing systems: models and implementation. In *Proceedings of the 2001 IEEE International Conference on Control Applications (CCA'01)(Cat. No. 01CH37204)*, pages 407–411. IEEE, 2001.
- [140] Xiaodong Yao, Emmanuel Fernández-Gaucherand, Michael C Fu, and Steven I Marcus. Optimal preventive maintenance scheduling in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 17(3):345–356, 2004.
- [141] Salvador Perez Canto. Application of benders' decomposition to power plant preventive maintenance scheduling. *European journal of operational research*, 184(2):759–777, 2008.
- [142] Mohsen Alardhi, Roger G Hannam, and Ashraf W Labib. Preventive maintenance scheduling for multi-cogeneration plants with production constraints. *Journal of Quality in Maintenance Engineering*, 13(3):276–292, 2007.
- [143] Gilbert Laporte. The traveling salesman problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59(2):231–247, 1992.
- [144] Thomas Christof and G Reinelt. Parallel cutting plane generation for the tsp. *Parallel Programming and Applications*, pages 163–169, 1995.
- [145] Jens Clausen. Branch and bound algorithms-principles and examples. *Department of Computer Science, University of Copenhagen*, pages 1–30, 1999.
- [146] Gilbert Laporte, Yves Nobert, and Serge Taillefer. A branch-and-bound algorithm for the asymmetrical distance-constrained vehicle routing problem. *Mathematical Modelling*, 9(12):857–868, 1987.

- [147] Gilbert Laporte and Yves Nobert. A branch and bound algorithm for the capacitated vehicle routing problem. *Operations-Research-Spektrum*, 5(2):77–85, 1983.
- [148] Michel Gendreau, Gilbert Laporte, and Frederic Semet. A branch-and-cut algorithm for the undirected selective traveling salesman problem. *Networks: An International Journal*, 32(4):263–273, 1998.
- [149] Branimir Kralj and Radivoj Petrovic. A multiobjective optimization approach to thermal generating units maintenance scheduling. *European Journal of Operational Research*, 84(2):481–493, 1995.
- [150] Kossi P Adzakpa, Kondo H Adjallah, and Farouk Yalaoui. On-line maintenance job scheduling and assignment to resources in distributed systems by heuristic-based optimization. *Journal of intelligent manufacturing*, 15(2):131–140, 2004.
- [151] A Crespo Marquez, Jatinder ND Gupta, and James P Ignizio. Improving preventive maintenance scheduling in semiconductor fabrication facilities. *Production Planning & Control*, 17(7):742–754, 2006.
- [152] Ibrahim El-Amin, Salih Duffuaa, and Mohammed Abbas. A tabu search algorithm for maintenance scheduling of generating units. *Electric Power Systems Research*, 54(2):91–99, 2000.
- [153] Mohan Gopalakrishnan, Srimathy Mohan, and Z He. A tabu search heuristic for preventive maintenance scheduling. *Computers & industrial engineering*, 40(1-2):149–160, 2001.
- [154] Joao Tomé Saraiva, Marcelo Leandro Pereira, Virgilio Torrado Mendes, and José Carlos Sousa. A simulated annealing based approach to solve the generator maintenance scheduling problem. *Electric Power Systems Research*, 81(7):1283–1291, 2011.
- [155] David E Golberg. Genetic algorithms in search, optimization, and machine learning. *Addison wesley*, 1989(102):36, 1989.
- [156] David E Goldberg and Kalyanmoy Deb. A comparative analysis of selection schemes used in genetic algorithms. In *Foundations of genetic algorithms*, volume 1, pages 69–93. Elsevier, 1991.
- [157] Gregory Levitin and Anatoly Lisnianski. Optimization of imperfect preventive maintenance for multi-state systems. *Reliability Engineering & System Safety*, 67(2):193–203, 2000.

-
- [158] Gregory Levitin and Anatoly Lisnianski. Optimal replacement scheduling in multi-state series-parallel systems. *Quality and Reliability Engineering International*, 16:157–162, 03 2000.
- [159] Yaoyu Wang and Edmund Handschin. A new genetic algorithm for preventive unit maintenance scheduling of power systems. *International Journal of Electrical Power & Energy Systems*, 22(5):343–348, 2000.
- [160] Yuo-Tern Tsai, Kuo-Shong Wang, and Hwei-Yuan Teng. Optimizing preventive maintenance for mechanical components using genetic algorithms. *Reliability engineering & system safety*, 74(1):89–97, 2001.
- [161] Rong-Ceng Leou. A new method for unit maintenance scheduling based on genetic algorithm. In *2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No. 03CH37491)*, volume 1, pages 246–251. IEEE, 2003.
- [162] B.-J Han, X.-M Fan, D.-Z Ma, and Yusen Jin. Optimization of equipment preventive maintenance cycle in the production system based on the genetic algorithm. *Jisuanji Jicheng Zhizao Xitong/Computer Integrated Manufacturing Systems, CIMS*, 9:206–209, 03 2003.
- [163] Celso Marcelo F Lapa, Claudio Marcio NA Pereira, and Marcio Paes de Barros. A model for preventive maintenance planning by genetic algorithms based in cost and reliability. *Reliability Engineering & System Safety*, 91(2):233–240, 2006.
- [164] BH Zhou, SY Jiang, SJ Wang, Bin Wu, and LF Xi. Integrated production and preventive maintenance scheduling algorithm for flow shops. *Journal of Dalian Maritime University*, 33(3):32–35, 2007.
- [165] Clym Stock-Williams and Siddharth Krishna Swamy. Automated daily maintenance planning for offshore wind farms. *Renewable Energy*, 133:1393–1403, 2019.
- [166] Hyunchul Kim, Koichi Nara, and Mitsuo Gen. A method for maintenance scheduling using ga combined with sa. *Computers & Industrial Engineering*, 27(1-4):477–480, 1994.
- [167] Jonathan S Tan and Mark A Kramer. A general framework for preventive maintenance optimization in chemical process operations. *Computers & Chemical Engineering*, 21(12):1451–1469, 1997.
- [168] Marzio Marseguerra, Enrico Zio, and Luca Podofillini. Condition-based maintenance optimization by means of genetic algorithms and monte carlo simulation. *Reliability Engineering & System Safety*, 77(2):151–165, 2002.

- [169] K Suresh and N Kumarappan. Combined genetic algorithm and simulated annealing for preventive unit maintenance scheduling in power system. In *2006 IEEE power engineering society general meeting*, pages 5–pp. IEEE, 2006.
- [170] Mohamad Samrout, Toufik Benouhiba, Eric Chatelet, and Farouk Yalaoui. Preventive maintenance optimisation using evolutionary hybrid algorithm. In *2006 International Conference on Service Systems and Service Management*, volume 1, pages 620–625. IEEE, 2006.
- [171] Yu-lan Jin, Zu-hua Jiang, and Wen-rui Hou. Optimal policy research on reliability-centered preventive maintenance for multi-components equipment. *Journal-Shanghai Jiaotong University*, 40(12):2051, 2006.
- [172] Craig C Sherbrooke. *Optimal inventory modeling of systems: multi-echelon techniques*, volume 72. Springer Science & Business Media, 2006.
- [173] Sebastián Martorell, M Villamizar, Sofía Carlos, and Ana Sánchez. Maintenance modeling and optimization integrating human and material resources. *Reliability Engineering & System Safety*, 95(12):1293–1299, 2010.
- [174] Peter Okoh. Maintenance grouping optimization for the management of risk in offshore riser system. *Process Safety and Environmental Protection*, 98:33–39, 2015.
- [175] Bruno Castanier. *Modélisation stochastique et optimisation de la maintenance conditionnelle des systèmes à dégradation graduelle*. PhD thesis, Troyes, 2001.
- [176] Estelle Deloux. *Politiques de maintenance conditionnelle pour un système à dégradation continue soumis à un environnement stressant*. PhD thesis, Université de Nantes, 2008.
- [177] John D Kalbfleisch and Ross L Prentice. *The statistical analysis of failure time data*, volume 360. John Wiley & Sons, 2011.
- [178] Richard E Barlow and Frank Proschan. Statistical theory of reliability and life testing: probability models. Technical report, Florida State Univ Tallahassee, 1975.
- [179] CE Love and R Guo. Utilizing weibull failure rates in repair limit analysis for equipment replacement/preventive maintenance decisions. *Journal of the Operational Research Society*, 47(11):1366–1376, 1996.
- [180] Ralph Edwin Wildeman. The art of grouping maintenance. Technical report, 1996.

-
- [181] Hai Canh Vu, Phuc Do Van, Anne Barros, and Christophe Bérenguer. Maintenance activities planning and grouping for complex structure systems. In *11th International Probabilistic Safety Assessment and Management Conference & the Annual European Safety and Reliability Conference-PSAM 11/ESREL 2012*, page CDROM, 2012.
- [182] Yihan Liu. *Optimisation de problème de tournées de véhicules de service à domicile*. PhD thesis, Ecole centrale de Lille, 2017.
- [183] Thi Phuong Khanh Nguyen, Bruno Castanier, and Thomas G Yeung. Maintaining a system subject to uncertain technological evolution. *Reliability Engineering & System Safety*, 128:56–65, 2014.
- [184] Nozer D Singpurwalla. Survival in dynamic environments. *Statistical science*, pages 86–103, 1995.
- [185] Slavomir Vukmirović, Zvonko Čapko, and Ana Babić. Model of using the exhaustive search algorithm in solving of traveling salesman problem (tsp) on the example of the transport network optimization of primorje-gorski kotar county (pgc). In *7th International OFEL Conference on Governance, Management and Entrepreneurship: Embracing Diversity in Organisations. April 5th-6th, 2019, Dubrovnik, Croatia*, pages 391–401. Zagreb: Governance Research and Development Centre (CIRU), 2019.

Résumé de la thèse en Français

Dans le contexte de la mondialisation actuelle, pour rester compétitives, les entreprises définissent leurs activités et leurs priorités en fonction de plusieurs facteurs liés à leurs systèmes de production, tels que la flexibilité, la productivité et la qualité. Par conséquent, la maintenance, définie comme " l'ensemble des activités nécessaires pour remettre l'équipement/système dans un état dans lequel il peut remplir les fonctions qui lui sont assignées, ou le maintenir dans un tel état" [3], joue un rôle de soutien essentiel pour garantir la pérennité de ces facteurs. En effet, d'une part, elle permet de maintenir les équipements en bon état de fonctionnement et augmenter leur durée de vie. D'autre part, elle permet également d'assurer les activités de production en répondant à toutes les performances attendues telles que la productivité, la qualité des produits et les exigences de sécurité. Par rapport à ce rôle essentiel reconnu, les entreprises sont obligées d'investir davantage dans les opérations de maintenance. Par exemple la part des coûts d'entretien mais aussi les coûts de préventifs a énormément augmenté [4]. En effet, les coûts de maintenance occupent environ 15 à 70 % des coûts globaux de production [5, 6] et le montant des dépenses consacrées à la construction d'infrastructures servant aux activités de maintenance n'a cessé d'augmenter aussi [7]. Il a été montré également dans [8] que les États-Unis ont consacré plus de \$300 milliards de dollars par an à la maintenance et à l'exploitation des installations au cours des années 1990s. Environ 80% de ce coût est utilisé pour les défaillances chroniques. L'élimination de ces défaillances peut réduire les coûts de maintenance de 40% à 60%. Dans l'industrie chimique, plus de 30% de l'effectif total et jusqu'à un quart des activités ont été consacrés aux activités de maintenance [9]. En outre, l'étude [10] mentionnait que les budgets de maintenance représentaient en moyenne 20% du budget total d'exploitation de l'usine, allant de quelques pour cent dans l'industrie légère à des pourcentages très élevés dans les industries à forte intensité d'équipement (i.e. sidérurgie, pétrochimie, industrie minière, etc.) ou dans le secteur dit des services publics (énergie électrique, pétrole et gaz, etc.).

Pour mieux contrôler ces budgets, le choix des stratégies de maintenance est donc une priorité. La stratégie choisie doit être adaptée à l'objectif de maintenance (réduire le coût de production, améliorer la disponibilité du système, etc.), aux caractéristiques des

systèmes (mono ou multi-composants, etc.) et aux conditions de fonctionnement des systèmes (stables ou dynamiques). Dans la littérature [11], beaucoup d'études s'intéressent au développement et à l'optimisation des stratégies de maintenance. La question est de savoir comment donner une décision de maintenance optimale qui réponde aux objectifs souhaités (i.e. minimiser les coûts de maintenance, maximiser la disponibilité du système, etc.) parmi de nombreuses options de maintenance relatives, par exemple, à la fréquence d'exécution, au niveau d'intervention (parfait ou imparfait) [12]. Par conséquent, de nombreuses stratégies de maintenance ont été élaborées depuis les années 1990 [7, 11, 13]. Cependant, ces travaux sont souvent limités à une classe de systèmes qui sont majoritairement des systèmes de production unique ou appelé système centralisé. Cette classe de système est réductrice car avec l'ouverture des marchés, les aspects de délocalisation, le développement des technologies de type Cloud, réseaux ... des entreprises manufacturières se sont orientées, pour des raisons de productivité, de coût, vers des systèmes de production appelés : systèmes de production géographiquement dispersés (GDPS en anglais) [14]. Un GDPS est un réseau de production géographiquement dispersé dont les sites de production sont éloignés les uns des autres mais soumis à la gestion d'un centre administratif (voir Figure 8). Les GDPS se caractérisent principalement par: multi-composant, multi-site, contextes dynamiques changeants et nécessité de routage. En effet, le GDPS est un système multi-composant et multi-site car il est construit par de nombreux sites de production différents dans lesquels chaque site est composé de différents sous-systèmes et composants. Par rapport à ces caractéristiques, l'exploitation et la maintenance d'un GDPS sont difficiles à mettre en œuvre car affectées par de nombreux facteurs opérationnels et dynamiques [15, 16]. Une autre caractéristique essentielle à considérer dans ces systèmes est le routage. Le routage est le processus de sélection d'un itinéraire pour effectuer les tâches données sous des contraintes telles que la capacité du véhicule, la fenêtre horaire, la main-d'œuvre, etc. Normalement, pour exécuter un groupe de nombreuses tâches sur différents sites de production, le personnel quitte le centre administratif et exécute séquentiellement toutes les tâches du groupe, puis retourne au centre administratif uniquement lorsque toutes les tâches du groupe sont terminées comme le montre la Figure 9. Dans ce cas, le routage aide les gestionnaires à trouver le meilleur itinéraire avec les objectifs donnés lors de l'exécution d'un groupe de tâches.

Grâce à cette vision « dispersée » du système de production, les entreprises peuvent économiser sur les coûts de main d'œuvre (situés dans des lieux à faible coût) et les coûts de livraison (proches des clients) [14], améliorer la qualité du service ou du produit (délais de livraison courts, activités après-vente de haute qualité). En particulier, ce type de système de production est considéré comme durable au sens exploitation [17] car sa production dispersée peut contribuer à réduire les risques de rupture dans la fabrication et la

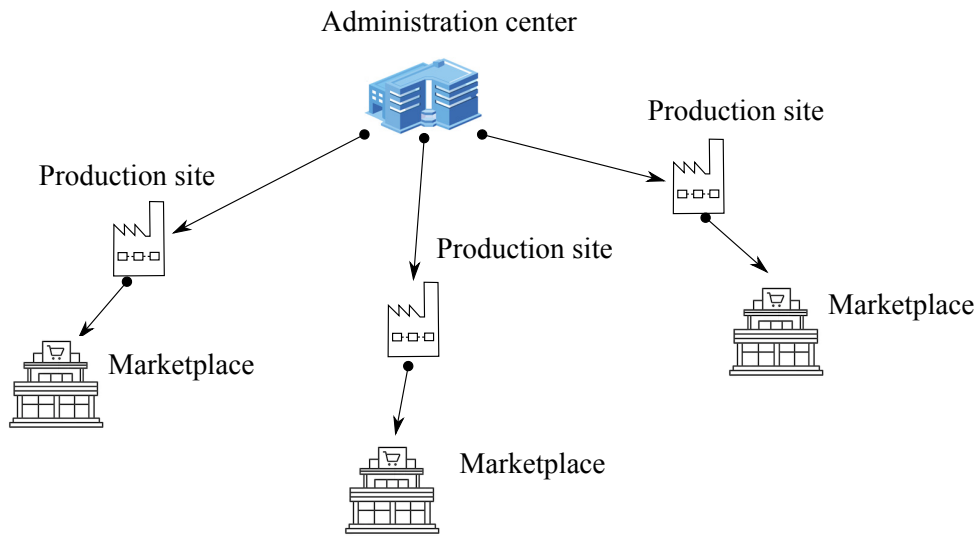


Figure 8: L'architecture des GDPS

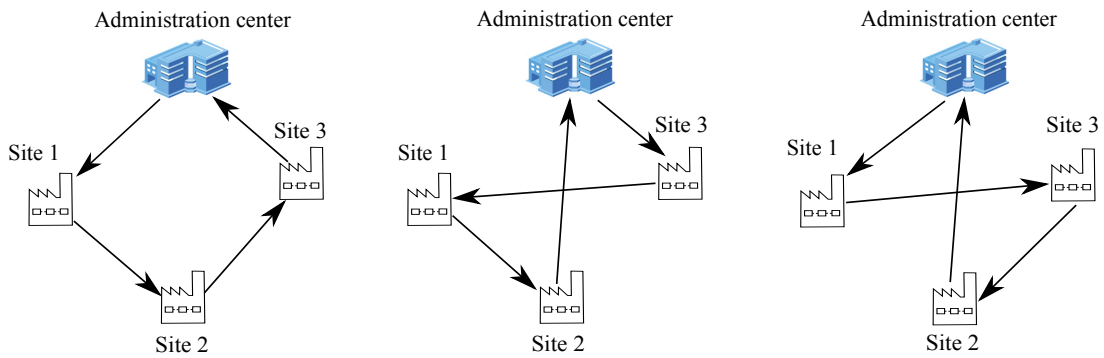


Figure 9: Différents itinéraires pour effectuer un groupe de tâches

distribution de la production [18]. Bien que les GDPS présentent de nombreux avantages, ils doivent faire face à de nombreux défis concernant les normes, la réglementation, la gestion de la production, et surtout la planification et l'optimisation de la maintenance en raison de la dispersion géographique des sites de production [19]. Dans ce cadre de la planification et de l'optimisation de la maintenance, le principal défi de cette thèse est donc:

Comment étendre des stratégies de maintenance conventionnelles pour les adapter aux GDPS en considérant ses caractéristiques en termes de multi-composants, multi-sites, contextes dynamiques et routage?

En fonction de ce défi et en considérant les fonctionnalités d'un GDPS, de nouvelles problématiques scientifiques sont nécessaires à attaquer.

Premièrement, dans le cadre de l'optimisation de la maintenance, les dépendances entre les composants ont des impacts importants sur la performance d'un plan de maintenance et doivent être considérées dans la modélisation et l'optimisation de la maintenance [11, 20]. Grâce à son système multi-composant et multi-site, le GDPS favorise les dépendances entre composants et entre sites. Dans la pratique, les dépendances entre les composants sont classiquement répartis en trois grands types [11, 20, 21]: dépendance structurelle (i.e. la maintenance d'un composant défaillant implique la maintenance des composants actifs ou, au moins, leur démontage), dépendance stochastique (i.e. l'état des composants influence la distribution de la vie des autres composants) et dépendance économique (i.e. le coût de la maintenance commune d'un groupe de composants n'est pas égal au coût total de la maintenance individuelle de ces composants). En outre, en raison de la dispersion géographique des GDPS, une autre dépendance, appelée dépendance géographique existe. La dépendance géographique implique que la distance/le temps total de voyage d'une maintenance conjointe d'un groupe de plusieurs composants est inférieur à la distance/le temps total de voyage pour la maintenance de composants individuels. La dépendance géographique est mentionnée car le regroupement des activités de maintenance permet non seulement de réduire les coûts de transport grâce à la réduction de la distance parcourue, mais également de réduire la durée du trajet. Tandis que la dépendance économique ne profite du profit économique que pour regrouper les activités de maintenance. Du point de vue économique, la dépendance géographique est un type particulier de dépendance économique. Cependant, ce n'est pas vrai quand on considère l'aspect du temps de trajet. Pour les GDPS, les dépendances économique et géographique sont deux des dépendances les plus importantes pour le choix de la stratégie de maintenance [22–27]. Toutefois, il n'existe pas vraiment de travaux considérant ces deux dépendances ensemble avec modélisation forte de leur interaction. Pour ces raisons, la première problématique scientifique est "**Comment formuler un modèle de dépendance pour un GDPS dans lequel la dépendance économique et la dépendance géographique sont considérées conjointement?**" (*Problématique 1*).

Deuxièmement, la question, que nous voulons ensuite attaquer, concerne les approches de maintenance pour le développement de stratégies au sein des GDPS. Dans la pratique, un grand nombre d'approches de maintenance ont été introduites, développées et appliquées avec succès à des systèmes multi-composants compte tenu de plusieurs types de dépendances [1, 20]. Parmi les approches existantes, l'approche de maintenance par regroupement dynamique initialement proposée dans [28] semble prometteuse puisqu'elle peut prendre en compte plusieurs types de dépendances entre composants et mettre à jour facilement la planification de la maintenance dans des contextes dynamiques (taux de détérioration variable des composants, possibilités de maintenance) [29]. Cependant,

ces approches sont généralement étudiées pour un système centralisé où il n'existe pas de dépendance géographique. Par conséquent, les approches existantes de regroupement ne peuvent pas être appliquées directement aux stratégies de maintenance d'un GDPS car elles sont inefficaces en raison de la non prise en compte de la dépendance géographique. En outre, un GDPS est considéré comme un système « à grande échelle » impacté par de nombreux contextes dynamiques par rapport à un système centralisé. Par conséquent, la mise à jour du plan de maintenance sous les impacts des contextes dynamiques est vraiment nécessaire afin que le plan réel soit toujours optimal. Pour ces raisons, la problématique scientifique numéro 2 est: **"Comment développer une stratégie dynamique de maintenance de regroupement pour le GDPS en tenant compte des dépendances économiques, géographiques et économiques?"** (*Problématique 2*).

La troisième problématique, que nous voulons attaquer, est de développer des modèles mathématiques supportant l'optimisation de la maintenance pour un GDPS. Dans les modèles disponibles, de nombreux chercheurs ont étudié les problèmes de routage de maintenance. Ces études se concentrent sur la formulation d'un modèle supportant une route optimale [25, 30, 31] puis sur le développement d'un modèle global de planification et de routage de maintenance qui supporte simultanément à la fois une route optimale et un plan de maintenance. Dans la pratique, la prise en compte simultanée du routage et de l'ordonnancement de la maintenance rend les modèles de maintenance plus complexes. Pour cette raison, peu de travaux ont mentionné la formulation d'un modèle global et optimal de routage et d'ordonnancement de la maintenance. Par conséquent, la problématique scientifique n°3 est: **"Comment formuler des modèles globaux d'ordonnancement et de routage de la maintenance dans le contexte du GDPS?"** (*Problématique 3*).

Enfin, une autre question de recherche porte sur les méthodes/algorithmes d'optimisation de la maintenance pour les stratégies de maintenance dans le contexte du GPDS. Du point de vue économique, l'optimisation de la maintenance peut être comprise comme l'optimisation de la planification de la maintenance avec un coût de maintenance minimal [11]. Pour les systèmes centralisés, le processus d'optimisation de la maintenance tente d'établir le meilleur planning de maintenance des composants afin que le coût total de maintenance soit minimal. Dans la littérature, de nombreux méthodes/algorithmes d'optimisation ont été développés pour résoudre l'optimisation de la maintenance des systèmes centralisés tels que les méthodes analytiques, les algorithmes exacts, les algorithmes heuristiques [32, 33], etc . Cependant, ces algorithmes, développés pour l'optimisation de la maintenance au sein de systèmes centralisés, ne peuvent s'appliquer directement aux GDPS en raison de leur dispersion géographique (multi-sites). En effet, pour effectuer la maintenance conjointe de plusieurs composants situés sur des sites différents, l'équipe de

maintenance se déplace du centre de maintenance vers tous les sites de production contenant des composants à maintenir et ne retourne au centre de maintenance que lorsque les activités de maintenance sont terminées. De cette façon, la gamme de maintenance est aussi importante que l'ordonnancement de la maintenance. Par conséquent, l'élaboration d'un algorithme d'optimisation pour l'optimisation de la maintenance dans le contexte GDPS devrait être considérée à la fois pour la planification de la maintenance et le routage. Pour cette raison, la dernière problématique scientifique n°4 est **"Comment développer un algorithme avancé pour supporter l'optimisation de la maintenance du GDPS en considérant la planification et le routage de la maintenance?"** (*Problématique 4*).

Pour répondre à ces quatre problématiques afin de supporter le défi de maintenance d'un GDPS, nous défendons globalement dans ce travail de thèse "Une stratégie de maintenance de regroupement dynamique pour un système de production géographiquement dispersé".

Cette défense se construit sur 4 contributions en lien avec les 4 problématiques scientifiques:

- **Formulation d'un modèle de dépendance économique et géographique pour un GDPS (*contribution 1*).**
- **Elaboration d'une stratégie de regroupement dynamique de maintenance pour un GDPS en tenant compte de la dépendance économique, de la dépendance géographique et des impacts des contextes dynamiques (*contribution 2*).**
- **Formulation de modèles de profit économique pour l'ordonnancement et le routage de la maintenance (*contribution 3*).**
- **Développement d'un algorithme avancé utilisant l'algorithme génétique et la méthode Branch and Bound pour résoudre un problème d'optimisation de la maintenance pour la stratégie de maintenance de regroupement dans le contexte du GDPS (*contribution 4*).**

En fonction de ces quatre contributions principales, la thèse est organisée comme suit.

Le chapitre 1 présente un aperçu des systèmes de production géographiquement dispersés (GDPS) et de leur maintenance. Tout d'abord, nous explorons les définitions potentielles et les caractéristiques générales des systèmes de production dispersés géographiquement. Ensuite, nous mentionnons plusieurs facteurs ayant une incidence sur la

maintenance de ces systèmes. Puis nous introduisons les questions de recherche liées aux difficultés de l'établissement de stratégies de maintenance pour les GDPS.

Le chapitre 2 présente un état de l'art pertinent en regard des questions de recherche précédentes, plus précisément sur les aspects: modélisation de la dépendance, stratégies de regroupement dynamique de maintenance, problèmes de routage et d'ordonnancement de la maintenance, méthodes d'optimisation de la maintenance. A partir de l'état de l'art sur les différents éléments, nous justifions les quatre problématiques scientifiques de la thèse.

En lien avec la problématique n°1, le chapitre 3 est consacré à la formulation d'un modèle de dépendance pour un GDPS prenant en compte la dépendance économique et géographique. Dans ce modèle de dépendance, la réduction des coûts de transport due à la dépendance géographique associée à la réduction des coûts de préparation due à la dépendance économique font que le coût total de maintenance diminue lorsque plusieurs composants sont maintenus conjointement.

En lien avec la problématique n°2, le chapitre 4 est consacré à l'élaboration d'une stratégie de maintenance de regroupement dynamique pour un GDPS en tenant compte des aspects économiques, géographiques et environnementaux, la dépendance et les impacts des contextes dynamiques. Dans cette stratégie, les composants du système sont maintenus préventivement et conjointement afin de réaliser des économies sur les coûts de préparation (dépendance économique) et de transport (dépendance géographique) au lieu de fonctionner séparément. De plus, la stratégie de maintenance permet de mettre à jour la solution optimale lorsque les contextes dynamiques (changement de capacité du véhicule, changement d'itinéraire de maintenance, etc.) se produisent.

En lien avec la problématique n°3, le chapitre 5 est consacré à la formulation de modèles globaux de planification et de routage de la maintenance. Dans le cadre du regroupement dynamique de la maintenance des GDPS, pour effectuer la maintenance préventive d'un groupe de plusieurs composants, l'équipe de maintenance peut suivre les itinéraires de maintenance pour maintenir ces composants avant de revenir au centre de maintenance lorsque toutes les activités de maintenance sont terminées. Différents itinéraires de maintenance conduisent à un programme de maintenance avec des coûts différents en raison de l'impact de la distance et du temps de déplacement. De plus, l'acheminement des moyens de maintenance dépend de l'affectation des ressources d'entretien (c.-à-d. réparateur, véhicule, etc.). Par conséquent, le routage de maintenance a un impact considérable sur la formulation de modèles mathématiques de maintenance. Il est pertinent que des modèles globaux soient élaborés dans ce chapitre pour tenir compte à la fois du routage et de l'ordonnancement de la maintenance.

En lien avec la dernière problématique, le chapitre 6 est consacré au développement

d'un algorithme avancé visant à optimiser la planification de la maintenance. Dans ce but, un algorithme d'optimisation utilisant l'algorithme génétique (GA) et la méthode Branch and Bound (BAB), appelé GAaBAB, est étudié. Cet algorithme ne nécessite pas de solution strictement optimale, mais il doit garantir : (i) l'intégration de nombreuses contraintes et contextes dynamiques facilement ; (ii) la réduction et l'ajustement du temps de calcul.

Au chapitre 7, les études numériques permettent d'évaluer la stratégie de maintenance proposée.

Enfin, des conclusions générales et des perspectives sont données à la fin de nos travaux.