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Integrated Decision-Making Framework for Preventive Maintenance Scheduling and Spare Part Logistic Planning

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Integrated Decision-Making Framework for Preventive Maintenance Scheduling and Spare Part Logistic Planning

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Maintenance scheduling for geographically distributed assets intricately and closely depends on the locations and availability of spare parts, which motivates the joint decision-making on the maintenance scheduling and spare part logistics, including optimization of the system operations, as well as the design of the underlying spare part logistic network. These close interactions between the maintenance and spare part logistic activities have been ignored or oversimplified in the existing research and practice, leading to the inappropriate maintenance resource allocations and excessive maintenance waiting times. Unfortunately, such kind of joint decision-making problems are challenging due to the exceptionally large size of the decision space, as well as the strong inter-dependencies in the system operations, especially for large-scale systems with complex maintenance/logistic structures. Challenges become even more pronounced if one acknowledges that those system operations and degradation processes of the assets are greatly influenced by numerous uncertain factors, yielding highly stochastic system behaviors. To address the aforementioned problems and challenges, in this doctoral dissertation, an integrated decision-making framework is proposed to effectively schedule preventive maintenance (PM) for geographically distributed assets and properly manage inventories in distributed logistic facilities storing the necessary spare parts. In addition,

several factors are discussed within the proposed decision-making framework, including the inventory-sharing structure, imperfect maintenance, transportation options and spare parts logistic network design. To capture the stochastic nature of the system operations and the trade-offs between decisions in the domains of maintenance scheduling, spare part inventory management, transportation selection and logistic network construction, a discrete-event simulation-based optimization paradigm was used to minimize generic and customizable cost functions, that reward functioning of the assets, while penalizing asset downtime and consumptions of maintenance/logistic resources. The benefits of the newly proposed integrated decision-making framework are illustrated in simulations, through comparisons between the integrated policies with several traditional, fragmented decision-making processes. Moreover, a design of experiment (DOE) based sensitivity analysis is introduced to evaluate the effects of a variety of relevant systems parameters on the resulting system operations. Future work should be aimed at incorporating robustness to uncertainties in model structures and system parameters into the newly proposed decision-making and system design methodologies, as well as implementing these methods in a real-life system settings, rather than simulations alone.

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Chapter 1
Introduction

1.1 MOTIVATION AND BACKGROUND

As an essential part of system operations, maintenance ensures the desired productivity to the equipment users and generates great profits to equipment providers. According to a 2003 study by Accenture [1], after sales services and parts contributes only 25% of revenues across all manufacturing companies, but are responsible for 40%-50% of profits. Particularly in the last couple of decades, the growing size of trans-regional companies has resulted in increasingly complicated spare part logistic networks that pose significant challenges to the decision-makers in term of maintenance activity scheduling and maintenance resource allocation at the enterprise level.

Preventive maintenance (PM) scheduling in a large and distributed system of degrading assets is a challenging decision-making problem because of inherent interactions between the maintenance and spare part logistics (SPL) operations. As PM operations are aimed at effectively restoring equipment reliability and reducing downtime costs by replacing degraded parts before they actually fail, getting the right amounts of spare parts available in the right places at right time for maintenance operations is of paramount importance for success of those operations. Therefore, the allocations of maintenance facilities and management of spare part inventory levels in them should be decided simultaneously with the maintenance schedules.

High level of uncertainties associated with the operations and degradation processes also contribute to the difficulties in decision-making in such large-scale systems. Sources of uncertainty include degradation processes of the working units, imperfect maintenance/inspection operations, unpredictable transportation interruptions/delays, changing environmental parameters, unreliable parametric estimations, *etc*. Therefore, the performance of operations in a realistic system is usually intrinsically affected by the accumulated stochastic effects. This necessitates understanding how these stochastic effects influence system operations and operational decision-making that is aware of the risks associated with the uncertainties in the system.

In general, two types of maintenance operations can be seen in practice: reactive maintenance (RM), which occurs after an asset starts behaving in an unacceptable manner or fails, and preventive maintenance (PM), which is performed on an asset before unacceptable behavior occurs. Since RM is an unforeseen and thus an unscheduled event, it is most often more costly and time consuming than PM [2]. On the other hand, generally speaking, PM policies can be classified as reliability-based maintenance (RBM), where maintenance is performed at certain times or usage intervals of an asset, and condition-based maintenance (CBM), where maintenance is performed based on monitoring the actual condition of an individual system. Compared to the RBM policies, whose decisions are based on the long-term statistical behavior of the degradation processes of the asset, CBM decisions take the real-time condition of the system into consideration, usually based on the sensor readings obtained from the asset and fitting of a data-driven or physically-based condition model [3]. As a result, CBM decisions are more dynamic and efficient [4], at least in theory. Unfortunately, CBM requires existence of appropriate sensors and building of appropriate condition models, which is often both costly and challenging from the engineering point of view. Hence, it is safe to say that RBM still dominates the PM practice, though significant research is aimed at enabling more pervasive use of CBM.

Typical research on the integrated decision-making of PM and SPL operations focuses on jointly optimizing the PM triggering policies for the assets and replenishment policies for the spare part inventories [5]. Though, in the literature, the majority of evaluated systems are still limited to a single-plant manufacturing system or a uni-component asset structure, recent research started incorporating multi-component asset structures and more realistic SPL operations into the integrated decision-making models, which will be reviewed in Chapter 2. From the side of geographical dispersion of a system, a joint PM and spare part inventory decision-making problem was studied by Chen *et al*. [6] for a multi-echelon SPL network, which considered a usage-based PM policy and continuous review inventory system. Though the main idea of this work is aligned with the ones of what will be considered in this doctoral thesis, generalization and applications of this work are impeded by several unrealistic assumptions, which will be addressed in this doctoral research.

Moreover, for a large-scale and geographically distributed system of degrading assets, a successful PM action is necessarily dependent on the locations of maintenance facilities and their ability to provide spare parts to the assets, which results in the inherent interactions between the SPL network construction and PM/SPL operations. Traditionally, the locations of maintenance centers and their association with the assets are considered as long-term strategic decisions that are made a priori and independently from the operational decisions, such as maintenance scheduling and inventory management. The possibility to jointly design SPL network and jointly optimize the maintenance schedules and spare part inventory decisions has been ignored until now, and this doctoral research exploits this opportunity to improve the efficiency of the SPL system and operations design.

1.2 RESEARCH OBJECTIVES AND CHALLENGES

The main objective of this Ph.D. research is to devise a decision-making framework to jointly optimize PM schedules and spare part logistics in a geographically dispersed network that consist of degrading assets and maintenance centers serving those assets with spare parts. This newly proposed decision-making framework is designed to be flexible enough so that different maintenance/logistic structures can be further studied, such as inventory-sharing structure, imperfect maintenance, transportation options and logistic network design. To capture stochastic nature of the system and the trade-offs between decisions in the domains of maintenance scheduling, spare part inventory management, transportation selection and logistic network construction, a discrete-event simulation-based optimization approach was used to minimize generic and customizable cost functions that reward functioning of the assets, while penalizing asset downtime and consumption of the maintenance/logistic resources. Simulation-based optimization paradigm is pursued as the solution technique, which allows one to further incorporate various forms of customizable cost functions as well as logistic/maintenance structures.

The challenges of devising such a flexible decision-making framework can be summarized as follows:

(a) Evaluating the system performance in the presence of uncertainties requires meticulous consideration of stochastic effects associated with the system topology and operations.

(b) The decision space for the SPL and maintenance decisions grows exponentially with the number of decision variables. Even for a small maintenance logistics system, the candidate space can be so large that an efficient optimization approach is needed.

(c) As multiple system components interact and multiple uncertainty factors exist in a SPL system, there is a tremendous challenge in developing a feasible mathematical model and measuring the impacts of those uncertainties.

(d) With the target to deal with realistic systems, the decision-making framework should be designed flexible enough to incorporate various and customizable maintenance/SPL operations and cost functions.

The contributions incorporated into this work can be summarized as follows:

1. An integrated decision-making framework for SPL and PM operations is derived, where multi-echelon SPL network, multi-component asset structure and several types of uncertain factors are taken into consideration. This integrated decision-making framework can incorporate various system operations and cost models without changing the principal modeling and optimization paradigm.
2. A study on incorporating imperfect maintenance operations and multiple transportation options into the proposed integrated decision-making framework is conducted.
3. A novel model that integrates the SPL network design with the joint optimization of spare part inventories and PM schedule is formulated.
4. A Design of Experiment (DOE) based sensitivity analysis is conducted to evaluate the effects and interactions of multiple system parameters on the system operations.

1.3 OUTLINE OF THE THESIS

The rest of this doctoral thesis is organized as follows. Chapter 2 presents a review of the literature relevant to the doctoral research. In Chapter 3, an optimization method is proposed for joint decision-making in the domains of spare part inventory and preventive maintenance scheduling for a system of geographically distributed assets. Also, in Chapter

3, a novel simulation-based metaheuristic is proposed to concurrently pursue the maintenance schedules and inventory replenishment policies for spare parts in maintenance centers that jointly optimize the cost effects of operations in the system. Chapter 4 offers an extension of what is described in Chapter 3 through incorporating imperfect maintenance operations and multiple transportation options. Chapter 5 considers the integration of the SPL network design problem with the joint optimization of PM and SPL operations. Finally, Chapter 6 details the scientific contributions of the proposed doctoral research and several possible directions for the future research, along with a summary of past/foreseen publications based on this doctoral research.

Chapter 2
Literature Review

In this chapter, we review a couple of literatures that are relevant to this doctoral research. Section 2.1 introduces maintenance strategies and their applications, while Section 2.2 reviews the existing works on spare part logistics (SPL) with focus on the joint optimization of SPL operations and maintenance scheduling. We also review the literatures on logistic network design in Section 2.3 and literatures on optimization methods for maintenance problems in Section 2.4.

2.1 MAINTENANCE STRATEGIES

In the recent years, maintenance and replacement problems in systems of deteriorating assets have been extensively studied. Bevilacqua and Braglia [7] claim that maintenance related costs can reach between 15% to 70% of production costs. Lack of knowledge and ability in properly scheduling maintenance can cause significant economic losses, as documented in semiconductor manufacturing [8], [9] and power generating systems [10], [11], and sometimes even cause catastrophic effects in systems, such as aircrafts [12] and nuclear systems [13]. Maintenance scheduling is crucial in reducing the economic losses and preventing catastrophic results, and consequently, it is of great interest to both academia and industry.

Generally, two overarching concepts of maintenance operations can be seen in practice: reactive maintenance (RM), which occurs after an asset starts behaving in an unacceptable manner or fails, and preventive maintenance (PM), which is performed on an asset before unacceptable behavior occurs. Since RM is an unscheduled event, it is most often more costly and more time consuming than PM [14].

Due to the complex nature of manufacturing systems, it is impossible to avoid RM operations through perfect prediction of breakdowns. However, with advanced computer-based monitoring systems and data analysis technologies, it is possible to detect and diagnose a breakdown immediately after it occurs, which can significantly reduce the downtimes and economic losses even in the case of RM [15].

2.1.1 Preventive Maintenance

Barlow and Hunter [16] conducted pioneering studies on PM policies in 1960. After that, the economic benefits of PM operation have gradually been recognized in various industries, leading to numerous studies of various PM models, with the focus on improving the effectiveness of PM under different operating environments. To obtain a general picture of the development process of PM studies and their applications, readers can refer to several literature surveys, including Smith [17], Valdez-Flores and Feldman [18], Zeng [19], Fernandez *et al*. [9], Wang [14], Garg and Deshmukh [20], Sharma and Yadava [21] and Froger *et al*. [11]. Among them, Wang [14] provided the most recent review on PM models for non-repairable, single/multiple units deteriorating systems, which is highly relevant to the systems considered in this doctoral thesis.

PM can be roughly grouped into reliability based maintenance (RBM), where maintenance is performed at certain times or usage intervals of an asset, and condition based maintenance (CBM), where maintenance is performed based on monitoring the actual condition of an individual system.

Compared to RBM policies, whose decisions are based on the long-term statistical behavior of the degradation processes of an asset, CBM decisions try to take the actual condition of the system into consideration, usually based on the sensor readings obtained from the asset and fitting of a data-driven or physically-based condition model [3]. As a result, CBM decisions are more dynamic and efficient [4], at least in theory. Unfortunately, CBM requires existence of appropriate sensors and building of appropriate condition models, which is often both costly and challenging from the engineering point of view. Hence, it is safe to say that RBM still dominates the PM practice, though significant research is aimed at enabling more pervasive applications of CBM.

2.1.1.1 Reliability based maintenance (RBM)

Depending on the way a PM operation is triggered, several types of PM policies have been found for RBM in literatures, among which age-dependent and periodic-dependent PM policies are two commonly used polices for single-unit systems.

Under an age-dependent PM policy (also known as age replacement policy), PM times are based on the age of the unit. Pioneering work on age-dependent PM was proposed by Barlow and Hunter in 1960 [16], in which a component is replaced at its age T or failure, whichever occurs first. Nakagawa [22] extended the age-dependent policy to replacing a unit at age T or at number N of failures. Block *et al*. [23] introduced a repair replacement policy, where units are minimally/perfectly repaired at failure, or they are replaced if they survive a certain fixed time since the last maintenance. Wang and Pham [24] used a “mixed age PM policy” to deal with a system suffering two types of failures, with perfect repairs on type 1 failures and minimal repairs on type 2 failures.

The periodic-dependent PM policy, also known as block replacement in some literature [16], indicates that a component is either correctly repaired at its failure, or preventively maintained at fixed time intervals, thus being independent of its failure history. Extensive works have been established, especially combing periodic-dependent policy with imperfect maintenance [25], [26]. Moreover, the PM intervals can be unequal (referred as sequential PM policy), usually becoming shorter as time elapses. Nakagawa

[27], [28] investigated a PM policy where PM is performed at fixed intervals x_k for $k = 1,2,..,N$, while Linderman *et al*. [29] claimed that economic benefits can be obtained from adapted PM intervals through linking the aggressiveness of PM schedules with the stability of the process. In addition, improvements in maintenance scheduling can also be achieved through combing the age-dependent and periodic policies, as can be seen in [30], where an intuitive way is proposed for unit replacements at a fixed interval t_0, or when the total operating time reaches T $(t_0 < T)$.

Besides the widely used age-dependent and period-dependent PM policies, other types of PM polices can also be encountered. Under a repair limit policy, a replacement of a unit is triggered by the repair cost [31], [32], the number of repairs [33], [34] or repair time [35], [36]. For a failure limit policy, PM is triggered by a failure rate [37], [38] or other reliability indices (e.g. accumulated stress[39]).

The aforementioned works on maintenance polices focus on single-unit systems. Nevertheless, due to the complex multi-unit nature of most equipment, maintenance problems in multi-unit systems have also received significant attention. For a multi-unit system that contains several subsystems having economic or failure dependencies, most maintenance policies originally proposed for single-unit systems can still be applicable after generalization [25], though opportunities for developing new maintenance policies to specifically deal with such complex environment are recognized [40], [25], [41]. Opportunistic maintenance policies seek positive cost effects through employing the dependencies inside a multi-unit system. Nakagawa and Murthy [42] investigated a multi-unit system having failure dependencies in the sense that times to failures of different units are statistically dependent. Dagpunar [43] introduced a control limit for every unit in a multi-unit system and reduced PM costs by preventively replacing units exceeding the control limit. As economic dependencies exist among wind turbine systems, Besnard *et al*.

[44] acknowledged dramatic PM cost savings (as high as 45% in their example) by implementing opportunistic maintenance policies in offshore wind power systems. Ding and Tian [45] further extended Besnard's work through considering three PM actions (perfect, imperfect or two-level PM interventions) for a wind turbine system.

2.1.1.2 Condition based maintenance (CBM)

The concept of CBM can be tracked back to 1940s [46]. Studies on CBM involve various disciplines like statistics, data mining artificial intelligence, and have been applied to various domains, including manufacturing, aerospace, medical, *etc*. The readers can refer to a recent survey conducted by Prajapati *et al*. [46] to find a thorough summary of various CBM models and up-to-dated techniques. Since CBM policies are not crucial to this doctoral dissertation, we will only review the works related to joint CBM and spare parts inventory optimization. Please note that this will be done in Section 2.2.3.

2.1.2 Uncertainty In Maintenance Systems

Uncertainties in manufacturing scheduling can cause infeasibilities and production disturbances, which is why manufacturing scheduling under uncertainty has received a lot of attention in recent years, especially from chemical engineering and operations research communities [47]. As a special type of production operation, robust scheduling of maintenance operations in the presence of uncertainties has also been widely studied.

Beyer and Sendhoff [48] provided a thorough introduction to robustness concepts and measures, and classified uncertainties in the general parameter design processes into four categories: (a) changing environmental and operating conditions, e.g. operating temperature, pressure, changing material properties and drift, (b) production tolerances and actuator impression, i.e. a type of uncertainties enters the system with decision variables,

(c) uncertainties in the system output and (d) feasibility uncertainties concerning the fulfillment of constraints of the system. Later, a complementary classification scheme of uncertainties is provided for engineering disciplines, in which uncertainties are classified as objective and subjective from an epistemological perspective. Objective uncertainties [49], [50] are intrinsically irreducible, e.g. white noises in devices, humidity and temperature, in contrast to subjective uncertainties that reflect the lack of knowledge of the system, e.g. inaccurate system parameters and model form errors [51].

In the field of maintenance scheduling under uncertainty, most existing works focus on dealing with objective uncertainties, such as inherent uncertainties in the degradation dynamics and imperfect maintenance operations.

2.1.2.1 Degradation dynamics

Modeling degradation dynamics is an active tropic in the reliability engineering community. In the field of maintenance scheduling, Noortwijk [52] pointed out that stochastic deterioration dynamics can be modeled by a failure rate function or a stochastic process.

A failure rate function, along with the corresponding lifetime distribution, represents the uncertainty in the time to failure of a unit (component or machine). The mostly used statistics distribution for a lifetime distribution is Weibull distribution, which interpolates between the exponential distribution and the Rayleigh distribution. According to Singpurwalla [53], the major disadvantage of the failure rate based approaches is that its parametric estimation suffers from lack of failure data and fails to be effectively adjusted to the changing operating environment.

Deteriorating processes can also be modeled by Markov processes [54]. A Wiener degradation processes was considered by Doksum and Hoyland [55], in which they applied Brownian motion with drift to data from a variable-stress accelerated life testing experiment. The methodology presented in [55] was extended by Whitmore [56] by involving imperfect inspections. It was also applied by Whitmore and Schenkelberg [57] to model degradation dynamics of self-regulating heating cables.

Furthermore, the gamma processes, which are continuous-time stochastic processes with independent, non-negative increments having a gamma distribution, was also successfully applied to model degradation dynamics for CBM [52], [58], [59]. Finally, in very recent research, Cholette and Djurdjanovic [60] and Zhang *et al*. [61] used a Hidden Markov Model to capture the degradation processes in unobservable systems and demonstrated the proposed methods on a large dataset obtained from a semiconductor manufacturing facility.

2.1.2.2 Imperfect maintenance

The fact that maintenance of a deteriorating system does not always restore the system to the as-good-as-new state adds another level of uncertainty into the system operations. The research addressing this challenge led to significant breakthroughs in studies on maintenance decision-makings. The concept of "imperfect maintenance" was first introduced by Chaudhuri and Sahu [62], and currently, three major maintenance strategies are recognized based on the degree to which the operating conditions of the system is restored by maintenance: perfect maintenance, minimal maintenance and imperfect maintenance. Pham [25] suggested that more than 40 mathematical imperfect maintenance models have been proposed.

The most popular modeling method for imperfect PM is known as the (p, q) rule proposed by Nakagawa [22], [63]. In this model, the operating component is returned to the as-good-as-new state (perfect PM) with probability p, and to the as-bad-as-old condition (minimal PM) with probability $1 - p$. Block *et al*. [64] further extended the (p, q) rule to age-dependent imperfect repairs $(p(t), q(t))$. Other basic methods to model imperfect maintenance include the improvement factor method [65], virtual age method [66], [67], shock model method [68], [69] and the (α, β) rule [70], [71].

Nakagawa [22] first considered imperfect maintenance models for the age-based PM policy and optimized PM interval times for imperfect PMs. Extensive models are proposed by Sheu *et al*. [72], [73] to allow imperfect maintenance for both PM and RM. Imperfect maintenance is also considered under periodic PM polices and early works include [27], [66], [74]. Sheu *et al*. [75] proposed periodic PM policies that maximize the availability of a repairable system, in which the probability of conducting a perfect PM depends on the number of imperfect PM conducted in that renewal cycle.

In recent studies, imperfect maintenance is treated as an important part of complex manufacturing systems and the concept is applied to numerous applications. One of the applications was in wind farms [45], where multi-level imperfect maintenance thresholds are evaluated under the proposed opportunistic maintenance policy. Lin *et al*. [76] developed an integrated model that considered an imperfect manufacturing process, with imperfect maintenance operations, inspection errors, PM errors and minimal repairs. Finally, one should also note series of papers that focus on implementing imperfect maintenance in used system [77]–[79], in which imperfect PM (RM) restores the system to a pristine state with a random initial damage.

2.1.2.3 Other types of uncertainties in maintenance

The system's degradation level can only be evaluated through inspections, and inspection does not necessarily have to perfectly reveal the true condition of the system. Maintenance scheduling under imperfect inspection was studied by Kallen and Noortwijk [59], who used an adaptive Bayesian decision model to determine optimal inspection plans under uncertain deterioration. Lin *et al*. [76] developed an integrated model in considering an imperfect manufacturing process with imperfect maintenance, inspection errors, PM errors and minimal repairs. Other works involving imperfect inspection include Yun and Bai [31], Berrade *et al*. [80], and Le and Tan [81].

Only limited numbers of works incorporate subjective uncertainties into maintenance scheduling. Vassiliasi and Pistikopoulos [82] derived optimal maintenance policies for continuous process operations in the presence of parametric uncertainty. In that paper, mix-integer nonlinear programming was used to identify the optimal number of PM/RM actions and sequence of these maintenance actions on the various components of the systems, and analysis of impacts of uncertainty on the optimal maintenance schedules was conducted. Sevaux *et al*. [83] looked at the task of scheduling maintenance on trains for a French railways company in the presence of uncertainties of changing environmental conditions. The optimal maintenance polices were obtained through optimizing a robust evaluation function, generated as a weighted average of several evaluations under sampled environmental parameters. With the assumption that knowledge uncertainties exist within asset management systems, Kuhn and Madanat [84] used robust dynamic programming model to solve a maintenance optimization problems in which the system parameters are not known precisely, but are known to belong to certain sets ("uncertainty sets").

2.2 JOINT MAINTENANCE AND SPARE PARTS INVENTORY OPTIMIZATION

Spare parts management is important but also challenging because the parts can be expensive and their demand is highly erratic and intermittent, while their shortage costs can be very high [85], [86]. Effective spare part management is crucial in many industries, and the successful industrial applications can be found for airlines [87], computer systems [88] and *etc*.

Different from inventory management for intermediate or final products, spare parts management targets at keeping equipment in operating condition, and largely depends on how equipment is used and maintained [89]. Therefore, in its nature, spare parts management is closely related to maintenance scheduling problems. The demand for spare parts is usually intermittent, erratic and slow moving [85]. To deal with spare part demands, most existing literature focuses on forecasting the demands, which will be reviewed in section 2.2.1. However, there are still a few papers that attempt to manipulate the demand side of the problem through jointly optimizing maintenance schedule and spare part inventories.

2.2.1 Forecasting Spare Parts Demand

Under the assumption that spare parts demand is predictable or partially predictable, the demand is usually modelled by a statistical distribution or a stochastic process, with the essential parameters being estimated from historical data. Syntetos *et al*. [90] and Boylan [91] provided a thorough review of the current forecasting methods and applications regarding spare part demands.

Due to the compound nature of the demand structure, most industrial software applications are based on Croston's method [92], in which single exponential smoothing is used to predict demand incidences and demand sizes. Extensive theoretical studies of Croston's method are given by Snyder [93], Syntetos and Boylan [94] and Shale *et al*. [95].

In terms of the demand distribution, Poisson distribution is chosen by most models as the hypothesized distribution of the slow-moving spare parts demand [86], [96], [97]. However, Porras and Dekker [98] proposed a bootstrapping approach to construct a non-parametric empirical distribution of the demand. In a later paper, Willemain *et al*. [99] proposed a patented non-parametric forecasting method designed for intermittent demand data. For short demand history, Miller and Willams [100] focused on the seasonal component estimations using time-series analysis techniques. Eaves and Kingsman [101] also employed a time series analysis approach to take advantages of the limited information gathered for the installed assets.

A series of works have been done to model the demand for spare parts in a dynamic way through incorporating the life cycle information on the parts. The earliest studies on incorporating the life cycle aspect into spare parts forecasting is conducted by Moore [102], who modeled the growth and decay of the demand for a spare part during its life cycle. Follow-up research was reported by Fortuin [103], Spengler and Schroter [104] and Tako and Robinson [105].

2.2.2 Joint RBM and Inventory Optimization

The first review of joint optimization of maintenance and inventory polices was provided by Dohi *et al* [106], but this review put emphasis on the spare part inventories, with the reviewed models only considering inventory related costs.

According to a recent review given by Horenbeek [5], existing joint RBM and inventory optimization models are classified based on their PM strategies. In the field of age-based replacement policy, a single-unit system was first examined by Armstrong and

Atkins [107], in which PM replacement and inventory ordering time (for a periodic review inventory) were optimized for a unimodal, pseudo-convex cost function. In the extensive work [108], they proved that positive cost effects can be achieved by allowing minimal repairs for minor failures. Kabir and Al-Olayan [109] considered the integrated decision-making problem for dispersed systems in which a maintenance facility serves several identical single-unit assets following the age-based PM policy and continuous review inventory policy. The decision-making problem was solved by a combination of discrete-event simulation and limited enumeration, with this optimization procedure being further improved in [110] to avoid local optima. For the same model as the one considered in [110], Hu *et al*. [111] introduced simulation-based optimization with a genetic algorithm to efficiently pursue the optimal solution. Chen *et al*. [112] firstly conducted a study on a multi-echelon network, consisting of multipole supplier, a distributor and different users. They used the Arena and OptQuest software packages to perform computations for their simulation-optimization model, and jointly optimized the continuous review inventory and age-based PM policies.

In the field of periodic PM (or block-based PM), Acharya *et al*. [113], Brezavscek and Hudoklin [114], and Huang *et al*. [115] considered block replacement policies inside a periodic inventory reviewing system, with maintenance inspection and inventory review having the same intervals. Other researchers combine a continuous review inventory policy with the block-based PM policy [116]–[123]. More specifically, Saker and Haque [116] proposed a joint optimization scheme relying on a similar model as the one considered in [110], containing a gamma distributed repair time and several working units consisting of several identical components. Based on the model from [116], Ilgin and Tunali [117] investigated a joint optimization model allowing a random lead time under multiple types of maintenance policies. Nguyen *et al*. [118]–[120] focused on applications in chemical process plants, and specifically modeled human resources (number of employees and their skills) as decision variables or constraints in the presence of imperfect maintenance operations. Some researchers also attempted to examine the effects of various failure modes in the joint decision-making model. In Panagiotidou's work [121], each operating unit in a multi-unit system is assumed to suffer two types of silent failures (minor or major). Meanwhile, other researchers focused on the effects of spare parts quality. In an interesting work by Horenbeek *et al*. [123], the effects of spare parts quality and variability in demands for spare parts are evaluated through a stochastic simulation model in N identical one-component systems under a single-echelon periodic inventory review policy. Recently, a deterministic deteriorating inventory model was used by Jiang *et al* [122], enabling them to make integrated decisions in the domains of block replacement and periodic review inventory policies in the presence of inventory deterioration.

For the reason of simplicity, the aforementioned works (except [116], [117]) on joint RMB and inventory optimization assume that the manufacturing system consist of either a single operating unit or several identical units operating independently, with every operating unit having a single component. To reflect the complexities of a manufacturing systems in reality, several extensive works consider multi-component structures of the operating units. In [116] and [117], each operating unit is assumed to contain several serially connect components. Bjarnason *et al*. [124], [125] jointly optimized inspection and inventory policies for a *k*-out-of-*n* system (it fails when fewer than k components are working), in which both planned periodic inspections and unplanned opportunistic inspections are performed to find the failed components. Alrabghi *et al*. [126] proposed a simulation-based method to optimize the age-based PM and continuous review inventory policy for a flexible-connected multi-component manufacturing system limited by labor resources.

As a comment, existing works on the joint RBM and spare parts inventory optimization still oversimplify the reality in several ways. First, with focus on the side of maintenance, the complexity of spare part logistics in reality is generally overlooked. For example, none of them consider the effects of geographical dispersion of assets and maintenance centers, let alone other more elaborate logistic factors. Second, dependencies of operating units (asset, component) are also not fully studied, as most works still have assumptions such as “single-component”, “single unit”, “identical multiple units”, *etc*.

2.2.3 Joint CBM and Inventory Optimization

Instead of sticking to the pre-estimated lifetime distributions based on the historical data of the unit/component, several predictive maintenance models are proposed to consistently update the estimation of the remaining useful lifetime (RUL) distributions via analysis of the condition of a component. Elwany and Gebraeel [127] incorporated updated RUL (after each inspection) into a nonlinear programming model and solved for optimal joint maintenance/inventory decision for the next operating period. According to Wang *et al*. [128], the system’s degradation trajectory is modeled by a Wiener process whose parameters are estimated in real time based on the newly arrived monitoring data, so that the joint inventory and maintenance polices are optimized using the prognostic information. They successfully validated their proposed method in an inertial navigation system in aircraft.

Some other works also jointly optimize CBM and spare parts inventory policies. Wang [129] investigated joint CBM and continuous review (s, S) policies using a simulation-based method, and claimed that the cost decreased by on average 3.78% when joint optimization is used instead of using fragmented optimization in their numerical examples. Wang *et al*. [129] developed a mathematical model to obtain a condition-based replacement and spare provisioning policy for a single-unit deteriorating systems. Then they extended the model to multiple identical units [130], in which the deterioration process is modeled by a Markov chain and a Monte Carlo simulation procedure (similar to the model proposed by Hu [111]). In another extensive work, Wang [131] modelled the failure rate as a function of the deterioration level of the system other than a function of time in traditional PM models. Li and Ryan [132] assumed Brownian deterioration for a periodic review inventory system and used a dynamic programming to derive the optimal inventory control and control limit maintenance policies.

2.3 LOGISTIC NETWORK DESIGN

2.3.1 General Logistic Network Design Model

Logistic network design problems and facility location models have been widely studied in the literature. A thorough introduction to facility location models was given by Dsakin [133], in which they categorized the existing models based on their underlying optimization formulation. Several related topics are also discussed in this book, including the coverage maximization problems, routing problems and production flow planning. In the review paper [134], Melo *et al*. reviewed facility location models for supply chain management, with the models being classified according to the features of networks, namely single/multiple location layers, single/multiple commodities and single/multiple planning periods. Moreover, this review paper had an independent chapter to introduce the facility location models proposed for reverse supply chain logistics, where the reverse network is referred to as *closed-loop network*, if the reverse network is integrated with the forward network, and *recovery network* if only the recovery activities are considered. Due to the fact that network parameters and system environments can be dramatically changed, stochastic and robust location models are also extensively studied to conduct logistics network design under uncertainties and Snyder [135] provided a detailed summary for the research relevant to that topic.

There is also a number of network design models that are specifically developed for certain network settings and/or system environments. For example, Eskandarpou *et al*. [136] reviewed 87 papers in the field of sustainable supply chain network design, with the focus on the mathematical models and their applications. Besides the typical economic factors, the network design models introduced in this paper incorporated various environmental and/or social factors relevant to the sustainable supply chain networks. Lemmens *et al*. [137] showed that supply chain network for vaccines do not behave like that for typical commodity goods and, therefore, studied several key issues for vaccine supply chain design, considering factors such as limited shelf life, cold chain distribution and access to remote areas. The problem of pharmaceutical supply chain network design was recently studied by Martins *et al*. [138], with the design factors including the number, location and capacity of the warehouses, allocation of customers to the warehouses, as well as the capacity of the distribution channels. The strategical and operational decisions in their model are optimized using a discrete-event simulation optimization approach.

Traditionally, for the SPL network design, the locations of maintenance centers and their priority in providing maintenance services are considered as strategic long-term decisions that are made before the tactical decisions, such as maintenance scheduling and spare part inventory management.

In the majority of the existing research, the SPL network design problem is only considered as a special case of the reverse logistic network design [134]. For instance, Guide Jr. *et al*. [139] analyzed the system factors that influence the closed-loop supply chain design with product recovery considerations, where Hayes and Wheelwright's product-process matrix was used to study characteristics of the closed-loop supply operations. Another close-loop logistics network design model for the end-of-lease computer product recovery was proposed by Lee and Dong [140] as a Mixed Integer Programming (MIP) problem. Their model relied on a two-stage heuristic approach to decompose the integrated design problem into a location-allocation problem and a network flow problem. Only recently, low demand rate and time urgency characteristics of an SPL have been considered, which led to studies specifically focusing on the SPL network design problems. As all aforementioned SPL network design methods are integrated with inventory considerations, in order to avoid redundancy, the review for these approaches will be given in Section 2.3.2.

2.3.2 Joint Inventory Management and Logistic Network Design

For general logistic systems, the integration of logistics network design with inventory considerations received increased attention recently, with the proposed models being referred to as *location-inventory models*.

Currently, most location-inventory models are designed for supply chain logistic networks. Berahona and Jensen [141] were the first to explicitly concurrently consider decisions on the facility locations and inventory levels in a modified un-capacitated facility location (UFL) problem, which is solved via a Dantzig-Wolfe decomposition. Nozick and Turnquist [142] included the inventory costs into a fixed-charged facility location optimization by modeling the inventory costs as a linear function of the number of open maintenance facilities, and in a later work, they specifically considered transportation costs and customer responsiveness [143]. Later, Nozick [144] further modified the method to consider coverage restrictions as the constraints, so that an proper level of service is maintained. The inventory cost was firstly incorporated into UFL model by Daskin and Coullard [145], where (Q,r) replenishment policy is applied. The model is formulated as a non-linear integer-programming problem and is solved via a classical Lagrangian relaxation solution algorithm, while Shen *et al*. [146] provided a column generation-based optimization method to the same problem.

At the same time, different types of uncertainty/risk factors are incorporated into the location-inventory models. Snyder *et al*. [147] introduced discrete scenario-based randomness into Daskin's model [142] and present a stochastic version of the location-inventory model with risk pooling (LMRP). For a three-echelon wholesale supply chain system (with suppliers, distribution centers and retailers), Zhang and Xu [148] used pre-estimated probability distribution to model uncertain customer demand to each retailer. They proposed a mixed-integer bi-level programming method to obtain integrated decisions in the domains of distribution center allocation, wholesale price of the products and transportation flows. Jin *et al*. [149] also assumed stochastic demands in their location-inventory method, but they focus on the multi-commodity logistic network design to serve multiple types of goods. To address facility disruption risks in a closed-loop supply chain, Asl-Najafi *et al*. [150] presented a location-inventory model with two objectives minimizing the total cost as the first objective and minimizing time as the second one. Their solution technique is a hybrid meta-heuristic algorithm based on multi-objective particle swarm optimization and genetic algorithm.

As for SPL network design problems, the facility allocation models are also integrated with the inventory considerations. Candas and Kutanoglu [151] focus on the low-demand nature of the SPL systems and introduced a linear optimization model to capture the interdependencies between the network design (facility locations and allocation of demands to facilities) and inventory stocking decisions (stock levels in one-for-one replenishment policy and their corresponding fill rates). This work was extended by Jeet *et al*. [152] by assuming lost sales for stock-out situations, instead of direct backordering. In a later study, Gzara *et al*. [153] extended the single-part model to a multiple-part model and also considered nonlinear time-based service constraints. For the part-warehouse situation, they provided a linear reformulation to the fill-rate function that can be solved by a commercial optimizer.

Other SPL structures are also considered for the integrated SPL network design and inventory optimization problem. Iyoob *et al*. [154] introduced an inventory sharing structure into a simplified version of the integrated SPL problem, where they considered 2-facility inventory sharing pools, with full inventory sharing between the facilities in each pool. In the model, demand allocation for the active facilities that stock inventories is optimized by minimizing a cost function consisting of the facility, inventory and transportation costs, subject to a time-based service level constraint. Wu *et al*. [155] included considerations of the part vendor and transportation selections into the location-inventory model, which yielded a multi-indenture, multi-echelon spare part supply chain system. Due to the model complexity, the resulting optimization problem was solved by an elaborately designed Neural Network-Genetic Algorithm-Tabu approach (NN-GA-Tabu).

To be noted, a major difference between the SPL networks and other types of logistic networks lies in that the fact demand rates for the spare parts in a maintenance system largely depend on the maintenance schedule and, therefore, are partially influenced by adjustments in the PM policies. However, the possibility to jointly design SPL networks and optimize the underlying maintenance decisions has never been addressed.

2.4 METHODS FOR MAINTENANCE SCHEDULING

In general, a maintenance scheduling problem can always be formulated as an optimization problem, with possible objective including minimization of the overall costs, or maximization of the system availability, as well as one or more constraints regarding the maintenance resources or system performance. Complexity of these models depends on the maintenance policies, system configurations, failure/economic dependencies, involvement of production/logistic operations and other problem-specific considerations [14]. In order to obtain the optimal maintenance schedule, numerous researchers used mathematical approach that yield analytical solutions. In those papers, optimization methods, such as deterministic programming, stochastic optimization and dynamic programming, ae used for maintenance scheduling. Though these mathematical methods can yield a strict optimal solutions for small scale decision-making problems, two major defectives limit the usefulness of these mathematical models. First, the curse of dimensionality prevents the applications of mathematical methods for large-scale decision making problems, as the candidate solution space usually grows exponentially with the number of decision variables. Second, the manufacturing systems in reality are complex and can hardly be faithfully represented by a tractable mathematical model. In order to account for complexities of real-life systems in terms of system operations, inter-dependencies and the numbers of influential factors and decision variables, in the recent years, many researchers turns their eyes to simulation-based modeling of system operations [156] and metaheuristic approaches to optimization [157] as methods for maintenance scheduling optimization.

Monte Carlo based simulation paradigm is widely used for modeling of system operations, with fitness of a candidate solution (maintenance schedule) being evaluated via repeated random sampling from relevant distributions (reliability, quality, cycle-time and other random factors that affect system operations). Borgonovo *et al*. [158] and Marquez *et al*. [159] used Monte Carlo methods to assess alternative scheduling policies that could be implemented dynamically on the shop floor. 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 infeasible. Therefore, in the majority of existing research in which evaluation of effects of various maintenance schedules is done via simulation-based approaches, a heuristic method is employed to pursue (sub)optimal solutions through partial but efficient exploration of the solution space. For example, Bevilacqua *et al*. [7] investigated a realistic maintenance scheduling problem in an Italian oil refinery using Monte Carlo simulation. The best maintenance policy is chosen based on risk priority numbers, which are calculated for components and machines through a joint analysis of failure mode and criticality level.

In contrast with most problem-specific heuristics, a metaheuristic is an algorithm designed to solve a wide range of optimization problems without having to deeply adapt to each one. According to Boussaid [157], metaheuristics algorithms are classified into two basic categories: single-solution based metaheuristics and population based metaheuristics. Single-solution based metaheuristic approaches, also known as trajectory methods, start with a single initial solution and iteratively move away from the current solution, thus denoting a trajectory in the search space. Typical single-solution based metaheuristic approaches include the tabu search (TS), simulated annealing method (SA) and greedy randomized adaptive search procedure (GRASP). On the other hand, population-based metaheuristic approaches deal with a set of solutions rather than with a single solution, with most of them involving the concept of either Evolutionary Computation or Swam Intelligence. Evolutionary Computation is inspired by the Darwin's Theory of Evolution, while the idea of Swam Intelligence is to produce computational intelligence by exploiting simple analogs of social interaction, rather than purely individual cognitive abilities [160].

Tabu Search (TS) is a single-solution based local search technique that enhances the exploration performance by using advanced memory structures of a computer. Starting from an initial solution, the algorithm iteratively moves to the next candidate solution by evaluating a local neighborhood set of the current solution, while a tabu list is maintained to prevent revisiting the same solution in consecutive iterations. A detailed description of the TS can be found in [161], [162]. TS has been used for maintenance scheduling only recently. A TS-based automatic scheduling method was first proposed for maintenance outage tasks in power systems by Sawa *et al*. [163]. El-Amin *et al*. [164] claimed that TS provides a viable approach for maintenance scheduling through a comparison between the results obtained using TS and using implicit enumeration. TS-based optimization method was also used to optimize the total priority of the scheduled tasks in [165] and flexible job shop scheduling in [166], [167].

Genetic algorithms are the most popular and most frequently used population-based metaheuristic that mimics the process of natural evolution. A basic GA is very robust, and there are many aspects that can be implemented differently according to the problem [168], [169]. Those aspects include representation of a solution (chromosomes), selection strategy, crossover operators, mutation operators, and other GA operators. As a brief description, the GA starts with an initial population (usually randomly generated) and evolves by implementing "the survival of the fittest" paradigm ([170], [171]). In each generation, multiple individuals are selected based on their fitness following a certain rule, e.g. roulette-wheel selection, tournament selection or ranking selection ([169], [172]). Crossover operators are then applied to the selected candidate solutions to combine them by exchanging some of their chromosome portions, yielding a set of offspring solutions. The offspring solutions are then subject to mutation operators to promote the genetic diversity of the population, after which a survivor selection is conducted to identify the individuals for the next generation based on their fitness.

Due to the complex nature of maintenance-related decision-making problems, which is further exacerbated by joint maintenance and inventory optimization problems, GA has been recognized as a power tool in searching for the optimal policies. For example, Hu [111] used GA to solve a joint maintenance/logistic decision-making problem for dispersed systems in which a maintenance facility serves several identical single-unit assets. Other related works that combine the use of GA and simulation-based models for joint maintenance and inventory optimization problem include [112], [117], [130], [131] and [173].

Several hybrid algorithms based on the combined use of GA and TS have also been proposed to improve search efficiency by combining TS's power in local search with GA's capability for global exploration, along with high suitability of both metaheuristics for computational parallelization [174]. Li *et al*. [175] developed a hybrid approach, which combined a graph-based search heuristic with a Tabu-enhanced GA to handle disassembly sequence planning for maintenance, and demonstrated that the Tabu-enhanced GA improves the search performance when tackling complex problems with larger number of disassembly operations. Another hybrid algorithm combing TS, GA and simulated annealing (SA) was proposed by Kim *et al*. [136] for a thermal unit maintenance scheduling problem, in which the acceptance probability of SA is used to improve the convergence of GA, while TS was adopted to find more accurate solutions.

2.5 CONCLUSION

To address the aforementioned gaps, in this doctoral dissertation, we establish a decision-making framework for the integrated decision-making of preventive maintenance and spare parts logistics in the system having multi-echelon logistic facilities and geographically dispersed, multi-part degrading assets. The continuous-review inventory policy for spare parts inventories in maintenance facilities, along with the age-based PM policy for degrading components, will be jointly optimized with several other SPL and PM operations, including imperfect PM operations and shipping mode selections. Moreover, the joint decision-making on PM and SPL operations has also been considered with SPL network design so that network construction decisions, such as locations of maintenance centers and their allocations to assets, are simultaneously optimized with system operations.

Chapter 3

Joint Optimization of Preventive Maintenance and Spare Part Inventory for Geographically Distributed Assets

3.1 INTRODUCTION[1]

Preventive maintenance (PM) scheduling in a large and distributed system of degrading assets is a challenging decision-making problem because of inherent interactions between maintenance decisions and logistic operations. PM operations aim to restore equipment reliability and reduce downtime costs by replacing degraded parts before they actually fail, and thus, getting the right amounts of spare parts available in the right places at the right time is of paramount importance for success of those operations. Therefore, the spare parts inventory levels in maintenance facilities should be considered simultaneously with maintenance schedules.

Two general types of maintenance operations can be seen in practice: reactive maintenance (RM), which occurs after an asset starts behaving in an unacceptable manner or fails, and preventive maintenance (PM), which is performed on an asset before unacceptable behavior occurs. Since RM is an unforeseen and thus an unscheduled event, it is most often more costly and more time consuming than PM [2]. On the other hand, generally speaking, PM policies can be classified as reliability-based maintenance (RBM),

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[1] This chapter is based on following publications:

(1) K. Wang and D. Djurdjanovic, "Joint Optimization of Preventive Maintenance and Spare Part Inventory for Multi-echelon Geographically Dispersed Systems", in *Proc. of the 2017 World Congress on Engineering Asset Management (WCEAM)*, Brisbane, Queensland, Australia, August 2-4, 2017, Paper No. 143, 2017.

(2) K. Wang and D. Djurdjanovic, "Joint Optimization of Maintenance and Spare Parts Logistics for a System of Geographically Distributed, Multi-part Assets", submitted to the *Journal of Intelligent Manufacturing*, Paper No. JIMS-D-17-00416, 2017.

Keren Wang wrote this publication under the supervision of Dragan Djurdjanvoic.

where maintenance is performed at certain times or usage intervals of an asset, and condition-based maintenance (CBM), where maintenance is performed based on monitoring the actual condition of an individual system. Compared to RBM policies, whose decisions are based on the long-term statistical behavior of the degradation processes of an asset, CBM decisions try to take the actual condition of the system into consideration, usually based on the sensor readings obtained from the asset and fitting of a data-driven or physically-based condition model [3]. As a result, CBM decisions are more dynamic and efficient [4], at least in theory. Unfortunately, CBM requires existence of appropriate sensors and building of appropriate condition models, which is often both costly and challenging from the engineering point of view. Hence, it is safe to say that RBM still dominates the PM practice, though significant research is aimed at enabling more pervasive applications of CBM.

In practice, companies plan PM operations of their assets independently from the optimization of the logistics and inventory of their maintenance resources. Though these planning strategies, referred to in this chapter as *fragmented approaches*, are easily implementable in realistic systems, lack of consideration of the interactions between these two domains potentially leaves significant inefficiencies in the operations. This is especially visible in the case of large networks of geographically dispersed assets, such as oil/gas extraction companies or airlines, where maintenance operations and the need for availability of the right amount of right spare parts at the right place are intricately interconnected.

According to a recent review on joint maintenance and inventory optimization systems [5], the existing works on jointly scheduling PM operations and optimizing spare parts logistics (SPL) can be differentiated based on the underlying PM strategies into those that use age-based/usage-based PM policies [110], [111], [116], [177] and those that use block-based/period-based PM policies [113], [114], [122], [123]. From the maintenance point of view, the complexity in asset structure is generally ignored, as the aforementioned works consider either a single asset, or multiple single-part assets that operate independently. However, several recent studies go beyond the simple single-part asset structure and consider a serially-connected multi-part asset structure [115], [117], [121], *k*-out-of-*n* structure of the assets [124], [125], flexible-connect multi-part asset structure [126] and single-part asset structure with multiple failure modes [178]. With focus on the degradation process and maintenance operations, these works inevitably assume simple logistic structure for service part management, with spare parts either being stocked locally, or being provided from a single source.

Other researchers considered the joint PM and inventory optimization problems in a more complex operational environment. Chen *et al*. [112] is, to our best knowledge, the only work that conducted a study on a multi-echelon logistic network, where there exist a distributor, multiple users and multiple suppliers. Nguyen *et al*. [118], [120] extended the definition of the maintenance resource by considering technicians of different skill levels for applications in chemical process plants. Other complex SPL operations or decisions are also evaluated, including equipment delivery decisions [179], inventory deterioration of spare part [122] and variability in demands for spare parts quality [123]. These works, though enhancing the knowledge from the logistic side, oversimplified the maintenance decision-making process by assuming a simple uni-component asset structure.

This decision-making framework proposed in this chapter firstly pursue an integrated decision-making policy that jointly optimizes PM and SPL operations in a geographically dispersed network. Specifically, the PM intervals and spare parts inventory levels are jointly optimized in a geographically dispersed network of degrading multi-part assets and multiple maintenance facilities serving those assets with spare parts needed for their maintenance. By formulating the decision-making process as a stochastic optimization problem and solving it via a discrete-event simulation-based metaheuristic approach, the framework proposed in this chapter is designed with flexibility to accommodate other more complicated logistic network and asset structures, as well as more elaborate system operations and cost functions than those considered in this work.

The rest of the chapter is organized as follows. In Section 3.2, the problem is described and the newly proposed integrated decision-making policy is introduced. A simulation-based optimization approach based on a genetic algorithm (GA) is described in Section 3.3 to solve the optimization problem from Section 3.2. In Section 3.4, the newly proposed integrated approach is evaluated in a simulated environment and compared to the more traditional, fragmented decision-making approach. Section 3.5 provides conclusions of this chapter and outlines several possible avenues for future work.

3.2 METHODOLOGY

3.2.1 System Structure

The following terminology will be used in the remainder of this chapter.

- The term *working part* refers to a basic unit of a machine. The condition of a part is assumed to degrade with its usage independently from other parts, and PM/RM can restore the part to the original, non-degraded condition. From the view of SPL, a working part on an asset corresponds to a certain type of a spare part that is stored in a maintenance facility and can be used to replace it.
- The term *asset* refers to a machine that can be operated independently to generate revenue. An asset consists of multiple parts and can be operated properly only if all its parts behave properly.

- A *maintenance center* (*MC*) fulfills maintenance orders from nearby assets by shipping new undegraded spare parts to their operating sites. Maintenance centers have finite inventory levels of spare parts and any maintenance order that cannot be immediately fulfilled by the maintenance center would be served directly by central warehouse as emergency order.
- A *central warehouse* replenishes spare parts for maintenance centers following a (s, S) replenishment policy [86]. The central warehouse can also provide new spare parts directly to the assets as emergency orders in maintenance events. The central warehouse is the primary source of all new spare parts and it is assumed to have infinite inventory levels of spare parts.

As illustrated in Figure 1, the system considered in this work can be seen as a multi-echelon logistic network with three levels of facilities. Degrading assets (Echelon 0) are serviced by maintenance centers (Echelon 1) from which the spare parts needed for maintenance of the relevant assets are provided. When the level of some spare part stocked in a maintenance center drops too low, it is restocked from the central warehouse (Echelon 2). Moreover, an "inventory sharing" logistic structure is considered in the sense that an asset can obtain maintenance service from multiple nearby maintenance centers. Consequently, there are multiple potential sources for an asset to obtain spare parts for a maintenance action - central warehouse, as well as several nearby maintenance centers. The asset will obtain the necessary spare parts from the maintenance facility that currently has them in stock and the delivery of those parts would incur lower operating cost compared to deliveries from other available maintenance facilities.

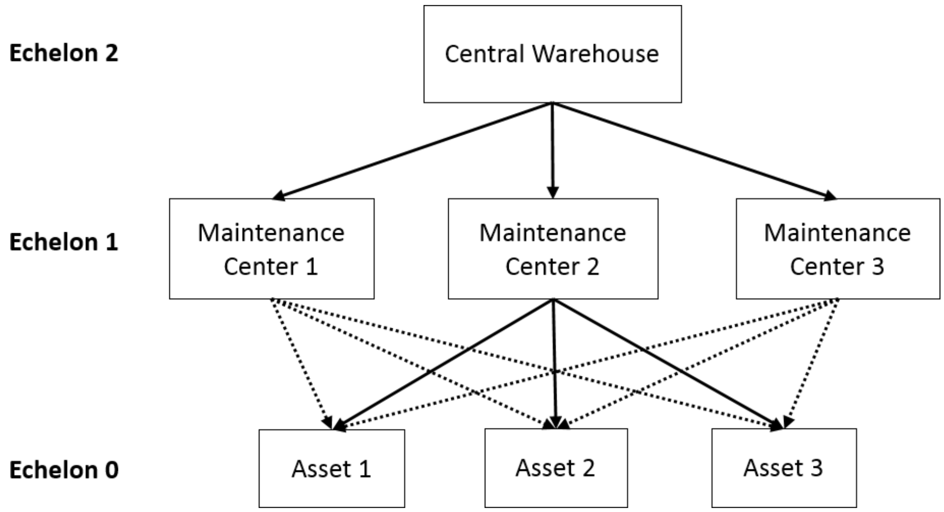

Figure 1: Connection topology of spare parts logistic network enabling the inventory sharing between maintenance centers

Figure 2 provides an illustration of the geographic dispersion of the maintenance logistic system studied in this chapter. The central warehouse is connected to n maintenance centers, labeled $MC_1, MC_2, \dots, MC_n$, and these maintenance centers provide maintenance services to a set of J nearby assets, $A_1, A_2, \dots, A_J$. Due to the geographical dispersion of the degrading assets and spare parts needed for their maintenance, delivery delays of the necessary spare parts must be taken into consideration. To reflect the uncertainties in transportation, these spare part delivery times characterizing inventory flows between the central warehouse, maintenance centers and assets are assumed to follow pre-estimated probability distributions.

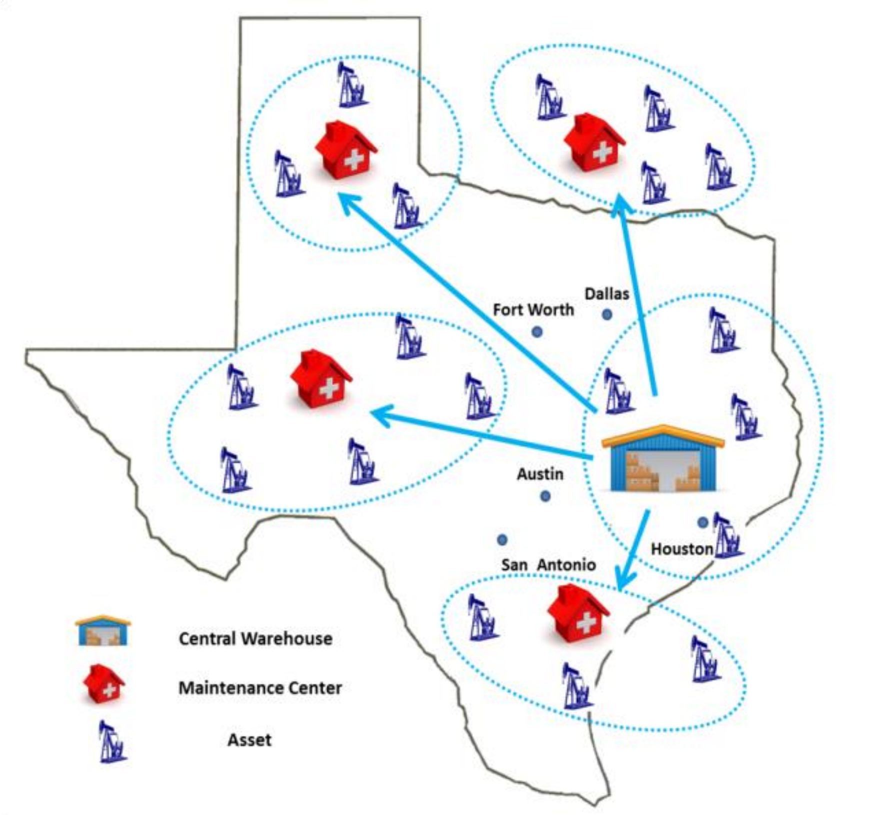

Figure 2: An illustration of geographically dispersed maintenance centers and assets

Each asset A_j is assumed to be made up of K_j serially connected parts, labeled $P_{j,1}, P_{j,2}, \ldots, P_{j,K_j}$, each of which degrades independently with its usage. Degradation dynamics of a part $P_{j,k}$ is described by a reliability function approximating the distribution of the part's usage to failure, denoted by $\mathcal{T}_{j,k}(\cdot)$. The reliability functions are assumed to be part-and-asset specific[2], and can be estimated through analysis of the long-term statistical behavior of the part's degradation process on the asset, or parts of the same type on other similar assets.

[2] Basically, we acknowledge that the same part can be utilized differently in different assets, necessitating the use of part-and-asset specific reliability functions.

3.2.2 Maintenance Scheduling and Spare Parts Inventory Management

A so-called *replacement maintenance policy* is assumed (Van Horenbeek, Buré, *et al*., 2013), that is to say, both PM and RM are assumed to consist of a new, undegraded spare part replacing a broken or severely degraded working part on the asset. A complete maintenance order is modeled as involving the following two steps: (*i*) shipping the necessary spare part from a maintenance center to the asset as a normal order, or from the central warehouse to the asset as an emergency order (when there are no appropriate spare parts in stock in the maintenance centers or when getting them from the maintenance centers is more expensive than delivering them directly from the central warehouse) and (*ii*) replacing the target working part on the asset with the newly delivered spare part.

The PM scheduling strategy pursued in this chapter can be summarized as a *usage-based PM replacement policy*. According to this policy, PM triggering usage level $x_{j,k}$ is set for each part $P_{j,k}$, indicating the part's critical usage level at which a PM operation is initiated. PM is initialized by ordering a new corresponding spare part, either from the maintenance center or from the central warehouse, with the replacement of a working part starting only when the necessary spare part is delivered to the location of the asset. Finally, it is assumed that after a PM operation, the status of the part (component in an asset) is restored to the "as good as new" condition (i.e. perfect maintenance operations are assumed [112]).

Maintenance interventions during RM and PM lead to asset downtimes. Besides the obvious downtime needed to perform a maintenance activity (replacement of a working part with a spare part), a significant portion of an asset downtime could also be due to the time needed for the new spare part to arrive. This waiting time is inevitably (and often much) longer in the case of unplanned RM events and depends on where from (the maintenance center vs. central warehouse) and when (newly shipped vs. already shipped and on route as a PM order) the spare part is shipped.[3]

From the side of SPL, let $SP_1, SP_2, \dots, SP_H$ denote all types of spare parts considered in this system. Inventories of spare parts in the maintenance centers are consumed whenever a PM/RM order arrives and get replenished directly from the central warehouse. Replenishment of spare parts in maintenance centers is assumed to follow a (s, S) replenishment policy. Under this policy, the decision-variables, $\{y_{i,h}\}_{1\le i\le n, 1\le h\le H}$, indicate the critical levels of spare parts inventory levels at which the maintenance center MC_i requests replenishment for the spare part SP_h, while decision-variables, $\{z_{i,h}\}_{1\le i\le n, 1\le h\le H}$, indicate the batch size of those replenishment orders.

3.2.3 Integrated Decision-Making Policy

In this chapter, we will seek an integrated decision-making policy described by the PM triggering usage levels $\{x_{j,k}\}_{1\le j\le J, 1\le k\le K_j}$, spare parts inventory levels $\{y_{i,h}\}_{1\le i\le n, 1\le h\le H}$ and replenishment order sizes $\{z_{i,h}\}_{1\le i\le n, 1\le h\le H}$ that minimize the expected system operating cost per unit time of the entire system. More precisely, the integrated decision-making policy will be pursued by solving the stochastic optimization problem formulated below.

[3] Obviously, unscheduled RM operations requiring spare parts that at the time are not available in the nearby maintenance centers lead to the longest asset downtimes, since the new spare part needs to be shipped from the far-away warehouse.

$$\underset{\substack{\{x_{j,k}\in X_{j,k}\}_{1\le j\le J,\ 1\le k\le K_j} \\ \{y_{i,h}\in Y_{i,h}\}_{1\le i\le n,\ 1\le h\le H} \\ \{z_{i,h}\in Z_{i,h}\}_{1\le i\le n,\ 1\le h\le H}}}{\text{Minimize}} \frac{1}{T}\,\mathbb{E}\left\{ \sum_{\substack{1\le i\le n \\ 1\le h\le H}} \left(d_{i,h}D_{i,h} + s_{i,h}S_{i,h}\right) + \sum_{\substack{1\le i\le n \\ 1\le j\le J \\ 1\le k\le K_j}} \left(r_{j,k}^{i}R_{j,k}^{i} + m_{j,k}^{i}M_{j,k}^{i}\right) \right.$$

$$\left. + \sum_{\substack{1\le j\le J \\ 1\le k\le K_j}} \left(r_{j,k}^{cw}R_{j,k}^{cw} + m_{j,k}^{cw}M_{j,k}^{cw}\right) + \sum_{1\le j\le J} l_j L_j \right\}$$

Optimization Problem 1

where the following notation is used,

- i, j, k, h : Indices for maintenance center (i), asset (j), working part (k) and spare part type (h).
- T : Decision-making time horizon.
- $D_{i,h}$: Inventory holding cost per unit time for the spare part S_h at the maintenance center MC_i.
- $S_{i,h}$: Replenishment delivery cost per order for spare part S_h to the maintenance center MC_i.
- $d_{i,h}$: Cumulative inventory holding time of the spare part S_h at the maintenance center MC_i.
- $s_{i,h}$: Cumulative replenishment orders of the spare part S_h to the maintenance center MC_i.
- $R_{j,k}^{i}$: Cost to order a RM for the working part $P_{j,k}$ from the maintenance center MC_i.

- $M_{j,k}^{i}$: Cost to order a PM for the working part $P_{j,k}$ from the maintenance center MC_i.
- $R_{j,k}^{cw}$: Cost to order a RM for the working part $P_{j,k}$ from the central warehouse.
- $M_{j,k}^{cw}$: Cost to order a PM for the working part $P_{j,k}$ from the central warehouse.
- $r_{j,k}^{i}$: Cumulative number of RM orders for the part $P_{j,k}$ served by the maintenance center MC_i.
- $m_{j,k}^{i}$: Cumulative number of PM orders for the part $P_{j,k}$ served by the maintenance center MC_i.
- $r_{j,k}^{cw}$: Cumulative number of RM orders for the part $P_{j,k}$ served by the central warehouse.
- $m_{j,k}^{cw}$: Cumulative number of PM orders for the part $P_{j,k}$ served by the central warehouse.
- L_j : Penalty cost per unit downtime of the asset A_j.
- l_j : Cumulative downtime of the asset A_j.
- $X_{j,k}$: Candidate solution set for the PM triggering usage level of the working part $P_{j,k}$.
- $Y_{i,h}$: Candidate solution set for the inventory level of the spare part S_h at the maintenance center MC_i.
- $Z_{i,h}$: Candidate solution set for the replenishment order size of the spare part S_h to the maintenance center MC_i.
- $\mathcal{LT}_j^{\,i}(\cdot)$: Lead time distribution for the asset A_j to obtain new spare parts from the maintenance center MC_i.
- $\mathcal{LT}_j^{\,cw}(\cdot)$: Lead time distribution for the asset A_j to obtain new spare parts from the central warehouse.

According to the "inventory-sharing" option, in order to perform a specific PM/RM operation on a working part $P_{j,k}$, the maintenance service is provided by the maintenance center that currently has the necessary spare part in stock and has the smallest associated cost $M_{j,k}^{i}$ (in the case of PM) or $R_{j,k}^{i} + l_j * \mathbb{E}(\mathcal{LT}_j^{\,i})$ (in the case of RM), compared to other available maintenance centers. In case of insufficient levels of necessary spare parts in all maintenance centers or the central warehouse can provide the maintenance service with lower associated cost ($M_{j,k}^{cw}$ / $R_{j,k}^{cw} + l_j * \mathbb{E}(\mathcal{LT}_j^{\,cw})$) than the available maintenance centers, the PM/RM orders would be fulfilled directly by the central warehouse.

For each candidate solution, stochastic effects induced by randomness in the reliability of working parts, delivery delays for spare parts inventory flows and maintenance repair times were captured by discrete-event simulations of system operations. In the objective function, the stochastic effects are reflected in the cumulative statistics (i.e. $d_{i,h}$-s, $s_{i,h}$-s, $r_{j,k}^{i}$-s, $m_{j,k}^{i}$-s, $r_{j,k}^{cw}$-s, $m_{j,k}^{cw}$-s and l_j-s). The objective function values obtained from multiple runs of those simulations were averaged to estimate the expected value in the objective function in (1).

It is easily visible that the cost function in the formulation (1) is composed of the inventory holding/replenishment cost, the penalty cost for asset downtime, and the maintenance costs (PM/RM). Among them, the RM/PM cost per order is a comprehensive cost consisting of all one-time costs incurred by this order, such as the spare part production costs, delivery costs and labor costs. Also, it is very important to note that this cost function is highly flexible in the sense that one can choose cost parameters and/or incorporate other potential operating costs, such as backorder costs and unfulfilled contract penalties. In effect, different companies, and often different parts of the same company will operate with different cost functions and cost parameters, and optimization formulation (1) may need to be adapted to reflect such specificities. A metaheuristic simulation-based optimization approach to solving the optimization problem (1), which will be elaborated in Section 3.3, allows such alterations to the objective function, and was one of the main reasons for choosing such an optimization approach.

Theoretically, the PM trigger usage level $x_{j,k}$ can be any positive value, but in periodic review systems, the status of a working part is evaluated periodically and, therefore, a finite discrete candidate solution set is assumed for $x_{j,k}$-s. For example, that set could be $X_{j,k} \in \{30, 35, 40, 45, 50\}$ in time units. If the size of the candidate solution set for each PM triggering usage level $x_{j,k}$ is P, the size of the candidate solution set for each spare part inventory level $y_{i,h}$ is Q and for each replenishment order size $z_{i,h}$ is R, then the solution space for the optimization problem of the integrated policy consists of up to $P^{\sum_{j=1}^{J} K_j}(RQ)^{nH}$ candidate solutions. Even for a small maintenance logistic system, this problem is infeasible to solve through a complete enumeration, especially with expected operating costs being estimated via multiple replication of discrete-event simulations. A metaheuristic approach to pursue a solution to this optimization problem will be presented in Section 3.3.

3.2.4 Fragmented Decision-Making Policy

Traditionally, scheduling of PM operations and optimization of spare part inventories are accomplished separately, with PM schedules being optimized for the system without considerations of spare part availability, after which spare parts inventory levels are optimized to serve those PM schedules. This approach, referred to in this chapter as the *fragmented policy*, is easily implementable in realistic systems, but it does not consider the interactions between these two domains and thus potentially leaves significant inefficiencies in the operations. Following this industrial common practice, a fragmented decision-making policy is described in this section and will be used as a benchmark policy.

The fragmented decision-making process is a two-phase procedure. Firstly, for each asset, the maintenance decisions are optimized, under the assumption that unlimited supplies of spare parts are stocked in all maintenance centers. For each asset A_j, PM triggering usage levels for its constituent parts are obtained by solving the following optimization problems

$$\underset{\{x_{j,k}\in X_{j,k}\}_{1\le k\le K_j}}{\text{Minimize}} \frac{1}{T}\,\mathbb{E}\left\{\sum_{\substack{1\le i\le n\\1\le k\le K_j}}\left(r_{j,k}^{i}R_{j,k}^{i}+m_{j,k}^{i}M_{j,k}^{i}\right)+\sum_{1\le k\le K_j}\left(r_{j,k}^{cw}R_{j,k}^{cw}+m_{j,k}^{cw}M_{j,k}^{cw}\right)\right.$$
$$\left.+\,l_jL_j\;\middle|\{y_{i,h}=+\infty\}_{\substack{1\le i\le n\\1\le h\le H}}\right\}\qquad \text{for}\quad 1\le j\le J$$

Optimization Problem 2

Unlike formulation (1), optimization problem (2) minimizes a cost function that only encompasses maintenance-related costs for the assets, including the asset downtime penalty, as well as PM and RM operation ordering costs (it does not incorporate inventory-related costs for the maintenance facilities). Moreover, the optimal solution to the optimization problem (2) provides a lower bound to the optimization problem (1) under the assumption that there is no inventory-related cost in the system.

The second phase is to optimize the logistic decisions for the entire system based on the locally optimized PM triggering usage levels $\{x_{j,k}^{*}\}_{1\le j\le J,1\le k\le K_j}$ from the first phase. More precisely, the spare parts inventory levels $\{y_{i,h}\}_{1\le i\le n,1\le h\le H}$ and replenishment order sizes $\{z_{i,h}\}_{1\le i\le n,1\le h\le H}$ are optimized with the objective of minimizing both maintenance and logistic cost per unit time of the entire system via the following stochastic optimization.

$$\underset{\substack{\{y_{i,h}\in Y_{i,h}\}_{1\le i\le n,1\le h\le H}\\ \{z_{i,h}\in Z_{i,h}\}_{1\le i\le n,1\le h\le H}}}{\text{Minimize}} \frac{1}{T}\,\mathbb{E}\left\{\sum_{\substack{1\le i\le n\\1\le h\le H}}\left(d_{i,h}D_{i,h}+s_{i,h}S_{i,h}\right)+\sum_{\substack{1\le i\le n\\1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{i}R_{j,k}^{i}+m_{j,k}^{i}M_{j,k}^{i}\right)\right.$$
$$\left.+\sum_{\substack{1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{cw}R_{j,k}^{cw}+m_{j,k}^{cw}M_{j,k}^{cw}\right)+\sum_{1\le j\le J}l_jL_j\,\middle|\,\left\{x_{j,k}^{*}\right\}_{\substack{1\le j\le J\\1\le k\le K_j}}\right\}$$

Optimization Problem 3

It should be noted again that maintenance decisions in the optimization problem (2) are made under the assumption that the necessary spare parts are always available in the relevant maintenance centers. This assumption of infinite spare parts stock in maintenance centers ensures that the maintenance decisions and logistic decisions can be pursued sequentially via optimizations (2) and (3). Compared to the integrated decision-making policy obtained via (1), ignoring the interrelations between PM decisions and spare parts inventory levels across different assets, as is done in the sequential, fragmented approach described above, leads to a computationally less complicated, fragmented decision-making policy. However, this comes at the expense of obtaining a suboptimal solution and it is this opportunity for improved cost effects of system operations that we are pursuing via the newly proposed integrated decision-making policy.

3.3 SIMULATION-BASED METAHEURISTIC OPTIMIZATION

Simulation-based optimization is shown to be a powerful paradigm for decision-making in complex spare part logistic systems [110]–[112], [116], [117], [177], [180], as well as for optimization of maintenance operations. Consequently, discrete-event simulations are utilized in this chapter to estimate the expected operating cost per unit time of the system under a candidate solution. The expected operating cost is estimated via multiple replications of discrete event simulations of target system operations, and is then fed back into a GA-based metaheuristic to guide the movements toward improved candidate decisions. Thus, ever improving integrated maintenance triggering and inventory replenishment policies minimizing the cost function in formulation (1) are sought.

The discrete-event simulation approach is needed to evaluate each candidate solution due to the existence of multiple uncertain factors, as well as the need to make dynamic decisions resulting from inventory-sharing option. At the same time, the metaheuristic approach is also necessary to search for the optimized solutions, as the high dependencies between system operations and decision variables make a full enumeration of the solution space or certain kinds of decomposition approaches infeasible to the proposed optimization problem.

There are all together $2nH + \sum_{j=1}^{J} K_j$ decision variables in the integrated policy, including $2nH$ logistic decision variables ($y_{i,h}$-s and $z_{i,h}$-s) and $\sum_{j=1}^{J} K_j$ maintenance decision variables ($x_{j,k}$-s). Therefore, each candidate solution is represented via $2n + 1$ chromosome portions $(X, Y^1, Y^2, \dots, Y^n, Z^1, Z^2, \dots, Z^n)$, in which X denotes a decision-variable vector containing all PM triggering usage levels, while Y^i and Z^i respectively denote vectors containing all spare parts inventory levels that trigger replenishment orders from the central warehouse to the maintenance center and the batch size of those replenishment orders[4].

Generally speaking, GA is a search heuristic that mimics the process of natural selection. The GA evolution starts from V randomly generated candidate solutions as the initial population, labeled $G_0 = \left\{\left(X_{0,v}, Y_{0,v}^1, \ldots, Y_{0,v}^n, Z_{0,v}^1, \ldots, Z_{0,v}^n\right)_{1 \le v \le V}\right\}$. The fitness of each candidate solution in the population is taken to be inversely proportional to the expected system operating cost per unit time, which is obtained via multiple replications of simulations of system operations under the maintenance/logistic policy represented by that candidate solution. To generate offspring solutions for the next generation, selection, crossover and mutation operators are applied to the current generation of candidate solutions. These operators are described below.

- *Selection operator*: A pair of parent candidate solutions, $\left(X_{u,\alpha}, Y_{u,\alpha}^1, \ldots, Y_{u,\alpha}^n, Z_{u,\alpha}^1, \ldots, Z_{u,\alpha}^n\right)$ and $\left(X_{u,\beta}, Y_{u,\beta}^1, \ldots, Y_{u,\beta}^n, Z_{u,\beta}^1, \ldots, Z_{u,\beta}^n\right)$, are chosen from the current generation u to mate and produce offspring candidate solutions for the next generation $u+1$, with the probability of being selected for each candidate solution being proportional to its fitness[5].
- *Crossover operator*: For a pair of selected parent solutions, a single-point crossover operator is executed on each of the $2n+1$ chromosome portions, leading to $2n+1$ pairs of recombined chromosome portions, namely $\{X_a, X_b\}$, $\{Y_a^1, Y_b^1\}$, …, $\{Y_a^n, Y_b^n\}$, $\{Z_a^1, Z_b^1\}$, …, $\{Z_a^n, Z_b^n\}$. Then an offspring solution is generated via randomly selecting a chromosome portion from each of $2n+1$ pairs, while the remaining chromosome portions form the other offspring solution.

---

[4] Specifically, we have $X = \left(x_{1,1,}, x_{1,2}, \ldots, x_{1,K_1}, \ldots, x_{J,1}, x_{J,2}, \ldots, x_{J,K_J}\right)$, $Y^i = \left(y_{i,1}, y_{i,2}, \ldots, y_{i,H}\right)$ and $Z^i = \left(z_{i,1}, z_{i,2}, \ldots, z_{i,H}\right)$.

[5] This is known as the so-called fitness proportionate selection [181]. Also, please note that a single solution may be chosen to serve as a parent more than once.

- *Mutation operator*: Each gene in an offspring solution chromosome is selected with a small probability, known as the mutation probability, and the selected gene value is randomly perturbed to an adjacent candidate in its candidate solution set[6]. The mutation operator promotes genetic diversity in the population from one generation to the next.

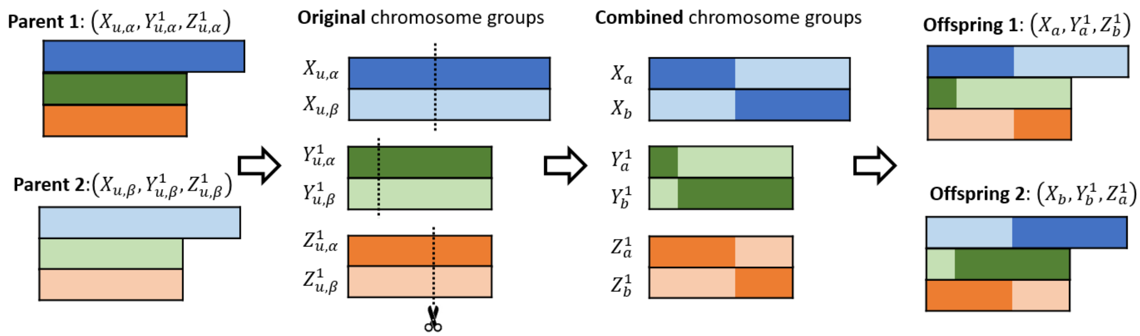

Figure 3: An illustration of crossover operator on two parent candidate solutions, $(X_{u,\alpha}, Y^1_{u,\alpha}, Z^1_{u,\alpha})$ and $(X_{u,\beta}, Y^1_{u,\beta}, Z^1_{u,\beta})$ considered for Optimization Problem 1

Overall, in each generation of candidate solutions, V pairs of parent solutions are selected to form $2V$ offspring solutions via the above-described GA operators. The offspring solutions with highest fitness are promoted to form the next generation, with elitism enforced by ensuring that the highest performing candidate from the parent generation gets added to the next generation, if its fitness is higher than the fitness of all offspring solutions.

This procedure yields ever-improving candidate solutions, consistently reducing the expected operating costs of the system. After a predetermined number of GA generations is reached, or the best fitness is not improved in a number of consecutive generations, the GA optimization is terminated and the integrated decision-making policy

[6] For example, assume that the PM triggering level $x_{j,k}$ takes value in $X_{j,k} = \{30, 35, 40, 45, 50\}$ and the current value for this gene is $x_{j,k} = 40$. If the mutation operator is performed on this gene, the decision will mutate into either $x_{j,k} = 35$ or 45, with the mutation probability.

is obtained as the best candidate solution in the last GA generation, denoted by $(X_*, Y_*^1, \dots, Y_*^n, Z_*^1, \dots, Z_*^n)$.

One should note that similar simulation-based metaheuristic algorithms can be derived in exactly the same way for each of the optimization problems (2)-(3), yielding decisions for the benchmark fragmented decision-making policy described in Section 3.2.4. Same as the optimization problem (1), due to the existence of uncertain factors and dynamic decisions, the discrete-event simulation approach is needed to evaluate the candidate solutions for the optimization problem (2)-(3). However, instead of GA metaheuristic, a complete enumeration of the entire solution space to an optimization problem in formulations (2)-(3) is feasible if the size of its decision space is sufficiently small.

3.4 RESULTS

3.4.1 Simulation Setup and Decision Summary Statics

In this section, we will evaluate the newly introduced integrated decision-making policy through a series of simulations of operations of a system illustrated in Figure 4. It consists of a central warehouse and three maintenance centers that provide maintenance services to 49 geographically dispersed assets[7]. These 49 assets consist of all together 126 parts, belonging to 5 different spare part types. The set of decision variables consists of 30 logistic decision variables and 126 maintenance decision variables. Time-to-failure distributions for the workings parts are modeled by Weibull reliability distributions, while

[7] In terms of the optimization formulation (1) in Section 3.2.3, we have here $n = 3, J = 49$ and $H = 5$.

all lead times and repair times are assumed to follow symmetric triangular distributions. Baseline parameters for this system are summarized in Appendix A[8].

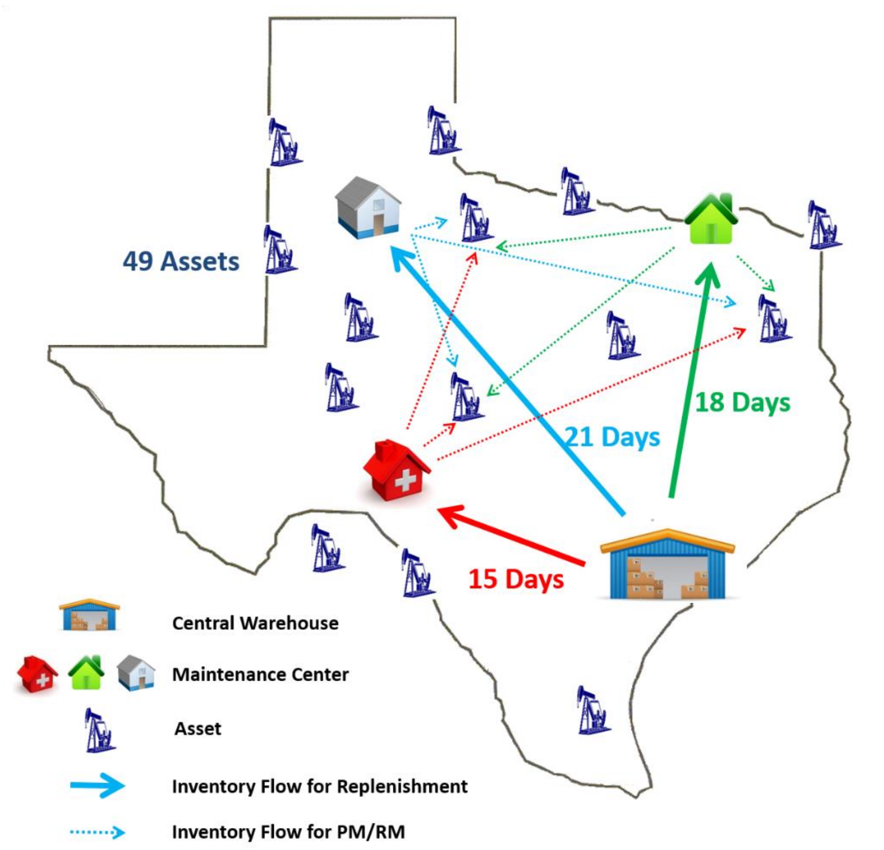

Figure 4: Illustration of the SPL network in the baseline system

The planning horizon (T) for optimization was taken to be $365 * 5$ time units. Within this horizon, the operating cost and other system statistics are evaluated as averages over 50 replications[9]. The integrated decision-making policy is obtained by using GA based algorithm described in Section 3.3, with the detailed parameter settings given in the

[8] Please note that different distribution forms and parameters could easily be implemented within the same simulation based optimization proposed in this chapter. As mentioned before, this flexibility of the simulation-based metaheuristic optimization paradigm is the main reason why it is used in this chapter.

[9] This parameter was obtained by increasing the number of replications until further increases did not lead to significant changes in the average cost effects.

Appendix A. In terms of computational costs, implementation on a relatively ordinary personal computer (Intel Core i5-3570 CPU, 16 GB RAM, 64-bit Window 7) led to average computational time of 17.5 seconds for one GA iteration. Considering that it takes less than 10 hours to obtain the integrated decision-making policy for the baseline example, it would be feasible to achieve daily updates on the integrated decisions for systems of similar scale, though the computations can be greatly accelerated further in a parallel computing environment.

In order to formally compare maintenance/logistic decisions under different policies, the following summary statistics are introduced: (1) *total spare part inventory level*, (2) *average PM triggering usage level* and (3) *system uptime*. The *total spare part inventory level* is calculated as the sum of the maximum inventory levels of spare parts that can simultaneously be stocked in the maintenance centers, and it can be used to evaluate the requirements on the logistic resources. More formally, it is expressed as

$$V = \sum_{h=1}^{H} \sum_{i=1}^{n} \left(y_{i,h} + z_{i,h} \right) .$$

Average PM triggering usage level for the system, denoted by $\bar{x}$, is calculated by averaging PM triggering usage levels (maintenance decision variables) for all the working parts in the system. It can be used to express how aggressively PM operations are planned across the entire system, and is calculated as

$$\bar{x} = \frac{1}{\sum_{j=1}^{J} K_j} \sum_{j=1}^{J} \sum_{k=1}^{K_j} x_{j,k} .$$

System uptime is introduced and calculated as the average uptime (time not spent under maintenance) per unit time of all assets in the system. It expresses the utilization of assets and is formally defined as

$$SU = \left(1 - \frac{\sum_{j=1}^{J} l_j}{T \cdot J} \right) \cdot 100\% .$$

3.4.2 Results for the Baseline System Settings

As shown in Figure 5, for the baseline system parameters, the integrated decision-making policy yields a lower expected operating cost compared to the fragmented policy, indicating a cost reduction of 3.03%. Furthermore, this cost reduction is statistically significant, with the significance level less than 0.0027, according to a one-sided z-test (corresponding to $\pm 3\sigma$ limits) [182].

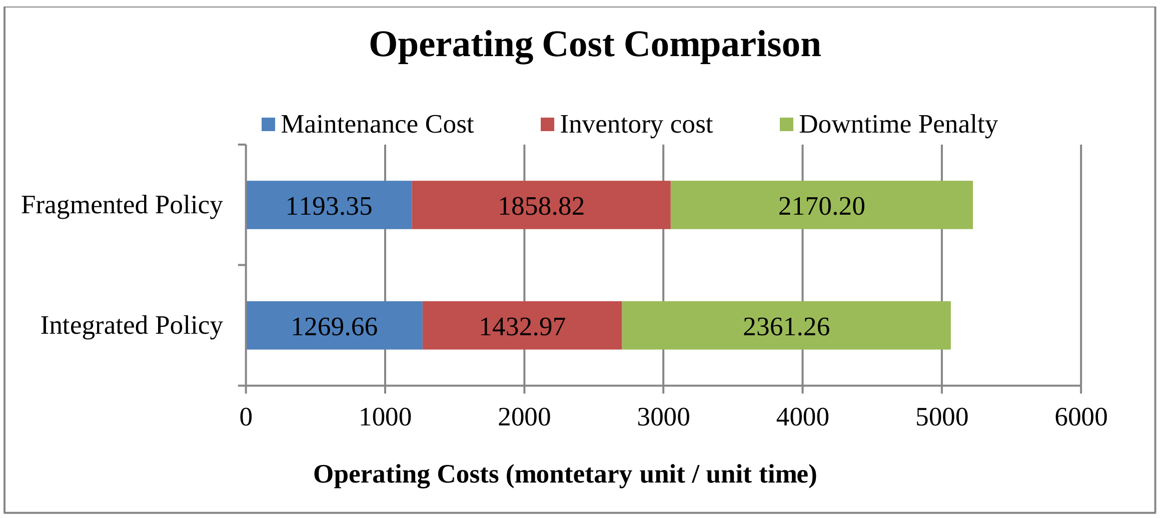

Figure 5: Cost comparison between the integrated and fragmented policies for baseline system

More detailed analysis showed that the fragmented policy had the tendency to stock higher levels of spare parts in the maintenance centers, compared to the integrated policy. Namely, it can be observed from Figure 6 that for each type of spare parts, the newly proposed integrated policy yielded lower total inventory levels, compared to the fragmented policy. Potential negative effects of lower levels of spare parts in stock, such as more frequent emergency orders and occasional prolonged asset downtimes due to waiting for spare parts[10], were relieved through lower logistic costs and more aggressive scheduling of PM operations, leading to better avoidance of negative effects of unscheduled RM operations and lower overall operating costs of the system.

This more aggressive PM scheduling under the integrated decision-making policy is clearly evident in Table 1, where one can see that average PM triggering usage level is smaller under the integrated policy, compared to the benchmark policy. However, as shown by the number of RMs per unit time in Table 1, aggressive PM scheduling did not necessarily lead to fewer RM operations under the integrated decision-making policy. The reason is that there were more situations when assets broke down while waiting for a spare part as a consequence of lower spare parts inventory levels in the relevant maintenance centers. Nevertheless, the downtimes caused by these RM events were reduced, since the relevant parts were already on their way, and these negative effects of breakdowns did not outweigh the benefits of lower inventory levels, at least for the baseline system parameters considered here.

[10] In Figure 5, these negative effects are visible in the higher maintenance costs and higher downtime penalty costs under the integrated policy, compared to those under the fragmented policy.

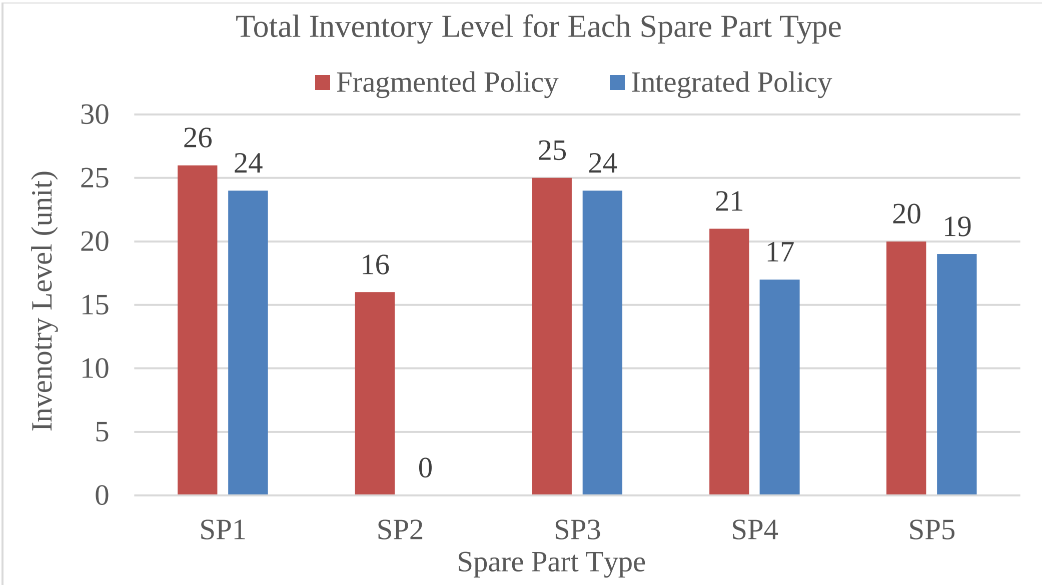

Figure 6: Total inventory level for each spare part in 3 MCs (i.e. $y_{1,h} + y_{2,h} + y_{3,h} + z_{1,h} + z_{2,h} + z_{3,h}$ for SP_h)

System Statistic	**Fragmented Policy**	**Integrated Policy**
Total spare part inventory level (V)	108	84
Average PM triggering usage level ($\bar{x}$)	55.83	48.69
System uptime	95.72%	95.30%
Number of PM orders per unit time	1.593	1.771
Number of RM orders per unit time	0.750	0.752

Table 1: Comparison of performance statistics between integrated and fragmented policy

Moreover, the optimal solution to the optimization problem (2) provides a lower bound to the expected operating cost under the integrated decision-making policy, by assuming no inventory-related cost in the system. For the baseline example, this lower bound is 3052.17 monetary unit/unit time, compared to 5063.89 monetary unit/unit time, the expected operating cost under the integrated policy. Tighter lower bounds can be derived through relaxing the optimization problem (1) in more elaborate ways, which would be one of the future works to this chapter.

In summary, the newly introduced, joint optimization of maintenance and logistic operations yields a lower operating cost by avoiding overstocking of spare parts and by taking advantage of more intense scheduling of PM operations. To gain better understanding of the newly proposed integrated decision-making policy, we will further study its sensitivity to fluctuations in the (i) geographical dispersion of maintenance centers from the central warehouse, (ii) cost rates of handling spare parts inventories, and (iii) penalty rates for asset downtimes.

3.4.3 Influence of the Geographic Dispersion Level

In this section, performance of the newly proposed integrated decision-making policy will be evaluated and benchmarked against the traditional fragmented decision-making policy in a series of systems having the same connection topology as the baseline system, but with maintenance centers and assets being at different distances away from the central warehouse (i.e. with different levels of geographic dispersion). This dispersion is modeled using a multiplier α, referred to as the dispersion scalar, which is used to simultaneously rescale the times needed to accomplish replenishment to the maintenance centers and the lead times for spare part deliveries from the central warehouse to the assets. As illustrated in Figure 7, we used $\alpha \in \{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\}$, with the most geographically concentrated system corresponding to $\alpha = \frac{1}{3}$, and the most dispersed system corresponding to $\alpha = \frac{5}{3}$, while $\alpha = 1$ corresponds to the baseline system settings.

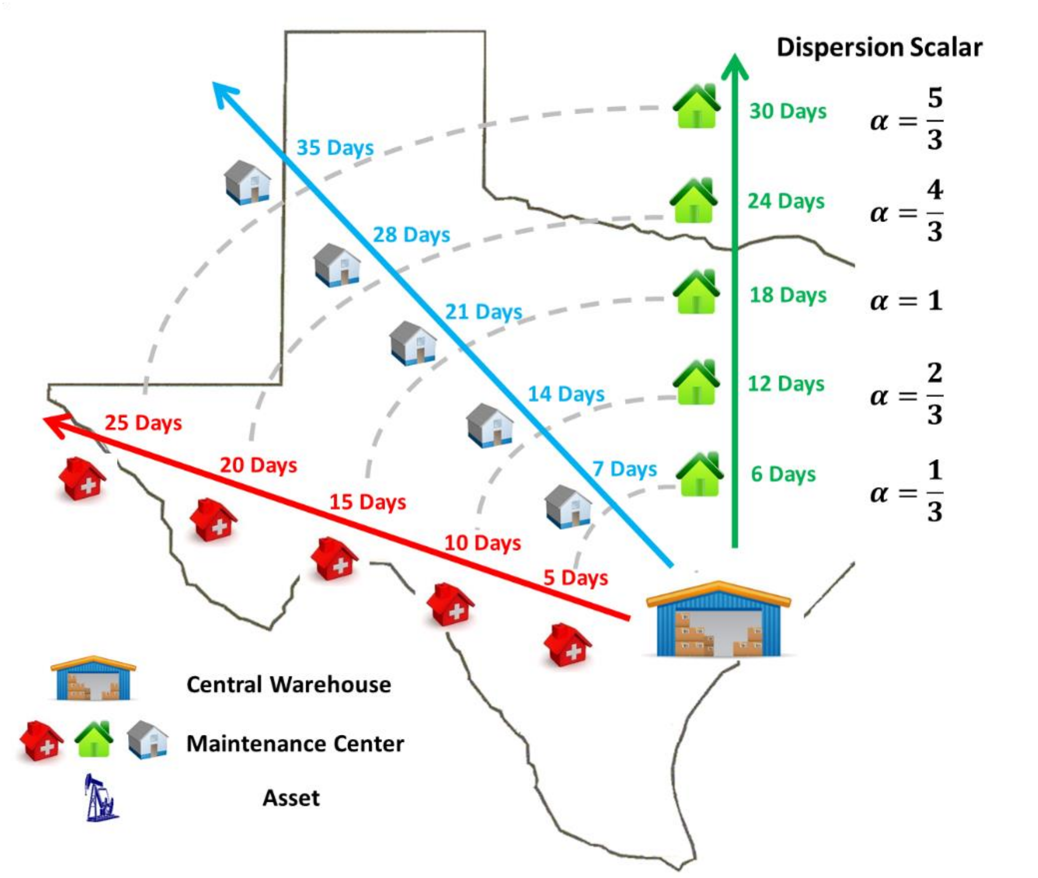

Figure 7: Logistic network under different dispersion scalars

No matter which policy is applied, the increase of geographic dispersion is inevitably associated with a higher operating cost of the system. However, as illustrated in Figure 8, both the relative and absolute cost reduction of the integrated policy over the fragmented policy consistently increase as the geographic dispersion of the system increases.

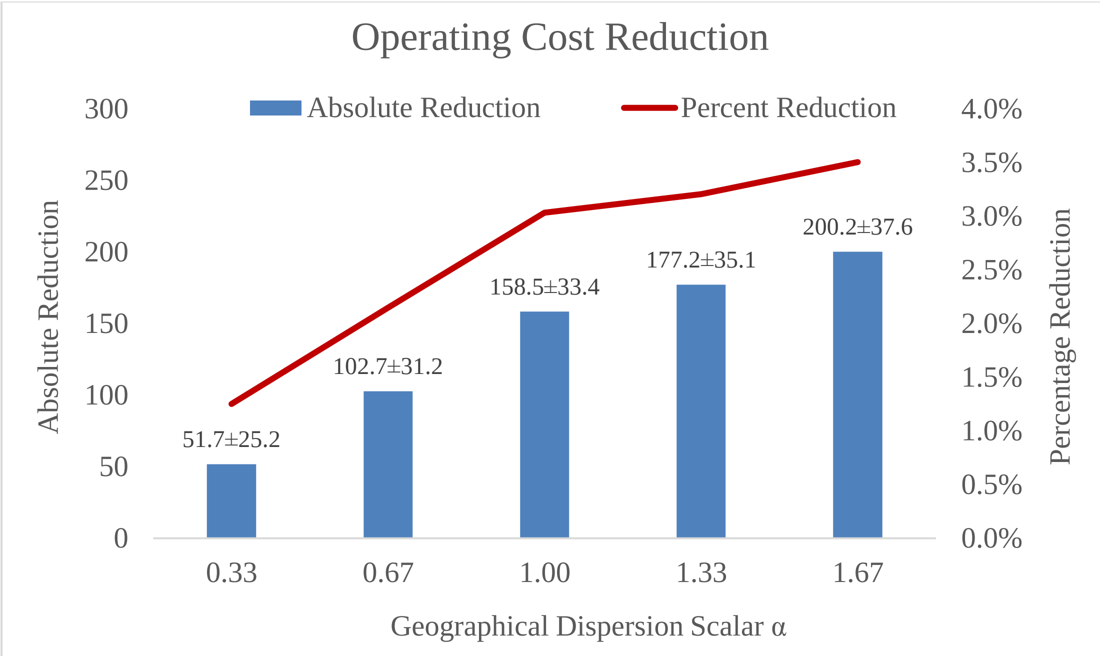

Figure 8: Reduction of operating costs per unit time for systems with α in $\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\}$. Absolute cost reductions are reported as averages and corresponding $\pm 3\sigma$ limits estimated from simulations.

Detailed analysis of simulation results showed that in order to perform maintenance operations in a more dispersed system, more spare parts need to be stocked locally in maintenance centers, pushing spare parts inventory levels higher under both polices. However, it is evident that logistic decisions under the integrated policy are less sensitive to changes in α than those under the fragmented policy (increases in inventory levels are not as pronounced as they are for the fragmented decision-making policy). This leads to the trend shown in Figure 9, where the differences between the optimized spare parts inventory levels (logistic decisions) under the two polices become larger for larger α, leading to increased savings in inventory handling in the more geographically dispersed systems.

Another fact that deserves noticing is that, as the locations of the logistic facilities change, maintenance decisions under the integrated policy are adjusted along with the logistic decisions, while the fragmented policy cannot deal with such changes in the system. As shown in Figure 9 and Figure 10: Average PM triggering usage levels for systems with $\alpha \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$, regardless of the value of α, the fragmented decision-making policy yields the same maintenance statistic (average PM triggering usage level) as the baseline system[11]. However, for the integrated decision-making policy, as α increases, there are two competing factors that drive the maintenance decisions in the opposite directions. On one hand, since longer replenishment delivery delays increase the cost of unscheduled downtimes and RM operations, this drives an incentive for more frequent PM operations. On the other hand, the higher inventory levels bring down the likelihood of emergency order, which reduces the impact and cost of RM operations and allows for less frequent PM scheduling. Consequently, the average PM triggering usage level under the integrated policy changes with the increasing dispersion scalar, but not monotonically.

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11 Actually, it keeps using the same maintenance decisions

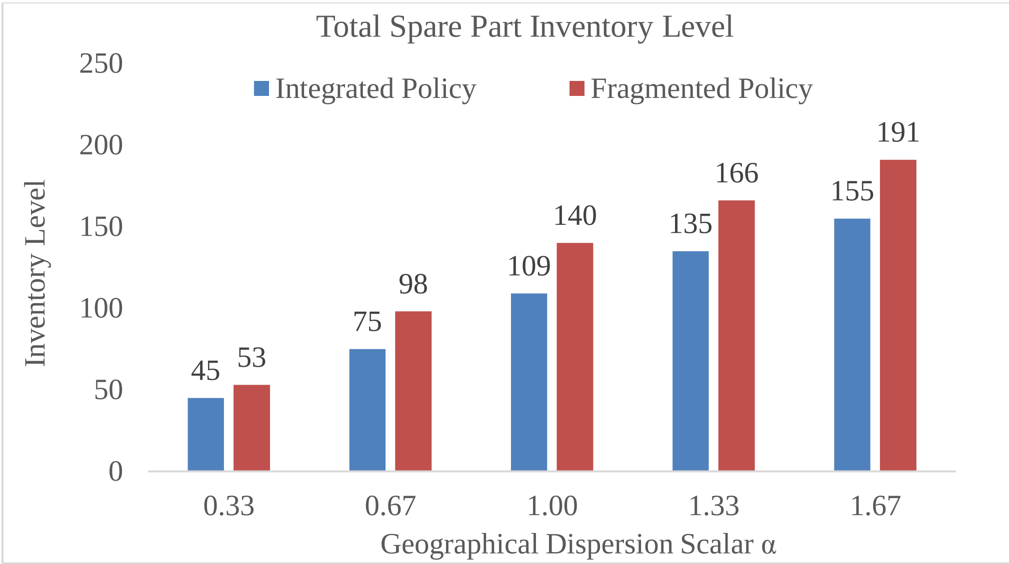

Figure 9: Total spare part inventory levels for systems with $\alpha \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$

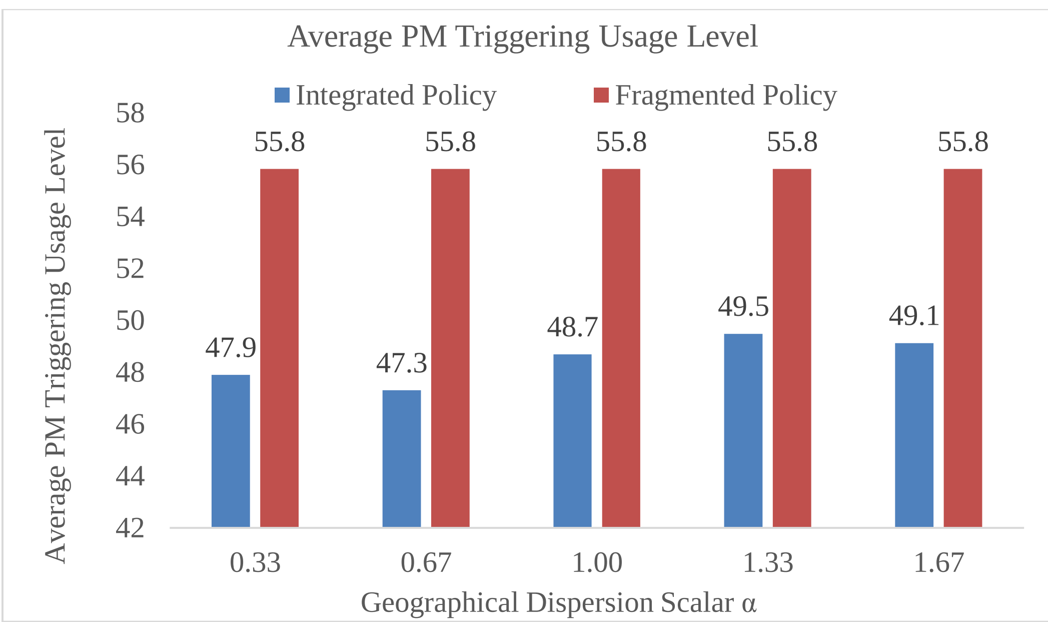

Figure 10: Average PM triggering usage levels for systems with $\alpha \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$

3.4.4 Influence of the Inventory Handling Costs

The cost rate of handling inventories could vary significantly due to factors such as the facility location or the type of the part being stocked [183]. In this section, we will investigate the performance of the newly proposed integrated decision-making policy under various inventory handling costs. To achieve this goal, both inventory holding costs (parameters $H_{i,h}$) and replenishment delivery costs (parameters $S_{i,h}$) are simultaneously rescaled in the baseline system setting, with the inventory cost scalar $\beta \in \{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\}$. Please note that $\beta = 1$ corresponds to the baseline system settings.

It can be observed from Figure 11 that as β rises, both absolute and relative operating cost benefits of the integrated policy over the benchmark policy increase. This is a plausible observation because, as inventory holding becomes more expensive, the beneficial effects of avoiding overstocking yielded by the integrated policy are magnified and therefore the benefits of the integrated policy become more pronounced.

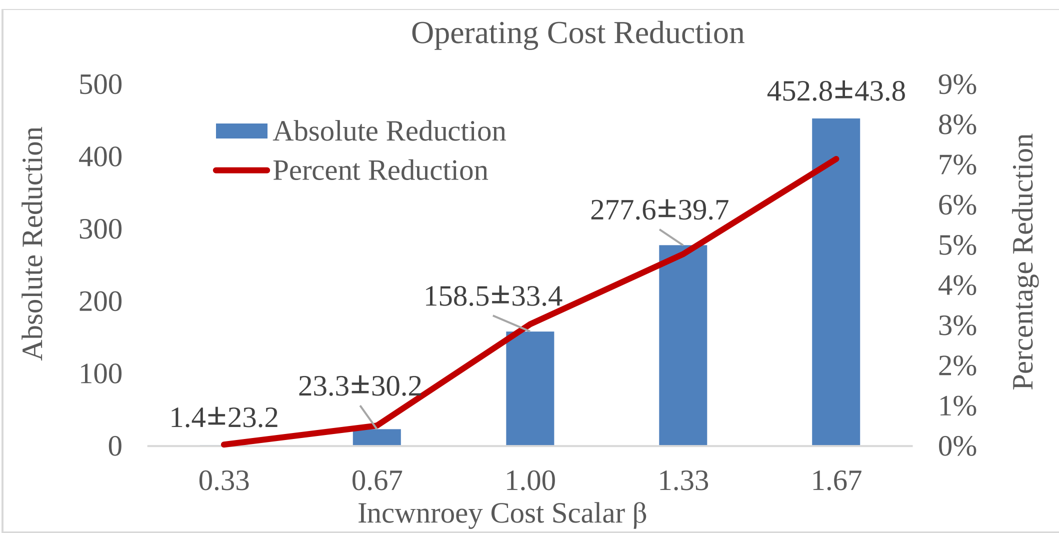

Figure 11: Reduction of operating costs per unit time for the systems with $\beta \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$, being reported as averages and corresponding $\pm 3\sigma$ limits estimated from simulations.

Also to be noted, the cost difference between the two policies becomes negligible when the inventory handling costs become cheap enough. Furthermore, the integrated and fragmented policies also converge in the sense of decisions as the inventory cost scalar goes towards zero. This is evident in Figure 12, where one can see that the decisions generated by the integrated and fragmented policies have approximately the same maintenance and logistic statistics at $\beta = \frac{1}{3}$. This makes sense because, with the inventory handling costs approaching zero, the "infinite inventories" assumption made in the fragmented policy becomes increasingly correct, since more and more spare parts can be stocked due to cheaper inventory stocking and replenishment costs.

In addition, the behaviors of summary statistics in Figure 12 and Figure 13 demonstrate that, unlike the fragmented policy, the integrated policy effectively adjusts to the changes in inventory handling costs. When the cost of handling inventories is raised, the maintenance schedule for the fragmented policy remains unchanged and cannot adjust to the situation of the changing logistic costs. Conversely, the maintenance schedule within the integrated decision-making policy can adjust to the decreasing availability of spare parts caused by higher inventory handling costs, which, in turn, partially offsets the negative influence of increasing logistic costs on the overall system operating costs.

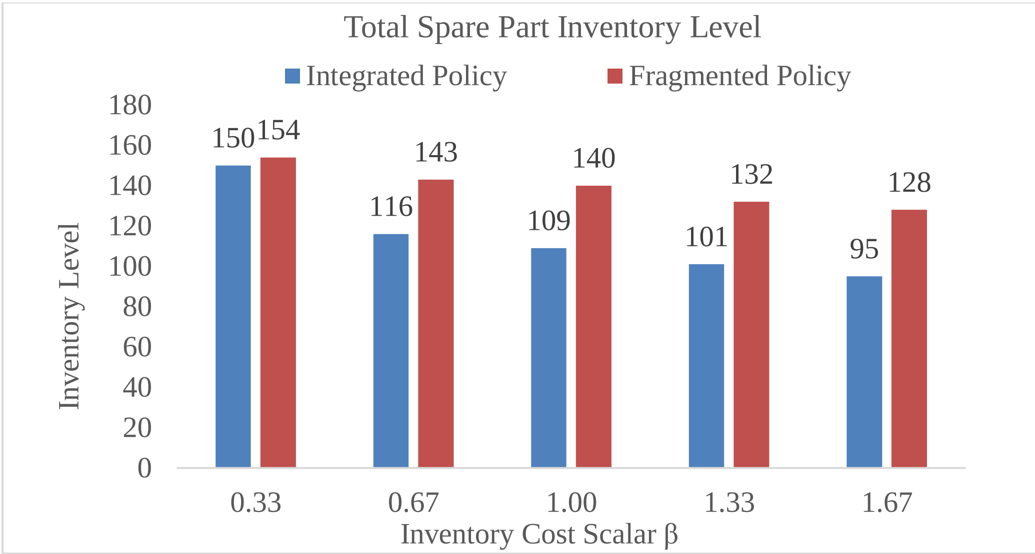

Figure 12: Total spare part inventory levels for systems with $\beta \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$

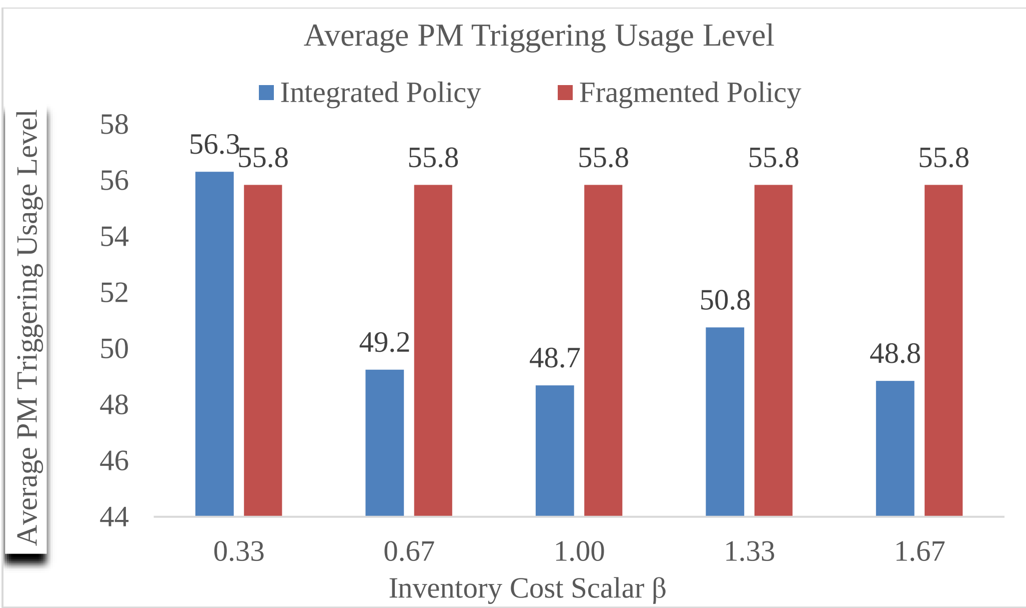

Figure 13: Average PM triggering usage levels for systems with $\beta \in \left\{\frac{1}{3}, \frac{2}{3}, 1, \frac{4}{3}, \frac{5}{3}\right\}$

3.4.5 Influence of the Downtime Penalties

In this section, influence of the penalty rate for asset downtimes on the integrated and fragmented decision-making policies will be evaluated through scaling of the original asset downtime penalties in the baseline system. To study these effects in a relatively tractable way, a downtime penalty scalar γ is introduced to simultaneously magnify/diminish the downtime penalties for all assets in the system, after which decisions made by the integrated and fragmented polices are compared. The downtime penalty scalar γ takes value in the set $\{\frac{1}{4}, \frac{1}{2}, 1, 2, 4\}$, with the baseline system obviously corresponding to $\gamma = 1$.

From Figure 14, it is evident that as downtime penalties decrease, the integrated decision-making policy becomes increasingly cost effective, both in terms of the absolute and relative cost savings over the fragmented decision-making policy. Furthermore, as downtime penalties increase, the integrated and fragmented policies gradually converge in the sense of both costs and decisions. Namely, as downtime penalties increase, the cost benefits of the integrated policy over the fragmented policy become negligible, as illustrated in Figure 14, with both the logistic and maintenance decision statics converging between the two policies, as visible in Figure 15 and Figure 16.

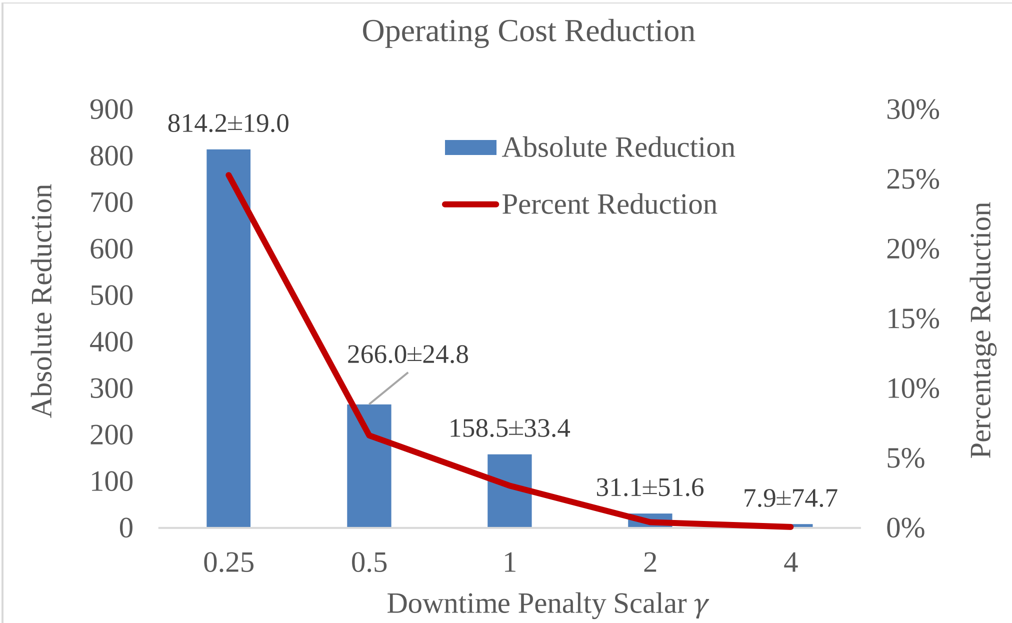

Figure 14: Reduction of operating costs per unit time for systems with γ in $\{\frac{1}{4}, \frac{1}{2}, 1,2,4\}$, being reported as averages and corresponding $\pm 3\sigma$ limits estimated from simulations.

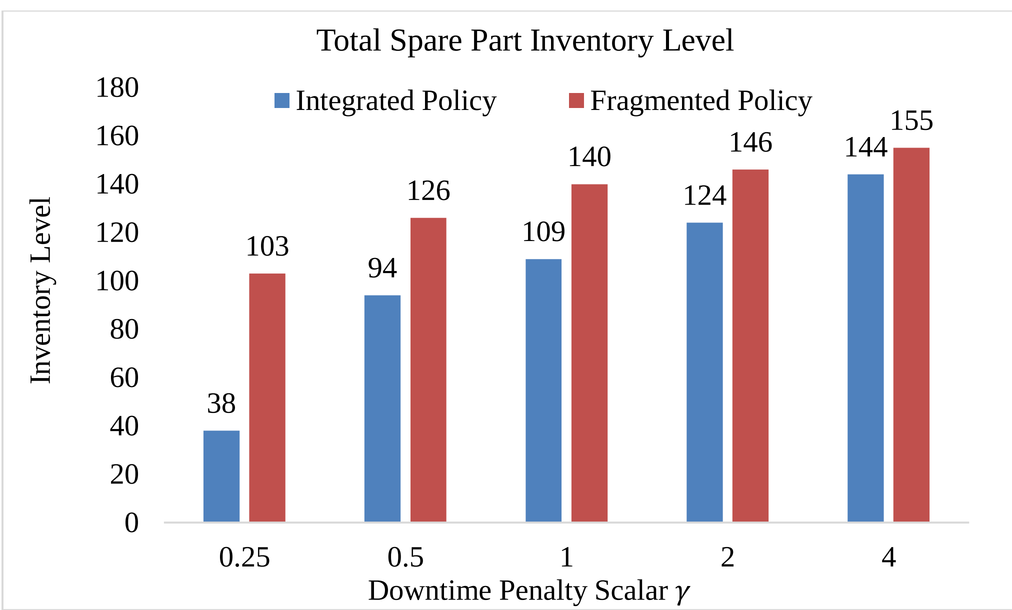

Figure 15: Total spare part inventory level for the systems with γ in $\{\frac{1}{4}, \frac{1}{2}, 1,2,4\}$

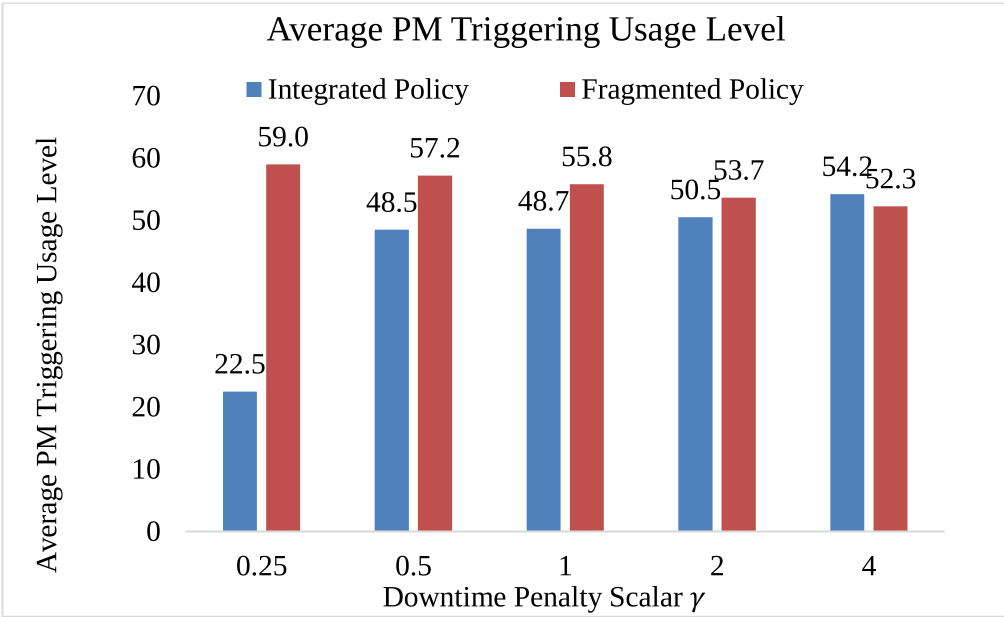

Figure 16: Average PM triggering usage level for the systems with γ in $\{\frac{1}{4}, \frac{1}{2}, 1,2,4\}$

Figure 17 shows *system uptime* for various γ-s and can be used to explain the apparent convergence between the two polices for larger γ-s. As the utilization of assets becomes crucial under higher downtime penalties (larger γ-s), the maintenance/logistic decisions under both polices are pushed to move in the direction of increasing the asset uptime, which is achieved via more spare parts being stocked in maintenance centers and PMs being executed more frequently. With higher optimized spare parts inventory levels, PM schedules obtained for the jointly optimized policy become increasingly close to those obtained via the fragmented policy, which, as mentioned earlier, optimizes PM schedules under the assumption of infinite spare parts inventory levels in the relevant maintenance centers (i.e. the relevant spare parts are assumed to be always available). Thus, the two policies approach each other in both the logistic and maintenance decisions as the downtime penalties grow.

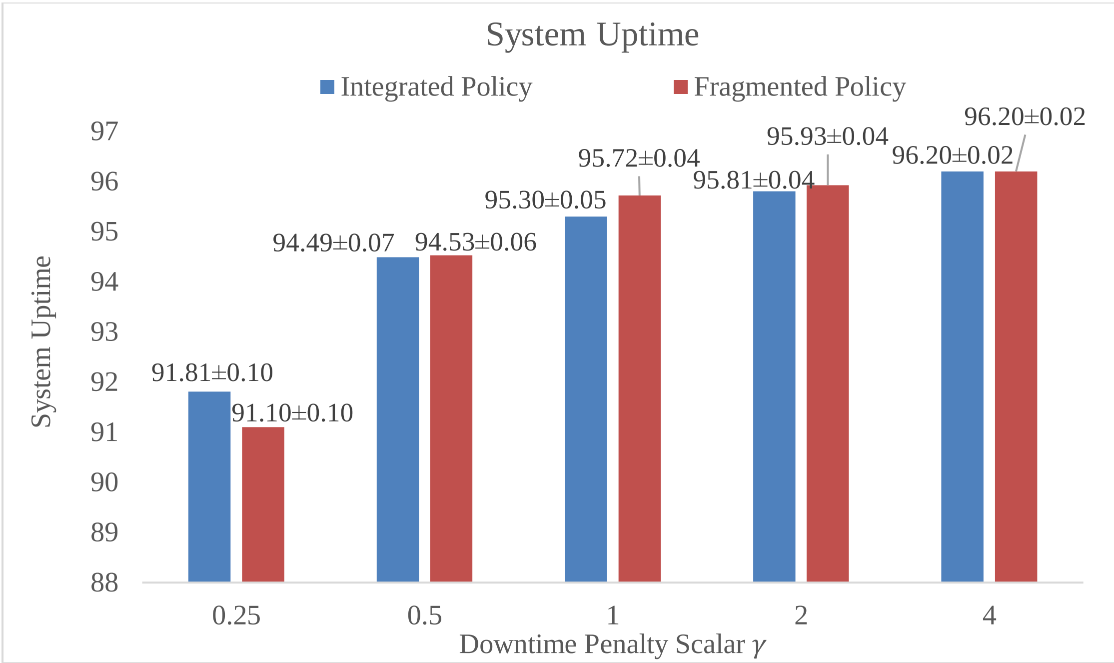

Figure 17: System uptimes for $\gamma \in \{\frac{1}{4}, \frac{1}{2}, 1, 2, 4\}$, being reported as averages and corresponding $\pm 3\sigma$ limits estimated from simulations.

3.5 Conclusion and Future Work

In this chapter, a decision-making method is proposed for concurrent spare parts inventory planning and preventive maintenance scheduling in a system of geographically dispersed assets and maintenance facilities that serve those assets. The newly proposed integrated decision-making method considers a usage-based PM replacement policy on the geographically dispersed degrading assets and a (s,S) replenishment policy for the maintenance centers that provide those assets with the necessary spare parts. This large-scale optimization problem was solved via a simulation-based metaheuristic optimization relying on a GA heuristic.

The integrated decisions-making policy introduced in this chapter was implemented in a simulated environment for a wide variety of cost parameters and system configurations, and is benchmarked against the traditionally used fragmented decision-making policy in which maintenance and logistic decisions are made sequentially.

An elaborate sensitivity analysis has been conducted to evaluate the influence of varying cost rates for handling spare part inventories, geographic dispersion levels of the system and penalty rates for asset downtimes. The results illustrate that the newly proposed integrated decision-making policy consistently outperforms the fragmented decision-making policy by enabling lower overall system operating costs. Detailed analysis of the cost effects showed that smaller spare part inventory levels (logistic decisions) and smaller PM triggering usage levels (maintenance decisions) take place under the integrated policy, indicating its avoidance of excessive stocking of spare parts in maintenance centers and avoidance of costly, reactive maintenance events via more aggressive scheduling of relatively more cost-efficient PM operations. Moreover, the sensitivity analysis showed that the integrated decision-making yielded increasing relative improvements over the fragmented policy in systems with more geographically dispersed assets and maintenance facilities, in systems with higher costs of handling inventories, as well as in systems with lower penalties for asset downtime. The reasons for these results can be summarized in the fact that the integrated decision-making policy can better adjust to changes in the systems by jointly optimizing logistic and maintenance decisions, compared to what we see when maintenance and logistic decisions are optimized sequentially under the traditional fragmented decision-making policy.

In another study, a comparison of the unit-time operating costs between the baseline system with stochastic time-related parameters and the system with deterministic time-related parameters is conducted. For the conciseness of the dissertation, details of this comparison will not be elaborated. However, the conclusions are provided here that additional uncertainties in the system lead to higher operating costs under the integrated policy and require more maintenance and logistic resources.

Several research extensions of the work presented in this chapter can be noted. Firstly, the methodology can be extended to account for more complex and elaborate logistic/maintenance operations, such as imperfect maintenance operations, multiple transportation options. Secondly, the integrated decision-making policy can be further improved to incorporate robustness to inaccuracies and uncertainties in the model of system operations due to, for example, inaccurate reliability parameter estimates or uncertainties in repair operations. Thirdly, further study on various asset structures would be useful to understand the effects of different numbers of components insider assets, different ways of their connection and different mappings between working parts and spare parts. Finally, another potential benefit from risk pooling under the integrated decision-making policy can be further studied through varying and/or adding uncertain factors. The paradigm of discrete-event simulation based modeling of system operations and GA based metaheuristic optimization described in this chapter offers a promising framework to tackle these more complex, but also more realistic operational problems than those considered in this manuscript.

Chapter 4

Joint Optimization of Imperfect Preventive Maintenance, Spare Parts Inventory and Transportation Options

4.1 INTRODUCTION[12]

For geographically distributed systems of degrading assets and maintenance facilities serving these assets, such as assets and maintenance facilities in airlines and oil/gas extraction companies, preventive maintenance (PM) scheduling is a challenging decision-making problem because of its inherent interactions with the availability of the required maintenance resources. As PM operations are aimed at ensuring the asset availability by replacing degraded parts before they actually fail, getting the right amounts and types of spares parts to the right places at the right time is of paramount importance for a successful PM execution. Therefore, the spare parts logistics (SPL), including inventory levels in maintenance facilities and the transportation options to deliver the spare parts, should be considered along with the maintenance schedules.

According to a recent review [184], the existing works on jointly scheduling of PM and SPL mainly focus on the optimization of reliability-based maintenance policies in a spare parts inventory system. From the side of maintenance, both the age-based (usage-based) [109], [180], [116], [111] and block-based (period-based) PM policies [113], [114], [122], [123] are considered. In addition, several recent studies considered joint PM and SPL decision-making for advanced asset systems, such as serial-connected multi-part asset structure [115], [117], [121], k-out-of-n asset structure [124], [125], flexible-connect

[12] This chapter is based on a submitted journal paper: K. Wang and D. Djurdjanovic, "Joint Optimization of Preventive Maintenance and Spare Part Inventory and Transportation Options for Systems of Geographically Distributed Assets", submitted to *Elsevier Journal of Computers and Industrial Engineering*, Paper No. CAIE-S-17-10392, 2017.
Keren Wang wrote this publication under the supervision of Dragan Djurdjanvoic.

multi-part asset structure [126] and simple asset structure with multiple failure modes [178].

From the side of SPL, the joint decision-making problems have been considered in both continuous-review inventory systems [109], [126], [180] and periodical-review inventory systems [121], [123]. These works evaluated several inventory management strategies, including the (R,S) replenishment policy [123], [185], (s,S) replenishment policy [109], [111], [178], [180] and the strategy with reserved inventories for PMs [186]. Beyond inventory management, Nguyen *et al*. extended the definition of the maintenance resource by considering technicians of different skill levels [118], [120], thus involving the human resource planning into the resulting decision-making policies, while Chen *et al*. [112] assumed the existence of multiple suppliers and proposed an integrated decision-making policy for the resulting multi-echelon logistic network.

Sensitivity studies for the integrated PM and SPL decision-making policies have also received attention in the literature [116], [121], [185]. These sensitivity studies are inspired by parametric uncertainties that often cannot be directly evaluated and have to be estimated based on the expert knowledge or the long-time observation of this system [48], [51]. However, there is still lack of a well-established methodological approach to quantitatively study the effects of changing system parameters and fully understand their interactions in the decision-making process.

In this chapter, we introduce an integrated decision-making process that jointly optimizes PM schedules, spare part inventory levels and transportation options for spare parts in a geographical dispersed network of multi-part assets and multi-level maintenance facilities serving those assets with the necessary spare parts. The unique contributions of this work to the area of joint PM and SPL decision-making can be summarized as follows. We will consider possibilities of imperfect PM operation, which will be the first in the literatures on joint PM and SPL decision-making. Furthermore, we will consider multiple shipping options for spare parts deliveries, which is also a first. Finally, for the purpose of sensitivity analysis, a design of experiment (DOE) based method is proposed and introduced to study the effects and interactions between various system parameters on the decision-making process and its performance.

The rest of the chapter is organized as follows. Section 4.2 describes the joint PM and SPL decision-making in the form of a stochastic optimization formulation. Section 4.3 introduces a simulation-based metaheuristic approach to solving the optimization problem described in Section 4.2. In Section 4.4, the proposed integrated decision-making process is evaluated in a simulated environment, using a DOE-based sensitivity analysis. Section 4.5 provides conclusion of this research and outlines several possible avenues for future work.

4.2 METHODOLOGY

4.2.1 Problem Statement

As illustrated in Figure 18, the topology of the SPL system considered in this chapter is a three-level logistic network, consisting of a *central warehouse*, a *maintenance center* and a set of multiple *assets*. Furthermore, the assets are assumed to have multi-part structure, each consisting of multiple independent *working parts*. These entities are explained in more detail below,

- A *central warehouse* is the primary source to all new spare parts and plays two roles in the spare part inventory flow - replenishing spare parts for the maintenance centers following a (s, S) replenishment policy [86], or providing spare parts directly to the assets as emergency orders when the maintenance order could not be satisfied from a maintenance center. Infinite inventory levels of spare parts are assumed for the central warehouse.

- A *maintenance center* fulfills maintenance orders from the nearby assets by shipping new undegraded spare parts to their operating sites. It is assumed to have finite inventory levels of spare parts and any maintenance order that cannot be immediately fulfilled by the maintenance center would be served by the central warehouse as an emergency order.
- The term *asset* is used to refer to a machine that can be operated independently to generate revenue. It is assumed that there is a fleet of geographically dispersed assets in the system, labeled $A_1, A_2, \ldots, A_J$. An asset consists of multiple independent working parts and can be operated properly only if all its parts behave properly.
- The term *working part* is used to refer to a basic unit of an asset. An asset A_j $(1 \leq j \leq J)$ is assumed to be made up of K_j serially connected parts, labeled $P_{j,1}, P_{j,2}, \ldots, P_{j,K_j}$. Degradation process of a part $P_{j,k}$ is characterized by a reliability function, $\mathcal{D}_{j,k}(\cdot)$, representing the distribution of that part's usage time to failure. From the point of view of logistics, a working part on an asset corresponds to a certain type of a spare part that needs to be stored in the maintenance center. During a PM/RM, a new spare part should be shipped either from the maintenance center or directly from the central warehouse to replace the degraded working part.

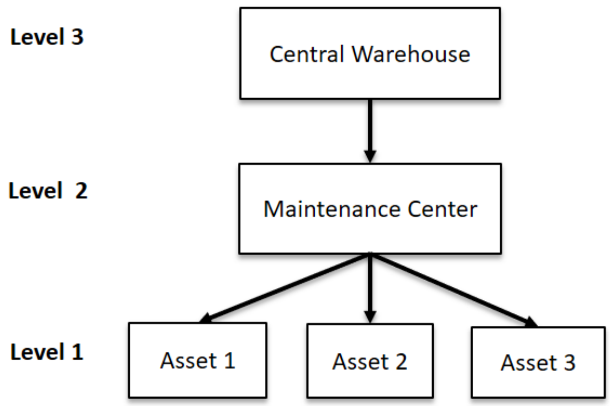

Figure 18: Three-echelon spare part logistic network considered in Chapter 4

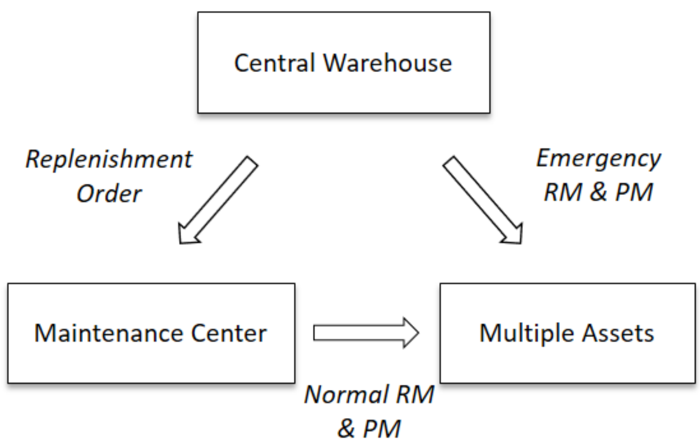

Figure 19: Illustration of spare part inventory flows within the SPL system

In this chapter, a continuous-review inventory system is considered and a (s, S) replenishment policy is followed to manage spare part inventories in the maintenance centers. Let $SP_1, SP_2, \ldots, SP_I$ denote all spare parts needed to be stocked in a maintenance center. For a spare part SP_i, the reorder inventory level y_i (corresponding to s in the replenishment policy) indicates the critical level of this spare part that triggers a replenishment order with batch size z_i (corresponding to S-s in the replenishment policy), indicating the number of the spare parts to be shipped from the central warehouse to that maintenance center. Furthermore, the replenishment cost per order (S_i) is assumed to be a linear function of the batch size (z_i), or more formally

$$S_i(z_i) = S_i^{fix} + S_i^{add} * (z_i - 1)$$

where S_i^{fix} denotes the fixed replenishment handling cost and S_i^{add} denotes the additional cost to have one more spare part added to the replenishment order.

From the side of maintenance decisions, the so-called replacement maintenance policy is assumed [184], that is to say, both PM and RM involve a new spare part replacing the broken or severely degraded working part on the asset. Moreover, a *usage-based PM triggering policy* is considered, which means that a PM triggering usage level $x_{j,k}$ is set for each working part $P_{j,k}$, indicating the part's critical usage level at which a PM operation is initiated.

Once initialized, a complete maintenance order consists of two phases: transportation and execution.

Phase I

Transportation consists of shipping the ordered spare part to the asset A_j from the maintenance center as a normal order, or from the central warehouse as an emergency order, with the lead times respectively following the distributions $\mathcal{MT}_j(\cdot)$ and $\mathcal{CT}_j(\cdot)$.

During RMs, a significant portion of the asset downtimes are caused by the waiting times for the new spare part. Therefore, several expedited shipping options will be considered, with fasters ones incurring more costs. More formally, decision variable u_j will be used to denote the relative acceleration of the expedited shipping option compared to a normal delivery to the asset A_j, with its influence on the lead time distributions and expedited shipping costs as follows:

- Lead time from the maintenance center to the asset A_j following the distribution $\mathcal{MT}_j\left(\left(1+u_j\right)*t\right)$
- Lead time from the central warehouse to the asset A_j following the distribution $\mathcal{CT}_j\left(\left(1+u_j\right)*t\right)$
- Expedited shipping cost to accelerate a RM delivery to the asset A_j given by $T_j * u_j$

Obviously, decision variable u_j scales the delivery times, with e.g. $u_j = 0$ corresponding to no acceleration in deliveries, $u_j = 1$ doubling the speed of deliveries, $u_j = 2$ tripling that speed *etc*.

Phase II

Execution is essentially the process in which the target part on the asset is replaced with the newly delivered spare part, resulting in a maintenance intervention. The times needed to execute maintenance interventions will be referred to as repair times.

It is assumed that a RM always restores the part $P_{j,k}$ to as-good-as-new condition, or, in other words, RM operations are assumed to be so-called perfect maintenance operations. However, it is assumed that PM operations of various performance qualities are available, with different costs and repair times. The character of a PM on an asset A_j will be described by the PM recovery rate v_j, representing its relative quality compared to a perfect PM. The decision variable v_j is assumed to take discrete values between 0 and 1 ($v_j = 1$ indicates a perfect PM and $v_j = 0$ indicates a minimal repair), influencing the PM-related parameters as follows,

- Usage to failure of the part $P_{j,k}$ after PM following the distribution $\mathcal{D}_{j,k}\left(\frac{t}{(1-\alpha)v_j+\alpha}\right)$
- PM cost per order on the part $P_{j,k}$ given by $M_{j,k}\left(v_j\right) = M_{j,k}^{fix} + M_{j,k}^{add} * v_j$

- PM repair time on the part $P_{j,k}$ given by $RT_{j,k}(v_j) = RT_{j,k}^{fix} + RT_{j,k}^{add} * v_j$

where $\alpha > 0$ denotes the relative quality of a minimal repair compared to a perfect operation, $M_{j,k}^{fix}$ ($RT_{j,k}^{fix}$) denotes the fixed PM cost (time) and $M_{j,k}^{add}$ ($RT_{j,k}^{add}$) denotes the additional cost (time) to improve PM performance.

4.2.2 Stochastic Optimization Formulation

In this chapter, we will seek an integrated decision-making policy for the usage levels triggering PMs for working parts ($x_{j,k}$-s), reorder and target inventory levels for spare parts being stocked in the maintenance centers (y_i-s and z_i-s), the expedited delivery rates for RMs (u_j-s) and the recovery rates of PMs (v_j-s). More formally, the integrated decision-making policy will be pursued through the following stochastic optimization,

$$\underset{\substack{\{x_{j,k}\in X_{j,k}\}_{1\le j\le J, 1\le k\le K_j} \\ \{y_i\in Y_i\}_{1\le i\le I} \\ \{z_i\in Z_i\}_{1\le i\le I} \\ \{u_j\in U_j\}_{1\le j\le J} \\ \{v_j\in V_j\}_{1\le j\le J}}}{\text{Minimize}} \frac{1}{T}\mathbb{E}\left\{\sum_{1\le i\le I}\left(d_i D_i + s_i S_i(z_i)\right) + \sum_{\substack{1\le j\le J \\ 1\le k\le K_j}}\left(r_{j,k}R_{j,k} + m_{j,k}M_{j,k}(v_j) + e_{j,k}E_{j,k}\right)\right.$$

$$\left. + \sum_{1\le j\le J} l_j L_j + \sum_{\substack{1\le j\le J \\ 1\le k\le K_j}} r_{j,k}T_j \cdot u_j \right\}$$

Optimization Problem 4

where the terms are explained in Table 2.

Category	Symbol	Description
General notation	i, j, k	Indices for spare part type (i), asset (j), working part (k)
	T	Planning horizon
Candidate value set for decision variable	$X_{j,k}$	A discrete real-number set for PM trigger $x_{j,k}$ with values in $(0, \infty)$
	Y_i	A discrete integer set for reorder level y_i with values in $[-1, \infty)$
	Z_i	A discrete integer set for batch size z_i with values in $[1, \infty)$
	U_j	A discrete real-number set for RM expedition rate u_j with values in $[0, \infty)$
	V_j	A discrete real-number set for PM recovery rate v with values in $[0,1]$
Inventory-related terms	D_i	Inventory holding cost per unit time for the spare part SP_i
	$S_i(z_i)$	Replenishment cost per order for the spare part SP_i at the batch size z_i
	d_i	Cumulative inventory holding time of the spare part SP_i
	s_i	Cumulative replenishment order of the spare part SP_i
PM	$M_{j,k}(v_j)$	Unit PM cost to perform PM on the part $P_{j,k}$ with the given v_j
	$m_{j,k}$	Cumulative number of PM orders for the part $P_{j,k}$
Normal RM	$R_{j,k}$	Unit RM cost to perform RM on the part $P_{j,k}$
	$r_{j,k}$	Cumulative number of RM orders for the part $P_{j,k}$

Table 2: Notation used in the optimization problem (4)

Table 2. Continued from previous page

Emergency RM	$E_{j,k}$	Additional charge of an emergency RM on the part $P_{j,k}$
	$e_{j,k}$	Cumulative number of emergency RM orders for the part $P_{j,k}$
Downtime penalty	L_j	Penalty cost per unit downtime of the asset A_j
Expedited Shipping	T_j	Expedited shipping cost per RM order to the asset A_j

Objective function in (4) represents the expected unit-time operating cost of the system. The expectation operator is applied due to the random effects induced by the reliability of working parts and the delivery delays of spare parts. In the objective function, the stochastic effects are reflected in the cumulative statistics (i.e. d_i-s, s_i-s, $r_{j,k}$-s, $m_{j,k}$-s, $e_{j,k}$-s and l_j-s).

For each integrated decision, these random effects are captured by discrete-event simulation and the expected operating costs are estimated through averaging of the objective function values obtained from multiple replications of simulations.

One can see that the cost function in formulation (4) consists of three groups of costs: *i*) inventory-related costs, including the cost to hold spare parts inventories in the maintenance center and the cost to order replenishment for the maintenance center, *ii*) penalties for the asset downtimes, and *iii*) maintenance costs incurred by execution of PM and RM operations. This objective function penalizes the consumption of maintenance and logistic resources, while rewarding the asset availability. Obviously, this is a relatively simple cost function and one may likely need to choose cost parameters and/or incorporate other potential operating costs, such as backordering costs and unfulfilled contract penalties. In effect, different companies, and often different parts of the same company operate with different cost functions and cost parameters, necessitating adequate changes in the optimization formulation (4). A metaheuristic simulation-based optimization approach to solving the optimization problem (4), which will be elaborated in the next section, allows such alterations to the objective function, and was one of the main reasons for choosing such an optimization approach

4.3 SIMULATION-BASED OPTIMIZATION APPROACH

In this section, we will describe a simulation-based metaheuristic optimization procedure that pursues a joint maintenance triggering, inventory management and transportation selection policy as a solution to the optimization problem (4).

Simulation-based optimization has become a powerful paradigm for decision-making in the area of SPL and maintenance scheduling due to its flexibility in accommodating advanced system operations, as well as complex cost structures observed in real-world systems [116], [111], [117], [126]. In this chapter, discrete-event simulations were utilized to estimate the expected operating cost for a candidate solution, which is then fed back into a metaheuristic algorithm to guide the movements towards improved candidate solutions.

Optimization procedure pursued in this chapter is based on the genetic algorithm (GA) paradigm [181]. Generally speaking, GA is a search heuristic that mimics the process of natural evolution. Each candidate solution, (X,Y,Z,U,V), is represented via five chromosome portions, each of which is a decision vector respectively relevant to the PM triggers, replenishment triggers, replenishment batch sizes, RM delivery speeds and PM qualities[13]. The GA evolution starts from N randomly generated candidate solutions as

[13] Specifically, we have $X=\left(x_{1,1,},x_{1,2}\dots,x_{1,K_1},\dots,x_{J,1},x_{J,2},\dots,x_{J,K_J}\right)$, $Y=(y_1,y_2,\dots,y_I)$, $Z=(z_1,z_2,\dots,z_I)$, $U=\left(u_1,u_2,\dots,u_J\right)$ and $V=\left(v_1,v_2,\dots,v_J\right)$.

the initial population, labeled $G_0 = \{(X_0^s, Y_0^s, Z_0^s, U_0^s, V_0^s) | 1 \leq s \leq N\}$. The fitness of each candidate solution in the population is taken to be inversely proportional to the expected operating cost of the system obtained via multiple simulation replications of system operations under the decision-making policy represented by that candidate solution. In order to generate offspring candidate solutions for the next generation, selection, crossover and mutation operators are applied to the current generation. These operators are described below.

- *Selection operator*: A pair of parent solutions, namely $(X^\alpha, Y^\alpha, Z^\alpha, U^\alpha, V^\alpha)$ and $(X^\beta, Y^\beta, Z^\beta, U^\beta, V^\beta)$ are chosen from the current generation g to mate and produce offspring candidate solutions for the next generation $g+1$, with probability of selection being proportional to their fitness (also known as fitness proportionate selection [181]).
- *Crossover operator*: For a pair of selected parent solutions, a single-point crossover operator is executed at a random point in each of the five chromosome portions, leading to five pairs of recombined chromosome portions, namely $\{X^a, X^b\}$, $\{Y^a, Y^b\}$, $\{Z^a, Z^b\}$, $\{U^a, U^b\}$ and $\{V^a, V^b\}$. Then an offspring solution is generated via randomly selecting a chromosome portion from each of the five pairs, while the remaining chromosome portions forms another offspring solution. The above-described crossover operator is pictorially illustrated in Figure 20.
- *Mutation operator*: To promote genetic diversity in the offspring population, each gene in an offspring solution chromosome is selected with a small probability (commonly referred to as the mutation probability), and its value is perturbed to an adjacent candidate in its candidate value set[14].

[14] For example, assume that the PM triggering usage level $x_{j,k}$ takes values in $X_{j,k} = \{35, 40, 45, 50\}$ and the current value for this gene is $x_{j,k} = 40$. If the mutation operator is performed on this gene, the decision will mutate into either $x_{j,k} = 35$ or 45, with a small mutation probability.

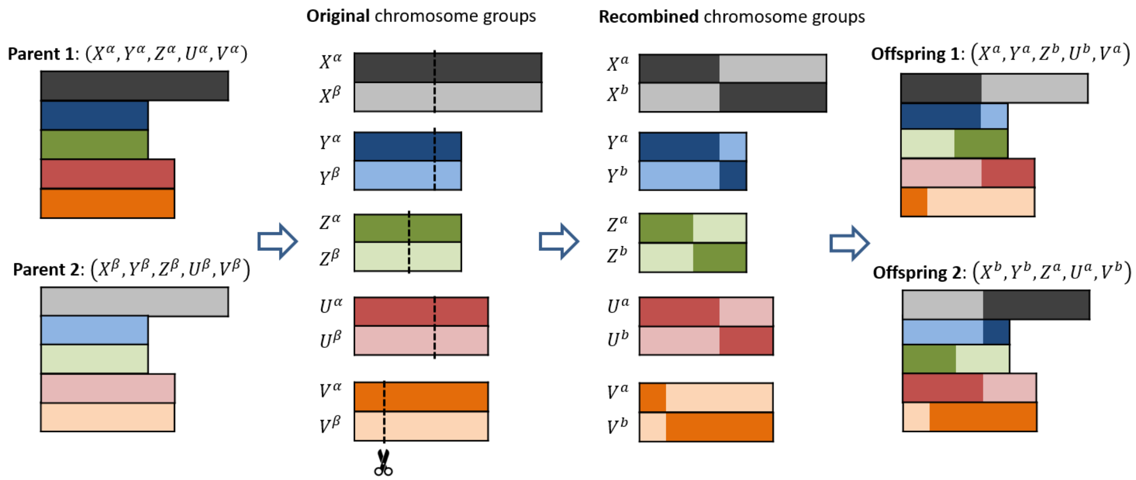

Figure 20: A realization of the crossover operator on two parent candidate solutions considered for Optimization Problem 4

Following [181], N pairs of parent solutions are selected from the current generation, leading to the birth of $2N$ offspring solutions. If the top performing candidate solution in the parent generation has higher fitness than the $2N$ offspring candidates, it is added to the offspring population, thus enforcing the well-known concept of elitism in this GA [181]. From this set, the fittest N solutions are selected to form the next generation of candidate solutions.

Successive progression of generations yields ever-improving solutions, leading to lower expected operating cost of the system. Termination criterion for this algorithm is either a predetermined number of GA generations being reached, or the best candidate solution not being improved over a number of consecutive generations. The integrated decision-making policy is then taken to be the fittest candidate solution in the last GA generation, denoted by $(X^*, Y^*, Z^*, U^*, V^*)$. Figure 21 illustrates the above-described algorithm.

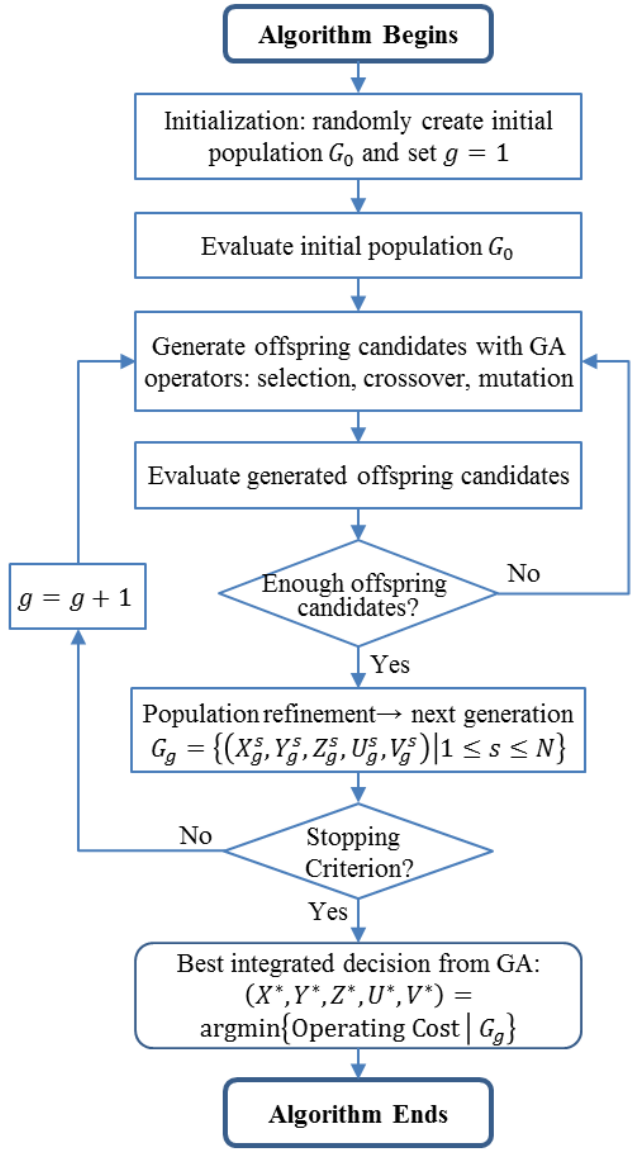

Figure 21: Flow chart of the GA-based optimization pursued in Chapter 4

4.4 RESULTS

4.4.1 Baseline System and Restricted Systems

The newly proposed integrated decision-making policy described in Section 4.2 is evaluated in a series of simulations. For the baseline system, a central warehouse is connected to a maintenance center that provides maintenance service to 20 geographically dispersed assets. All together, 52 working parts are associated with the assets, and the corresponding spare parts (5 types of spare parts) need to be stocked in the maintenance facilities. Therefore, the integrated decision-making policy for the baseline system contains 102 decision variables, including 52 usage levels that trigger PM operations for the corresponding working parts, 5 reorder levels and 5 replenishment batch sizes for managing spare part inventories in the maintenance center, 20 recovery rates that represents the quality of PM operations and 20 acceleration rates that denote shipping options of the RM service. More details on the parameters of the baseline system can be found in the Appendix B.

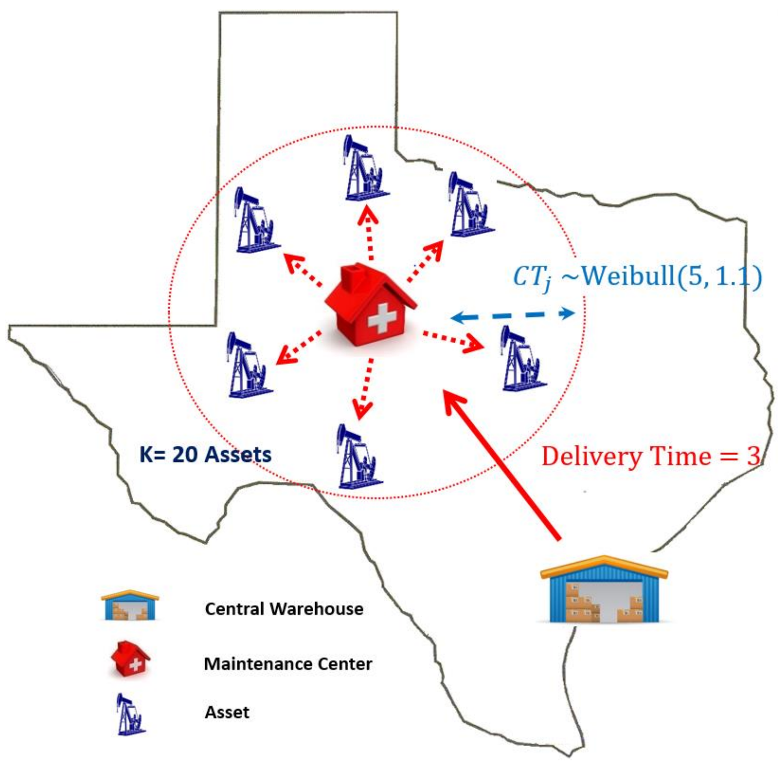

Figure 22: Illustration of the spare part logistic network for the baseline system in Chapter 4 (single maintenance center and 20 assets)

The decision-making planning horizon (T) is 365*5 time unis, and 100 replications of simulations are generated to estimate the unit-time operating cost for each candidate solution[15]. The simulation-based metaheuristic algorithm described in Section 4.3 is repeated 10 times, with different randomly selected initial candidate solutions (i.e. 10 GA runs) to better explore the solution space [181]. In terms of computational costs, it always took less than 10 hours to obtain a decision-making policy for this system on a relatively simple personal computer (Intel Core i5-3570 CPU, 16GB RAM, 64-bit Window 7). It should be noted that the simulation based metaheuristic optimization proposed in this chapter is highly parallelizable (each candidate solution and each replication could be evaluated in parallel) and thus, this algorithm could be greatly accelerated in a multi-processor environment [187].

The integrated decision-making policy proposed in this chapter derived under the assumption that multiple options exist for PM execution, RM transportation and the size of replenishment orders. Special cases of the integrated decision-making policy can be obtained by restricting some of those options, and the indicators, $\mathbb{I}_1$, $\mathbb{I}_2$ and $\mathbb{I}_3$, will be used to denote such restrictions in the following manner:

1) $\mathbb{I}_1 = 0$ denotes the existence of multiple PM operations with different quality levels, while $\mathbb{I}_1 = 1$ corresponds to the situation with perfect PM only. Thus, $\mathbb{I}_1 = 1$ implies fixing $v_j = 1$ $(1 \leq j \leq J)$ in the formulation (4).
2) $\mathbb{I}_2 = 0$ denotes the existence of multiple spare parts shipping options for RM, while $\mathbb{I}_2 = 1$ corresponds to normal RM delivery only. Thus, $\mathbb{I}_2 = 1$ implies fixing $u_j = 0$ $(1 \leq j \leq J)$ in the formulation (4).

[15] This number of replication was selected in an *ad hoc* manner, by increasing the number of replications until their average effects did not change significantly with further increases.

3) $\mathbb{I}_3 = 0$ denotes a (*s*, *S*) replenishment policy for spare parts inventory management in the maintenance center, while $\mathbb{I}_3 = 1$ indicates a (*S-1*, *S*) replenishment policy in which only one spare part is shipped as a replenishment order. Thus, $\mathbb{I}_3 = 1$ implies fixing $z_i = 1$ $(1 \leq i \leq I)$ in the formulation (4).

The benefits of considering multiple options for PM operations, RM deliveries and replenishment size can be seen via the comparisons between the integrated decision-making policy and its special cases. As shown in Figure 24, restriction on any of the three options leads to the increase in the system operating costs. Moreover, a two-way analysis of variance (ANOVA) model [188] is used to study the statistical effects of these multiple-choice options. In other words, ANOVA factorial analysis is used to study effects of factors $\mathbb{I}_1$, $\mathbb{I}_2$ and $\mathbb{I}_3$ on the unit-time operating costs under the integrated decision-making policy. As visible from Figure 24, the main effects of $\mathbb{I}_1$, $\mathbb{I}_2$ and $\mathbb{I}_3$ are all statistically significant, with the significance level of 0.01 or less, confirming the cost benefits of executing these multiple-choice options. Moreover, 2nd order interaction effects of $\mathbb{I}_1 \times \mathbb{I}_2$ and $\mathbb{I}_1 \times \mathbb{I}_3$ are marginally significant, illustrating weak interactions between these factors (options).

More detailed analysis of system performance under different decision-making options shows that when $\mathbb{I}_1 = 1$ and $\mathbb{I}_2 = \mathbb{I}_3 = 0$ [16], the PM service becomes less efficient in terms of increased repair interventions (+93.3%) and higher cumulative PM costs (+71.7%). Furthermore, when $\mathbb{I}_2 = 1$ and $\mathbb{I}_1 = \mathbb{I}_3 = 0$ [17], the prolonged RM delivery delays lead to a 11.0% increase in asset downtimes. Finally, when $\mathbb{I}_3 = 1$ and $\mathbb{I}_1 = \mathbb{I}_2 = 0$ [18], more replenishment deliveries are needed (+120.3%), leading to the increase in the replenishment delivery costs. Please note that a detailed list of statistics

[16] The scenario that PM operations restricted to perfect PM only.
[17] The scenario that spare part deliveries for RM orders restricted to normal shipping speed only.
[18] The scenario that inventory management policy restricted to the (*S-1*, *S*) replenishment policy.

describing the system performance under the integrated decision-making policy is provided in the Appendix B for the baseline and restricted systems.

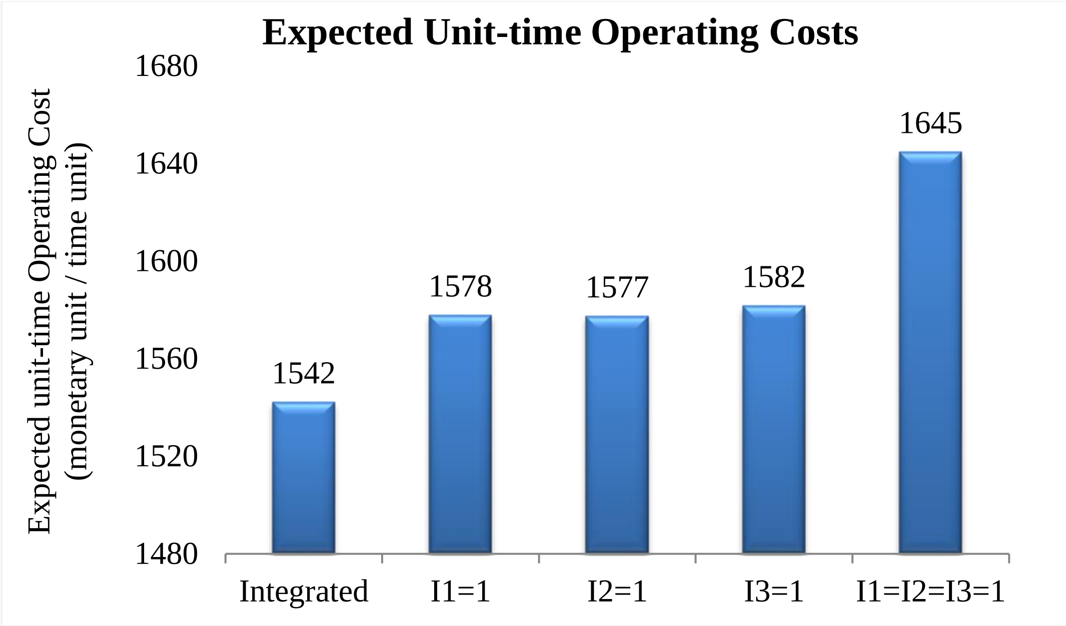

Figure 23: Comparison of unit time operating costs between the baseline and restricted systems

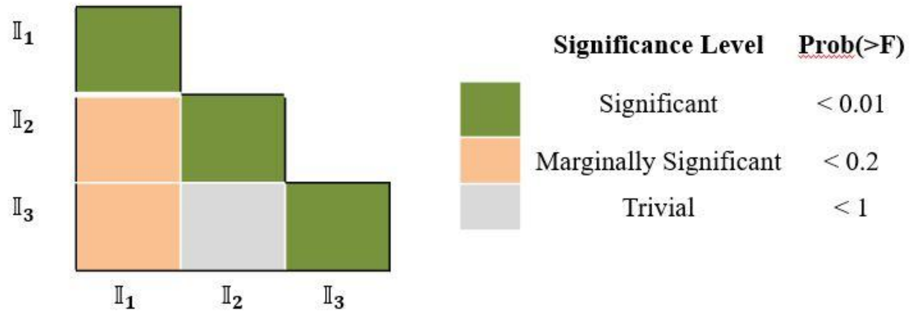

Figure 24: ANOVA analysis of the unit time operating costs, with significance levels for the effects of factors $\mathbb{I}_1$, $\mathbb{I}_2$ and $\mathbb{I}_3$

4.4.2 Sensitivity Analysis for Operating Costs

ANOVA method can also be used to conduct sensitivity studies regarding various system parameters. In this section, the unit-time operating cost under the integrated decision-making policy is used as the response in a two-level factorial ANOVA, in which six input factors are considered. Specifically, factor F1 denotes the geographical dispersion level of the logistic network and factors F2-F6 are relevant to cost-related system parameters, respectively denoting inventory holding cost per unit time (F2), replenishment cost per order (F3), PM quality improvement cost per order (F4), penalty cost per unit downtime (F5) and RM acceleration cost per order (F6). Each factor is varied at two levels (low & high), resulting in 64 experimental levels in a 2^6 DOE. More details on the DOE settings can be found in the Appendix B.

In Figure 25, significance levels for the 6 main effects and 15 interaction effects are shown as the result of ANOVA. The main effects of the geographical dispersion level (F1) and four cost-related factors (F2, F4-F6) along with some of their interaction effects (F1×F2, F2×F5, F4×F5, F4×F6, F5×F6) were found to be critical to the system operating cost. Criticality of these effects is plausible, since changes in these factors directly affect either the maintenance scheduling or spare parts logistic planning in the integrated decision-making policy.

Moreover, it is interesting to see that the replenishment cost per order (F3) is only marginally significant to the operating cost under the integrated decision-making policy, while its interaction effect with another inventory-related cost parameter, inventory holding cot per unit time (F2), is more significant than its main effect. It illustrates the fact that when only the replenishment costs become expensive, the negative effects can be partially offset through properly adjusting the inventory management policy, such as shipping more spare parts in a replenishment batch.

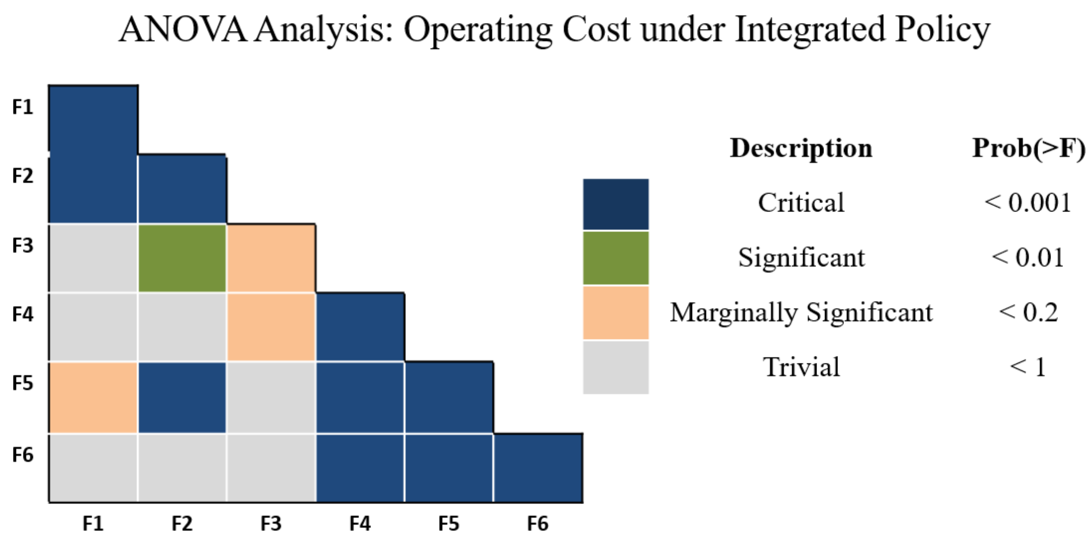

Figure 25: ANOVA analysis of the unit time operating costs under the integrated policy, with significance levels for the main/interaction effects of F1-F6

4.4.3 Sensitivity Analysis for Cost-Reduction Effects of Multi-Option Operations

In this section, we will focus on the sensitivity analysis on cost-reduction effects of considering multi-mode PM operations, RM expedition options and flexible batch size of replenishment orders. To prevent interaction effects between these operations, the cost-reduction effect for each of them is defined as the difference between,

(1) the operating cost of the system with all three operations being restricted, i.e. $\mathbb{l}_1 = \mathbb{l}_2 = \mathbb{l}_3 = 1$, and

(2) the operating cost of the system allowing multiple options for the operation of interest, but having other two operations restricted, e.g. set $\mathbb{l}_2 = 0$ and $\mathbb{l}_1 = \mathbb{l}_3 = 1$ to analyze RM expedition options.

The results of two-way ANOVA studies for the three cost-reduction effects are shown in Figure 24 - Figure 26. Generally, the cost-reduction effects of all three operations are sensitive to the magnitude of PM quality improvement cost per order (F4), penalty per unit downtime (F5) and their interaction effect (F4×F5). It makes senses as these two factors directly affect the PM schedule that plays the core role of the integrated decision-making policy. Furthermore, another fact deserved noting that, if the main effects of two factors are both critical to a response, then their interaction effect also tends to be critical to the same response.

Besides the aforementioned effects (F4, F5, F4×F5), each of the three responses is sensitive to some other factors. Firstly, the inventory holding cost per unit time (F2) is an important factor to the cost-reduction effect of multi-mode PM operation, illustrating that the availability of the spare parts also affects PM schedule. Secondly, it is plausible that RM acceleration cost (F6) affects the cost-reduction effect of RM expedition options. However, F6 is a noncritical factor to other two responses, where the normal shipping speed is the only option to RM deliveries, leading to zero RM acceleration cost under the corresponding restricted systems. Thirdly, the replenishment policy guides the inventory management for spare parts in maintenance center, therefore, the cost-reduction effect as the shift from (S-1,S) to (s,S) replenishment policy is sensitive to the magnitude of two inventory-related cost parameters, namely inventory holding cost (F2) and replenishment cost per order (F3).

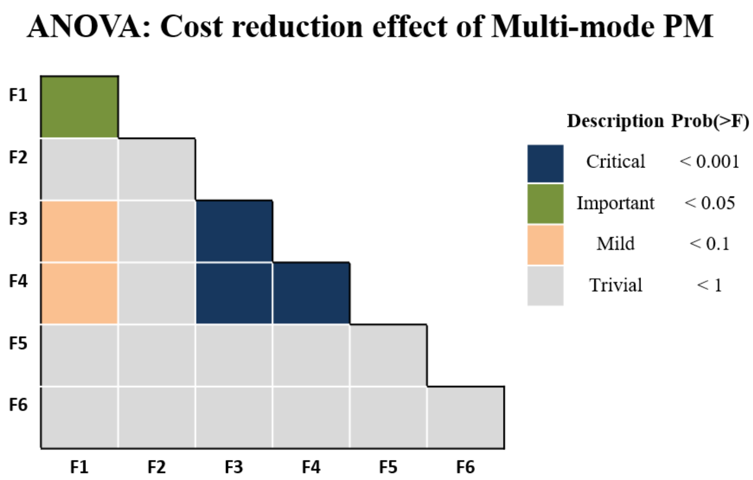

Figure 26: ANOVA analysis for cost-reduction effect of multi-mode PM operations: significant levels for main/interaction effects of F1-F6

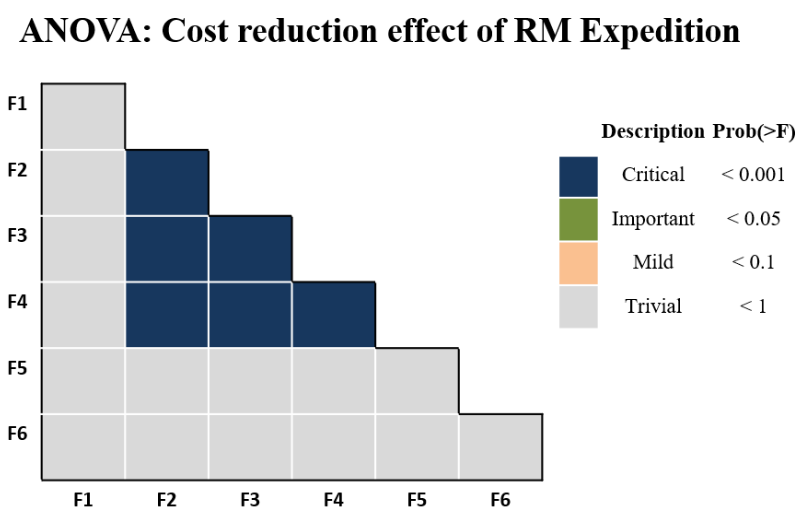

Figure 27: ANOVA analysis for cost-reduction effect of expedited RM options: significant levels for main/interaction effects of F1-F6

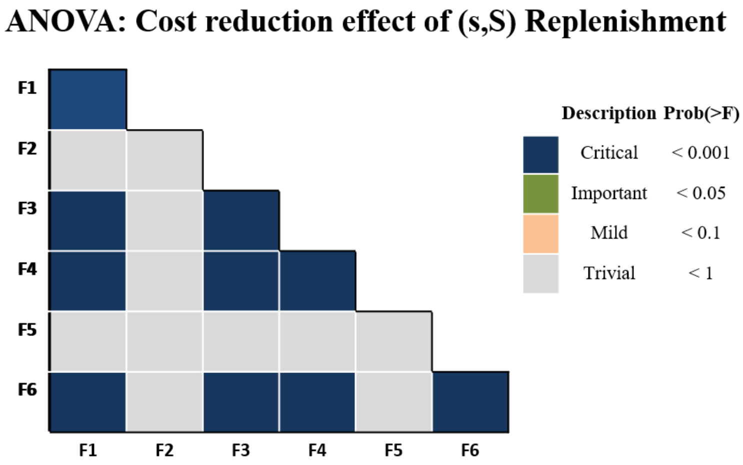

Figure 28: ANOVA analysis for cost-reduction effect of (s,S) replenishment policy: significant levels for main/interaction effects of F1-F6

4.5 CONCLUSION AND FUTURE WORK

In this chapter, an integrated decision-making policy is proposed for concurrent preventive maintenance scheduling, spare parts inventory management and transportation planning in a system of geographically dispersed multi-part degrading assets and maintenance facilities that serve them. This integrated decision-making policy considers both perfect and imperfect maintenance options, as well as multiple shipping methods for spare part deliveries. This decision-making process was modeled as a stochastic optimization problem and was solved via a simulation-based optimization approach relying on a GA-based metaheuristic.

The integrated decision-making policy introduced in this chapter was implemented in a series of simulations. The results illustrated statistically significant cost benefits of involving the options of multi-mode PM operations, expedited RM shipping and flexible replenishment deliveries into the integrated decision-making process, while their interaction effects turned out to be only marginally significant according to a two-level

ANOVA analysis. Furthermore, a DOE-based factorial analysis showed that operating costs under the integrated decision-making policy were sensitive to changes in geographical dispersion levels of the logistic network, as well as several maintenance/logistic cost parameters. Finally, the factorial analysis also illustrated that when only replenishment costs for spare parts become expensive, proper adjustment in inventory management under the integrated policy would allow the system to operate without a significant increase in operating costs.

Several possible avenues for possible future research can be identified. Firstly, the integrated decision-making process can be improved in the sense of robustness to uncertainties in the model parameters, which could be caused by limited availability of historical data or expert knowledge from which they need to be identified. Secondly, the assumptions of fixed network topology can be relaxed, leading to optimization of the maintenance facility locations and their interconnections with assets that need maintenance service. Finally, human resource planning also deserves further research, including optimization of the number, skills and allocation of technicians needed to properly execute maintenance activities.

Chapter 5

Spare Part Logistic Network Design for Jointly Optimized Preventive Maintenance and Spare Part Logistic Operations

5.1 INTRODUCTION[19]

Preventive maintenance (PM) operations aim to restore equipment reliability and reduce downtime costs by replacing degraded parts before they actually fail. For a large and distributed system of degrading assets, a successful PM schedule is inevitably dependent on the locations of maintenance facilities and the availability of the necessary spare parts in those facilities, which results in the inherent interactions between the decisions in the domains of constructing the spare part logistics (SPL) network, spare part inventory management and maintenance scheduling. Traditionally, the locations of maintenance centers and their priorities in providing maintenance service are considered as long-term strategic decisions that are made *a priori* and independently from the tactical decisions, such as maintenance scheduling and inventory management [189].

In the majority of the existing literature, the design of a SPL network is only considered as a special case of the general logistic network design problem[20]. Meanwhile, integration of the logistic network design with the inventory considerations has also become an active research topic, with the underlying models being referred to as the location-inventory models [146], [150]. Several recent works specifically studied the SPL network design problem and focus on the unique features of SPL networks, such as low demand rates and time urgency [86]. Candas and Kutanoglu [151] were the first to study

[19] This chapter is based on a submitted journal paper: K. Wang and D. Djurdjanovic, "Spare Part Logistic Network Design for Jointly Optimal Preventive Maintenance and Spare Part Logistic Operations", submitted to *European Journal of Operations Research*, Paper No. EJOR-S-17-03980, 2017. Keren Wang wrote this publication under the supervision of Dragan Djurdjanvoic.

[20] Thorough reviews of various logistic network design models can be found in [190], [191], [133].

the low-demand nature of the spare part logistic systems and introduced a linear optimization model to capture the interdependencies between the network design and inventory stocking decisions under the one-for-one replenishment policy. This work was extended by Jeet *et al*. [152] who considered lost sales for stock-out situations instead of assuming direct backordering. This was further extended by Gzara *et al*. [153] who assumed a multiple-part model for the asset structure. Due to the time sensitivity of maintenance services, Iyoob *et al*. [154] introduced the inventory-sharing structure into the SPL network design so that an asset can be served by multiple maintenance facilities, while Wu *et al*. [155] considered multiple 3rd party vendors and multiple transportation options to improve the efficiency of the logistic system. Nevertheless, the existing models for SPL network design always assumed known demand rates of spare parts, which is not the case in reality, as the demand rates for spare parts fully depend on the maintenance schedule.

Another stream of literature relevant to this work is the joint optimization of PM and SPL operations. Most early studies in this area focus on the integration of PM scheduling with spare part inventory planning in relatively simple asset systems and a thorough review in this domain can be found in [5]. Several recent studies modelled assets as multi-part structures, including serially-connected multi-part assets [115], [117], [121], *k*-out-of-*n* structure assets [124], [125], and flexible-connect multi-part assets [126]. Among all these works, Chen *et al*. [112] is, to the best of our knowledge, the only work that conducted a study on a multi-echelon SPL network, with a distributor, multiple users and multiple suppliers in the network.

In this chapter, we propose a novel design method to integrate the SPL network design problem with the optimization of PM and SPL operations in that network. The design factors for SPL network include the locations of maintenance centers and their interconnections with the geographically dispersed assets, which will be simultaneously optimized with the PM schedules and spare part replenishment policies for the maintenance centers. The resulting design will be an SPL network providing spare parts to the relevant geographically dispersed assets with the lowest cumulative cost of the network construction and resulting SPL and maintenance operations.

The rest of the Chapter is organized as follows. Section 5.2 describes the model of the SPL network and system operations. In Section 5.3, the newly proposed method for joint optimization of the SPL network design and the SPL/PM operations in it is formulated as a stochastic optimization problem, which is solved via a discrete-event simulation-based metaheuristic approach proposed in Section 5.4. The new methodology is evaluated through a set of simulations in Section 5.5, while the conclusions of this research as well as several possible directions for the future work are provided in Section 5.6.

5.2 METHODOLOGY

5.2.1 SPL Network Design

The following terminology will be used in the remainder of this chapter.

- The term *working part* refers to a basic unit of a machine. The condition of a part is assumed to degrade with its usage independently from other parts, and PM/RM can restore the part to the original, non-degraded condition. From the view of SPL, a working part on an asset corresponds to a certain type of a spare part that is stored in a maintenance facility and can be used to replace it.
- The term *asset* refers to a machine that can be operated independently to generate revenue. An asset consists of multiple parts and can be operated properly only if all its parts behave properly.

- A *maintenance center* fulfills maintenance orders from nearby assets by shipping new undegraded spare parts to their operating sites. Maintenance centers have finite inventory levels of spare parts and are replenished from the central warehouse.
- The *central warehouse* replenishes spare parts for maintenance centers following a (*s*, *S*) replenishment policy [86]. It can also provide spare parts directly to the assets as emergency orders in maintenance events. The central warehouse is the primary source of all new spare parts and is assumed to have infinite inventory levels of spare parts.

As illustrated in Figure 29, the central warehouse and a fleet of J nearby assets, labeled $A_1, A_2, \dots, A_J$, are geographically dispersed across a large region. To provide timely maintenance service, multiple maintenance centers can be constructed and each constructed maintenance center will be further connected to one or multiple assets. It is assumed that there are N candidate sites to build maintenance centers, labeled $MC_1, MC_2, \dots, MC_N$, and a binary decision-variable u_i $(1 \leq i \leq N)$ is used as the indicator to denote if the candidate site MC_i is built or not. Specifically, $u_i = 1$ denotes a decision to construct maintenance center MC_i, while $u_i = 0$ denotes the decision not to construct it.

Moreover, the interconnections between the built maintenance centers and the assets also need to be decided. Formally, a binary decision variable $v_{i,j}$ $(1 \leq i \leq N, 1 \leq j \leq J)$, referred to as the facility-asset connection indicator, will be set to 1 if the connection between the candidate site MC_i and asset A_j is to be established[21], and 0 otherwise.

[21] A one-time construction cost will be incurred if a connection between the maintenance center MC_i and asset A_j is established.

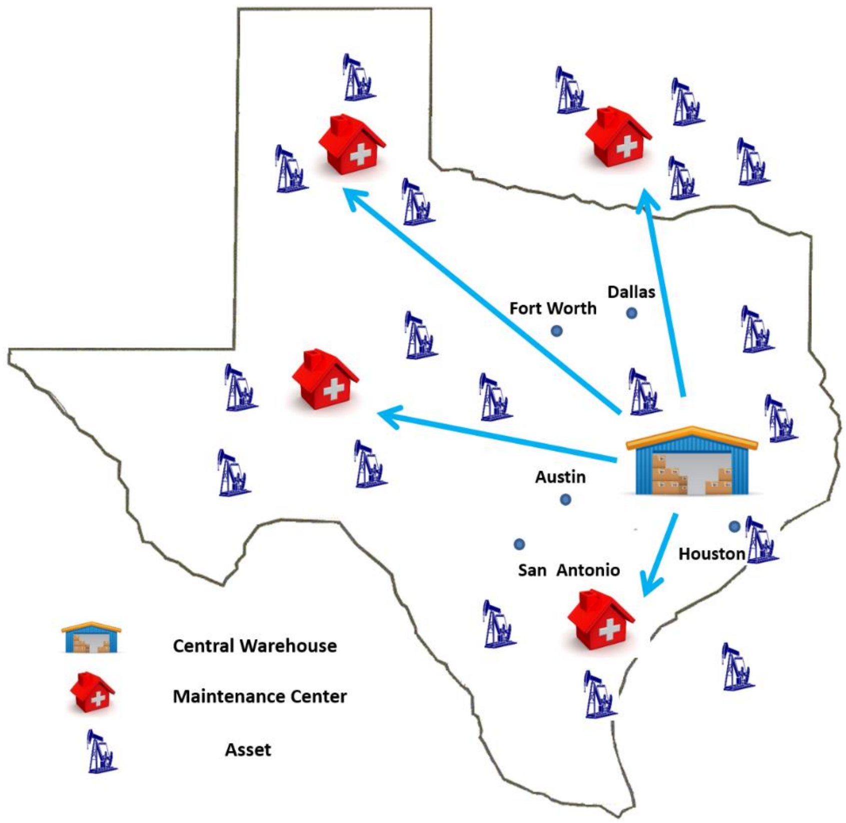

Figure 29: Geographically dispersed logistic facilities and assets considered in Chapter 5

The system considered in this chapter allows logistic operations with inventory-sharing, in the sense that an asset can obtain necessary spare parts from multiple maintenance centers, as well as the central warehouse [154]. More precisely, for a specific PM/RM action, the affected asset will obtain the necessary spare parts from the maintenance facility that currently has them in stock and the delivery of those parts would incur the lowest operating cost compared to other available maintenance facilities. In the case of insufficient levels of necessary spare parts in all connected maintenance centers, or if the central warehouse can provide the spare parts with the lowest associated costs, the PM/RM orders would be fulfilled directly by the central warehouse.

Finally, the delivery times for the spare part inventory flows between the central warehouse, maintenance centers and assets are characterized by the following distribution functions, which are assumed to be known:

- $\mathcal{LT}_j^{\,i}(\cdot)$: Lead time distribution for an asset A_j to obtain new spare parts from the maintenance center MC_i.
- $\mathcal{LT}_j^{\,0}(\cdot)$: Lead time distribution for an asset A_j to obtain new spare parts from the central warehouse.
- $\mathcal{RT}_j\,(\cdot)$: Lead time distribution for replenishing spare parts to the MC_i from the central warehouse.

5.2.2 Assumptions on the PM and SPL Operations

From the aspect of PM and SPL operations in the system, the following assumptions are made:

1. An asset A_j is assumed to consist of K_j serially connected parts[22], labeled $P_{j,1}, P_{j,2}, \dots, P_{j,K_j}$. From the view of SPL, each working part on an asset corresponds to a certain type of a spare part that is stored in a maintenance facility. It is assumed that there are H types of spare part in this system, labeled $SP_1, SP_2, \dots, SP_H$.

[22] I.e., assets are assumed to have a multi-part structure.

2. Degradation dynamics of a part $P_{j,k}$ is described by a reliability function approximating the distribution of its usage time to failure[23] and denoted by $\mathcal{T}_{j,k}(\cdot)$.

3. A *replacement maintenance policy* is assumed, that is to say, both PM and RM are assumed to consist of a new, undegraded spare part replacing a broken or severely degraded working part on the asset. Each maintenance action is modeled as a two-step process consisting of the following steps: **(1)** shipping the necessary spare part from a maintenance center to the asset as a normal order, or from the central warehouse to the asset as an emergency order[24] and **(2)** replacing the target working part on the asset with the newly delivered spare part (actual repair intervention on the asset).

4. A *usage-based PM policy* is assumed, in the sense that a PM triggering usage level $x_{j,k}$ is set for each part $P_{j,k}$, indicating the critical usage level at which a PM operation is initiated for that asset. PM is initialized by ordering a new corresponding spare part, either from the maintenance center or from the central warehouse, with the replacement of a working part starting only when the necessary spare part is delivered to the location of the asset.

5. *Perfect maintenance* operations are assumed, i.e. after each maintenance operation, the part (component in an asset) is assumed to be in the "as good as new" condition [112].

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[23] Reliability functions are assumed to be part-asset specific and can be estimated through a long-term statistical analysis behavior of failure times for that part on that asset, or of parts of the same type on similar types.

[24] When there are no appropriate spare parts in stock in the maintenance centers or when getting the spare parts from the available maintenance centers is more expensive than getting it directly from the central warehouse.

6. Inventory management for spare parts in maintenance centers is assumed to follow a *(s, S) replenishment policy*. In order to model this policy, decision-variables, $\{y_{i,h}\}_{1\leq i\leq n,1\leq h\leq H}$, are introduced to denote critical spare part inventory levels at which a maintenance center MC_i requests replenishment for the spare part SP_h, while decision-variables, $\{z_{i,h}\}_{1\leq i\leq n,1\leq h\leq H}$, indicate the batch sizes of those replenishment orders (corresponding to the parameter *S-s* in the replenishment policy).

5.3 OPTIMIZATION FORMULATION

5.3.1 Formulation for SPL Network Design with System Operation Considerations

Let us now describe the optimization formulation for the new SPL network design that is jointly optimized with the SPL and PM system operations in that network. The following five groups of decision variables will be used to describe any SPL network design and the underlying SPL and maintenance operations: construction indicators for maintenances center $\{u_i\}_{1\leq i\leq N}$, connection indictors between maintenances centers and assets $\{v_{i,j}\}_{1\leq i\leq N,1\leq j\leq J}$, PM triggering usage levels $\{x_{j,k}\}_{1\leq j\leq J,1\leq k\leq K_j}$, spare part inventory levels that trigger replenishments from the central warehouse $\{y_{i,h}\}_{1\leq i\leq N,1\leq h\leq H}$ and replenishment order sizes $\{z_{i,h}\}_{1\leq i\leq N,1\leq h\leq H}$. The optimization objective will be to minimize the expected cumulative costs of the network construction and operations of the system per unit time. The underlying stochastic optimization problem is formulated as follows

$$\underset{\substack{\{u_i\in\{0,1\}\}_{1\le i\le N}\\ \{v_{i,j}\in\{0,1\}\}_{1\le i\le N,1\le j\le J}\\ \{x_{j,k}\in X_{j,k}\}_{1\le j\le J,1\le k\le K_j}\\ \{y_{i,h}\in Y_{i,h}\}_{1\le i\le N,1\le h\le H}\\ \{z_{i,h}\in Z_{i,h}\}_{1\le i\le N,1\le h\le H}}}{\text{Minimize}} \quad \frac{1}{T}\left(\sum_{1\le i\le N} u_i F_i + T\sum_{1\le i\le N} u_i O_i + \sum_{\substack{1\le i\le N\\1\le j\le J}} v_{i,j}C_{i,j}\right)$$

$$+\frac{1}{T}\,\mathbb{E}\left\{\sum_{\substack{1\le i\le N\\1\le h\le H}}\left(d_{i,h}D_{i,h}+s_{i,h}S_{i,h}\right)+\sum_{\substack{1\le i\le N\\1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{i}R_{j,k}^{i}+m_{j,k}^{i}M_{j,k}^{i}\right)\right.$$

$$\left.+\sum_{\substack{1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{0}R_{j,k}^{0}+m_{j,k}^{0}M_{j,k}^{0}\right)+\sum_{1\le j\le J} l_jL_j \;\middle|\; \{u_i\}_{1\le i\le N} \text{ and } \{v_{i,j}\}_{\substack{1\le i\le N\\1\le j\le J}}\right\}$$

Optimization Problem 5

where the following notation is used,

- i, j, k, h: Indices for the maintenance centers (i), assets (j), working parts (k) and spare parts (h).
- T : Decision-making time horizon.
- F_i : One-time construction cost of the maintenance center MC_i.
- O_i : Fixed facility-maintenance cost per unit time to operate the maintenance center MC_i.
- $C_{i,j}$: One-time connection cost between the maintenance center MC_i and asset A_j.
- $D_{i,h}$: Inventory holding cost per unit time for the spare part SP_h at the maintenance center MC_i.

- $S_{i,h}$: Replenishment delivery cost per order for spare part SP_h to the maintenance center MC_i.
- $R_{j,k}^{i}$: Cost to order a RM for the working part $P_{j,k}$ from the maintenance center MC_i.
- $M_{j,k}^{i}$: Cost to order a PM for the working part $P_{j,k}$ from the maintenance center MC_i.
- $R_{j,k}^{0}$: Cost to order a RM for the working part $P_{j,k}$ from the central warehouse.
- $M_{j,k}^{0}$: Cost to order a PM for the working part $P_{j,k}$ from the central warehouse.
- L_j : Penalty cost per unit downtime of the asset A_j.
- $d_{i,h}$: Cumulative inventory holding time of the spare part SP_h at the maintenance center MC_i.
- $s_{i,h}$: Cumulative replenishment orders of the spare part SP_h to the maintenance center MC_i.
- $r_{j,k}^{i}$: Cumulative number of RM orders for the part $P_{j,k}$ serviced by the maintenance center MC_i.
- $m_{j,k}^{i}$: Cumulative number of PM orders for the part $P_{j,k}$ serviced by the maintenance center MC_i.
- $r_{j,k}^{0}$: Cumulative number of RM orders for the part $P_{j,k}$ serviced by the central warehouse.
- $m_{j,k}^{0}$: Cumulative number of PM orders for the part $P_{j,k}$ serviced by the central warehouse.
- l_j : Cumulative downtimes of the asset A_j.

Objective function in optimization problem (5) represents the expected unit-time cost of the system construction and operations over the planning horizon of length T. The expectation operator is applied due to the random effects induced by the reliability of working parts, delivery delays of the spare parts and repair times of maintenance interventions. In the objective function, the stochastic effects are reflected in the cumulative statistics (i.e. $d_{i,h}$-s, $s_{i,h}$-s, $r_{j,k}^{i}$-s, $m_{j,k}^{i}$-s, $r_{j,k}^{0}$-s, $m_{j,k}^{0}$-s and l_j-s). The objective function consists of two major parts: facility-related costs and system operational costs. More specifically, the facility-related costs involve the construction costs to build the maintenance centers and connect them to the assets, as well as the fixed facility-maintenance costs associated with operating those maintenance centers, while the operational costs associated with the PM and SPL operations involve (*i*) inventory-related costs (costs of holding spare parts inventories in the maintenance center and costs of replenishment orders for the maintenance center), (*ii*) penalties for the asset downtimes, and (*iii*) maintenance costs incurred by execution of the PM and RM operations.

In order to perform a specific PM/RM operation on a working part $P_{j,k}$, the necessary spare part is provided by the maintenance center that currently has that part in stock and has the smallest associated spare part delivery cost [25] compared to other maintenance centers. In the case of insufficient levels of the necessary spare parts in all maintenance centers, or if the central warehouse can provide the maintenance service with the lowest corresponding maintenance cost [26], then the necessary spare part is provided directly by the central warehouse.

5.3.2 Benchmark Network Designs

The newly proposed SPL network design method that leads to the jointly optimized network design and the resulting PM and SPL operations will be compared to two other, more traditional SPL network designs. For both benchmark designs, the SPL network is

[25] This cost is $M_{j,k}^{i}$ in the case of PM, or $R_{j,k}^{i} + l_j * \mathbb{E}(\mathcal{LT}_j^{\,i})$ in the case of RM.
[26] This cost is $M_{j,k}^{0}$ in the case of PM, or $R_{j,k}^{0} + l_j * \mathbb{E}(\mathcal{LT}_j^{\,0})$ in the case of RM.

determined independently of the SPL and PM operations, which are optimized *post-festum*, based on the SPL network design obtained from the previous stage. These benchmark network designs along with the optimization of the corresponding system operations will be described below.

5.3.2.1 Network Design without Maintenance Centers

The simplest SPL network design is the one where no maintenance center is built. This design, referred to in this chapter as the "No-MC Network", avoids the network construction costs, as well as the costs associated with the management of spare part inventories in the maintenance centers. Nevertheless, the resulting operational performance of this network will inevitably be associated with low efficiency in servicing the assets during the maintenance activities. Essentially, since all maintenance orders have to be served directly by the central warehouse as emergency orders, prolonged asset downtimes and increased maintenance costs for emergency orders can be expected.

Formally, the No-MC SPL network design is obtained by restricting all construction indicators for the maintenance centers (u_i-s) and all connection indicators for the facility-asset pairs ($v_{i,j}$-s) to 0. Given this pre-designed network, the PM triggering usage levels $\left\{x_{j,k} \in X_{j,k}\right\}_{1 \le j \le J, 1 \le k \le K_j}$ are optimized to minimize a cost function that only considers the maintenance costs associated with emergency orders and the corresponding asset downtime penalties, as formulated below,

$$\underset{\{x_{j,k}\in X_{j,k}\}_{1\le j\le J,1\le k\le K_j}}{\text{Minimize}} \frac{1}{T}\,\mathbb{E}\left\{\sum_{\substack{1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^0 R_{j,k}^0 + m_{j,k}^0 M_{j,k}^0\right) + \sum_{1\le j\le J} l_j L_j \;\middle|\; \{u_i=0\}_{1\le i\le N} \text{ and } \{v_{i,j}=0\}_{\substack{1\le i\le N\\1\le j\le J}}\right\}$$

Optimization Problem 6

5.3.2.2 Nearest-MC Network Design

Another pre-designed SPL network is obtained under the assumptions that (*i*) all candidate maintenance centers are built and (*ii*) the assets are serviced by the nearest maintenance facility. This SPL network design will be referred to as the "Nearest-MC Network". An asset A_j is serviced by the maintenance facility that has the smallest expected lead-time for the inventory flow between them, i.e. maintenance center with the index[27]

$$i^*(j) = \underset{0\le i\le N}{\text{argmin}}\ \mathbb{E}\left(\mathcal{LT}_j^i(t)\right).$$

Given this network, the corresponding PM and SPL operations are concurrently optimized by selecting PM triggering usage levels $\{x_{j,k}\}_{1\le j\le J,1\le k\le K_j}$, spare parts inventory levels $\{y_{i,h}\}_{1\le i\le n,1\le h\le H}$ and replenishment order sizes $\{z_{i,h}\}_{1\le i\le n,1\le h\le H}$ that minimize the resulting maintenance costs, SPL costs and downtime penalties per unit time in the system, or more formally,

[27] Particularly, $i^*(j)=0$ indicates that the asset A_j is closer to the central warehouse than any maintenance center and, thus, no facility-asset connection will be built for this asset.

$$\underset{\substack{\{x_{j,k}\in X_{j,k}\}_{1\le j\le J,1\le k\le K_j}\\ \{y_{i,h}\in Y_{i,h}\}_{1\le i\le N,1\le h\le H}\\ \{z_{i,h}\in Z_{i,h}\}_{1\le i\le N,1\le h\le H}}}{\text{Minimize}} \frac{1}{T}\,\mathbb{E}\left\{\sum_{\substack{1\le i\le N\\1\le h\le H}}\left(d_{i,h}D_{i,h}+s_{i,h}S_{i,h}\right)+\sum_{\substack{1\le i\le N\\1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{i}R_{j,k}^{i}+m_{j,k}^{i}M_{j,k}^{i}\right)\right.$$

$$+\sum_{\substack{1\le j\le J\\1\le k\le K_j}}\left(r_{j,k}^{0}R_{j,k}^{0}+m_{j,k}^{0}M_{j,k}^{0}\right)$$

$$\left.+\sum_{1\le j\le J} l_jL_j\,\right|\,\{u_i=1\}_{1\le i\le N}\text{ and }\left\{v_{i,j}=\mathbb{I}\big(i=i^*(j)\big)\right\}_{\substack{1\le i\le N\\1\le j\le J}}\left.\vphantom{\sum}\right\}$$

Optimization Problem 7

where $\mathbb{I}(\cdot)$ is indicator function that equals 1 if the corresponding condition is true, and 0 otherwise.

5.4 SIMULATION-BASED METAHEURISTIC OPTIMIZATION APPROACH

In this section, we will describe a simulation-based metaheuristic optimization procedure pursuing a solution to the optimization problem (6) and yielding the SPL network design that is jointly optimized with the SPL and PM operations in it. Due to its flexibility in accommodating realistic system structures and operation models, simulation-based optimization has become a powerful paradigm for logistic network design [138], as well as for joint decision-making in the domains of PM and SPL operations [116], [111], [117], [126]. Moreover, the cost function considered in this chapter is relatively simple and one may likely need to incorporate other types of cost structures. Metaheuristic simulation-based optimization allows such alterations, which is another motivating factor for choosing such an optimization paradigm.

Optimization procedure pursued in this chapter is based on the genetic algorithm (GA) paradigm [181]. Generally speaking, GA is a search heuristic that mimics the process of natural evolution. Each candidate solution is denoted by a chromosome (U, V, X, Y, Z) containing five portions, each of which is a decision vector respectively relevant to the construction indicators of the maintenance centers, connection indicators of facility-asset pairs, PM triggering levels, replenishment triggering levels and replenishment batch sizes[28].

The GA algorithm starts with an initial population G_0 consisting of S randomly generated candidate solutions, labeled $G_0 = \{(U_0^s, V_0^s, X_0^s, Y_0^s, Z_0^s) | 1 \leq s \leq S\}$. The fitness of each candidate is taken to be inversely proportional to the corresponding expected unit-time cumulative costs[29] obtained via multiple replications of simulations of system operations represented by that candidate solution. In order to generate offspring candidate solutions for the next generation, selection, crossover and mutation operators are applied to the current generation. These operators are described below.

- *Selection operator*: A pair of parent solutions, say $(U^\alpha, V^\alpha, X^\alpha, Y^\alpha, Z^\alpha)$ and $\left(U^\beta, V^\beta, X^\beta, Y^\beta, Z^\beta\right)$, is chosen from the current generation g to mate and produce offspring candidate solutions for the next generation $g+1$, with probability of selection being proportional to their fitness[30].
- *Crossover operator*: For a pair of selected parent candidate solutions, a two-point crossover operator is executed for each of the five chromosome portions, leading to

[28] Specifically, $U = (u_1, u_2, \dots, u_N)$, $V = \left(v_{1,1}, v_{1,2}, \dots, v_{1,J}, \dots, v_{N,1}, v_{N,2}, \dots, v_{N,J}\right)$ $X = \left(x_{1,1.}, x_{1,2} \dots, x_{1,K_1}, \dots, x_{J,1}, x_{J,2}, \dots, x_{J,K_J}\right)$, $Y = \left(y_{1,1}, y_{1,2} \dots, y_{1,H}, \dots, y_{N,1}, y_{N,2} \dots, y_{N,H},\right)$ and $Z = \left(z_{1,1}, z_{1,2} \dots, z_{1,H}, \dots, z_{N,1}, z_{N,2} \dots, z_{N,H}\right)$. One should note that there are dependencies between these decision variables in the sense that, for a candidate maintenance center MC_i, its connection indicators with assets ($v_{i,j}$-s) and inventory decision-variables ($y_{i,h}$-s and $z_{i,h}$-s) are non-trivial only if MC_i is built, i.e. if $u_i = 1$.
[29] Objective function in optimization problem (5).
[30] This selection approach is also known as the fitness proportional selection [181].

five pairs of recombined chromosome portions, namely $\{U^a, U^b\}$, $\{V^a, V^b\}$, $\{X^a, X^b\}$, $\{Y^a, Y^b\}$ and $\{Z^a, Z^b\}$. Then, one offspring solution is generated by randomly selecting a chromosome portion from each of the five pairs, while the remaining chromosome portions form the other offspring solution. The above-described crossover operator is pictorially illustrated in Figure 30.

- *Mutation operator*: To promote genetic diversity in the offspring population, genes in all offspring solution chromosomes are subject to mutation with a small probability, commonly referred to as the mutation probability. The value of each gene selected for mutation is perturbed to an adjacent candidate in its candidate value set[31].

For each generation, *S* pairs of parent solutions are selected from the current generation, leading to the birth of 2*S* offspring solutions. If the top performing candidate solution in the parent generation has higher fitness than the 2*S* offspring candidates, it is added to the offspring population, thus enforcing the well-known GA concept of elitism [181]. From this set, the fittest *S* solutions are selected to form the next generation of candidate solutions.

[31] For example, assume that the PM triggering usage level $x_{j,k}$ takes values in $X_{j,k} = \{20,25,30,35\}$ and the current value for this gene is $x_{j,k} = 25$. If the mutation operator is performed on this gene, the decision will mutate into either $x_{j,k} = 20$ or 35, with a small mutation probability.

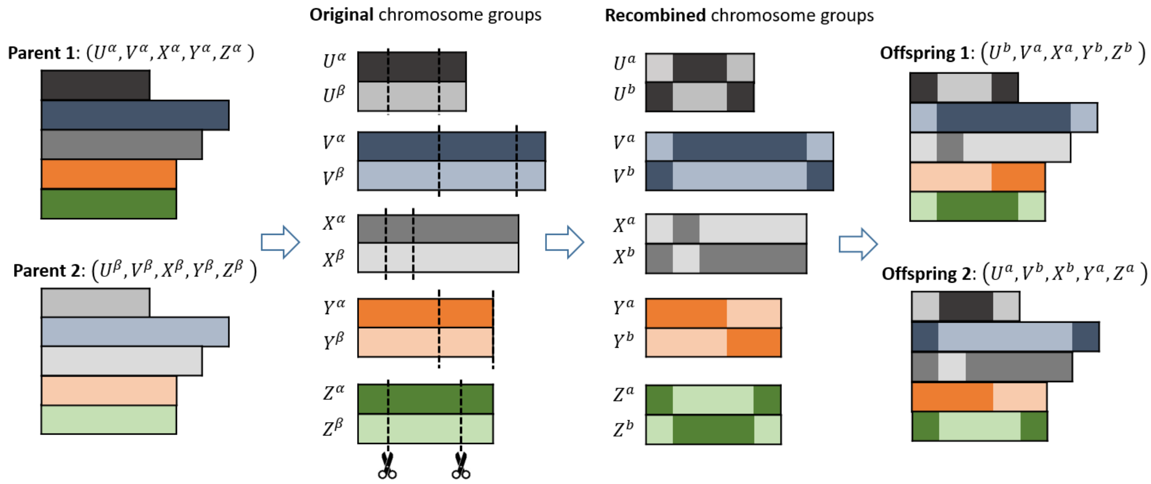

Figure 30: A realization of the two-crossover operator on two parent candidate solutions in Chapter 5

Successive progression of generations obtained via the above-mentioned operations lead to ever improving candidate solutions, yielding lower and lower expected unit-time costs associated with the SPL network construction and system operations. Termination criterion for this algorithm is either a predetermined number of GA generations being reached, or the best candidate solution not being improved over a number of consecutive generations. The final solution for the newly proposed SPL network design, denoted by $(U^*, V^*, X^*, Y^*, Z^*)$, is selected as the fittest candidate solution in the last GA generation.

The discrete-event simulation approach is always required to evaluate each candidate solution due to the existence of multiple uncertain factors, as well as the need to make dynamic decisions following inventory-sharing option. At the same time, the metaheuristic approach is also necessary to search for the optimized solutions, as the high dependencies between system operations and decision variables make a complete enumeration of the solution space or certain kinds of decomposition approaches infeasible to the formulated optimization problem.

One should also note that similar simulation-based metaheuristic algorithms can be derived in exactly the same way for each of the optimization problems (6) and (7), yielding optimized operational decisions for the benchmark SPL network designs described in Section 3.2.

5.5 RESULTS

5.5.1 System Description

The newly proposed method of integrating SPL network design model with system operation optimization is evaluated via a series of simulations. The baseline system consists of a central warehouse and 49 geographically distributed multi-part assets, as pictorially illustrated in Figure 31. From the side of network design, 9 candidate maintenance centers can potentially be built and connected to those 49 assets, resulting in 9 decision-variables for facility construction and 441 decision-variables for facility-asset connections. From the aspect of system operations, the operational decisions involve 126 usage levels that trigger PM operations for the corresponding working parts, as well as 45 inventory levels and 45 replenishment batch sizes describing the spare part inventory management policies in the maintenance centers.

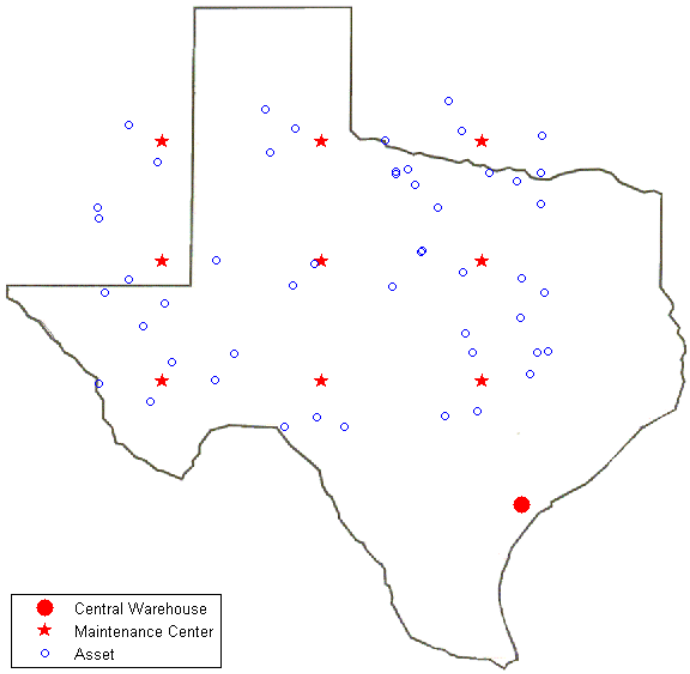

Figure 31: Geographically dispersed logistic facilities and assets of the baseline system in Chapter 5

The planning horizon (T) for optimization was taken to be $365 * 10$ time units[32]. Within this horizon, the expected costs and other system statistics are evaluated as averages over 40 replications[33]. The newly proposed SPL network design is obtained using the GA-based algorithm described in Section 4, with the detailed parameter settings given in the Appendix C. In terms of computational costs, implementation on a relatively ordinary personal computer (Intel Core i5-3570 CPU, 16 GB RAM, 64-bit Window 7) led to average computational time being less than 30 hours for the above-described system, with an

[32] Corresponds to 10 years, with each time step being one day.

[33] This parameter was obtained by increasing the number of replications until further increases did not lead to significant changes in the average cost effects.

important note that the computations can be greatly accelerated further in a parallel computing environment.

In order to evaluate the system performance under the newly proposed optimized design, several summary statistics are calculated and compiled in Table 3.

Statistic	**Formula**	**Description**
Number of active maintenance centers	$\sum_{i=1}^{N} \mathbb{I}(u_i = 1) \prod_{1 \le h \le H} \mathbb{I}(y_{i,h} \ge 0)$	Number of maintenance centers that are built and are used for stocking the spare parts.
Number of active facility-asset connections	$\sum_{j=1}^{J}\sum_{i=1}^{N} u_i v_{i,j}$	Number of connections between assets and the maintenance centers that are built.
Total spare part inventory level	$\sum_{h=1}^{H}\sum_{i=1}^{N} u_i(y_{i,h} + z_{i,h})$	Sum of the maximum inventory levels of spare parts that can be stocked in the maintenance centers, crudely expressing storage requirements in the maintenance centers
Average PM triggering usage level	$\frac{1}{\sum_{j=1}^{J} K_j}\sum_{j=1}^{J}\sum_{k=1}^{K_j} x_{j,k}$	Roughly expressing the overall aggressiveness of the PM schedules across the entire system
System uptime	$\left(1 - \frac{\sum_{j=1}^{J} l_j}{T \cdot J}\right)$	Average uptime (time not spent under maintenance) per unit time of all assets in the system, crudely expressing the utilization of assets

Table 3: Summary statistics for network design and system performance

5.5.2 Comparison Between the Optimized and Benchmark Designs

For the baseline system described above, the SPL network designed using the newly proposed approach that enables optimized PM and SPL operations is illustrated in Figure 32. One can see that only two maintenance centers need to be built and most assets are serviced by one or both of them. However, it is interesting to find that asset A_{47} is assigned to be serviced with spare parts directly from the central warehouse (marked by the dashed red line) instead of one of the maintenance centers. Considering that asset A_{47} has a simple single-part structure and thus requires only one type of spare parts (SP_1), it is economically more efficient to just send those parts from the central warehouse than incurring the costs of constructing and allocating a maintenance center to it. To mitigate the prolonged asset downtimes due to emergency orders, asset A_{47} ended up having a small PM triggering usage level, implying an aggressive PM policy that enables reduction of unplanned RM events through performing more PM operations.

Furthermore, let us compare the system performance under the newly proposed SPL network design with that corresponding to the two benchmark designs described[34] in Section 5.3.2.

[34] The corresponding pre-built SPL networks are pictorially illustrated in Figure 33 and Figure 34.

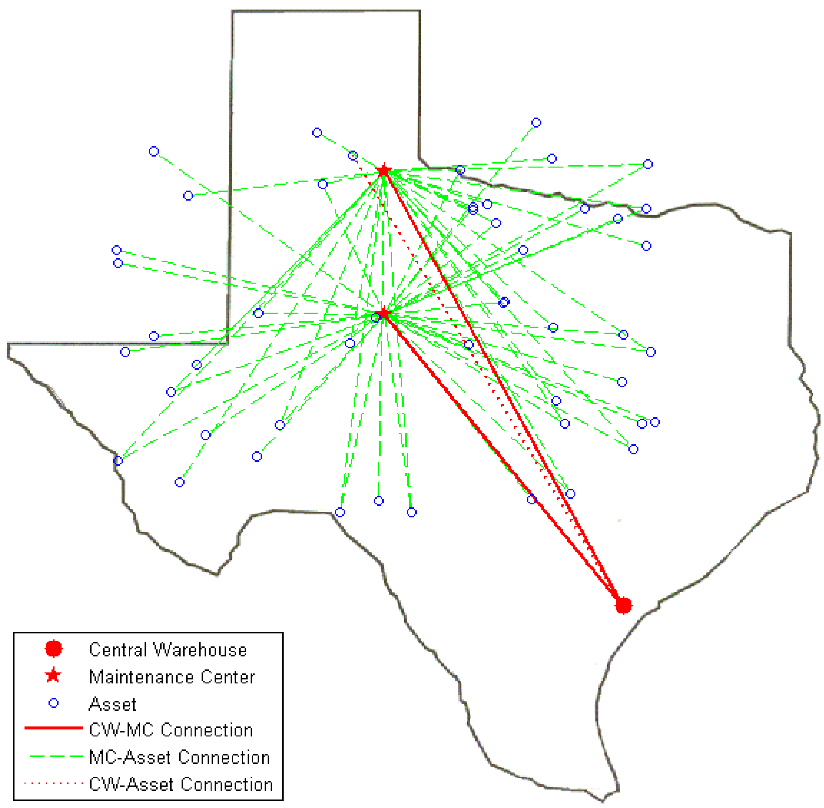

Figure 32: Proposed SPL network design that enables optimized PM and SPL operations.

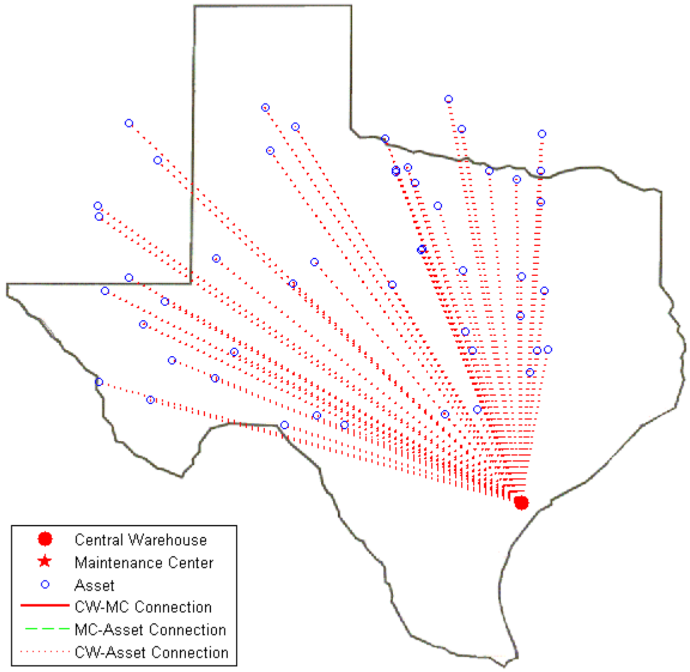

Figure 33: Pre-built SPL networks for No-MC network design.

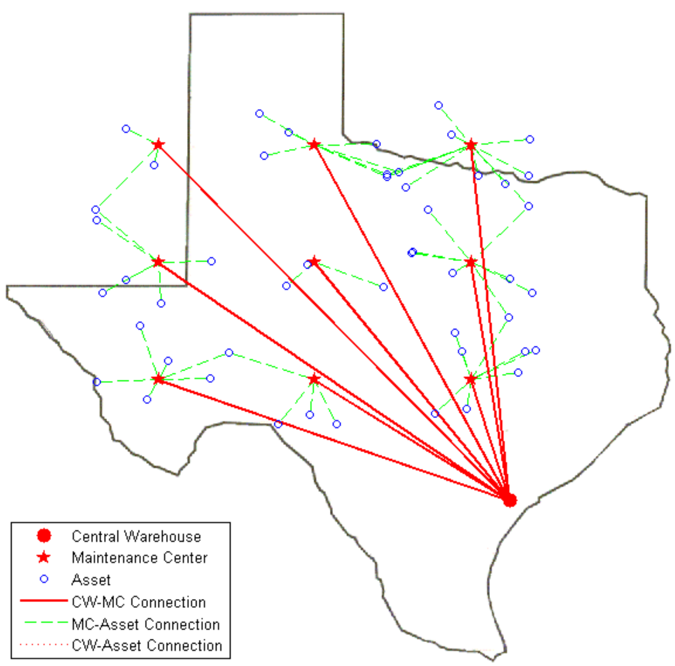

Figure 34: Pre-built SPL networks for Nearest-MC network design.

As shown in Figure 35, the newly proposed network design enables the system to operate with a much lower expected unit-time overall costs compared to the two benchmark network designs. These cost reductions are statistically significant according to a one-sided z-test [182], with the significance levels less than 0.0001.

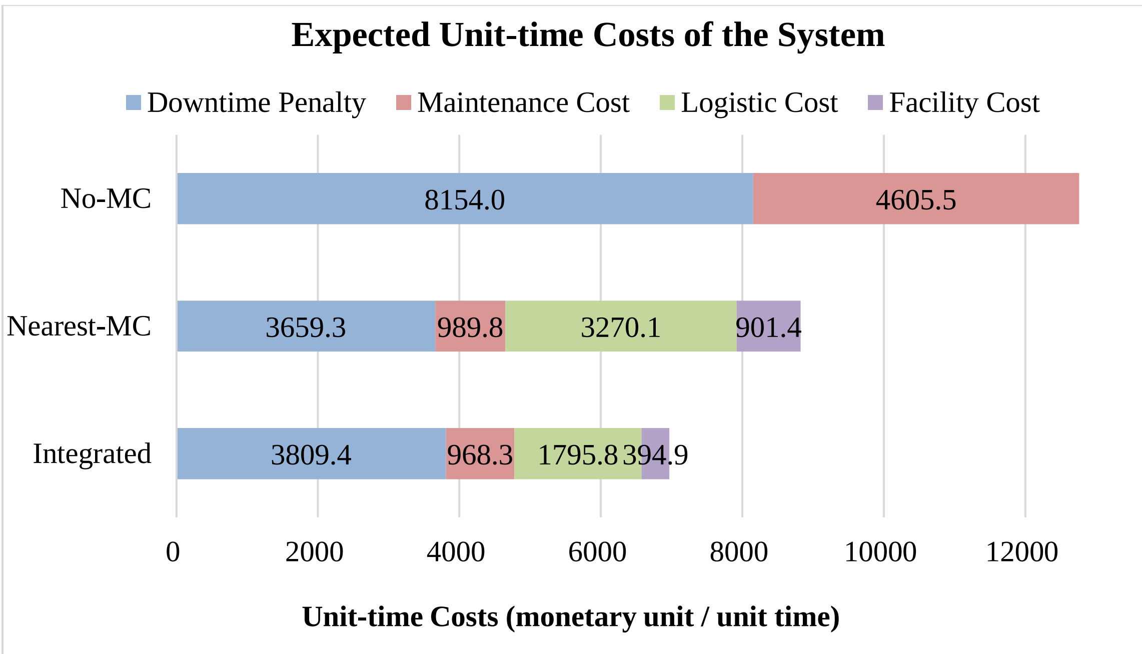

Figure 35: Cost-effects of optimized system operations associated with the proposed SPL network design and two benchmark designs.

A more detailed comparison between the three network designs can be made based on the summary statistics provided in Table 4. In the No-MC SPL network, all RM/PM orders are serviced directly by the far-away central warehouse instead of some local maintenance center, leading to the worst asset uptime performance caused by prolonged delays in providing maintenance services. Thus, though it avoids the costs of building maintenance centers, connecting them to the assets and managing spare parts inside them, the overall operations in the No-MC network still underperform by far the other two network designs because of the excessive costs caused by the asset downtimes, as well as the higher costs associated with the emergency orders.

For the Nearest-MC SPL network design, all 9 candidate maintenance centers are built and assets always obtain spare parts from their nearest maintenance center, allowing more timely deliveries of spare parts to the assets, but at the expense of the highest costs to build and operate the SPL network.

It is also evident from Table 4 that the newly proposed optimized design provides a more efficient usage of the logistic resources. Though system uptime of 92.35% is only slightly smaller than that in the Nearest-MC network[35] (92.58%), the optimized SPL network design requires significantly fewer maintenance facilities to be built/connected and enables the system to operate with relatively lower spare part inventories. At the same time, potential negative effects of a sparse logistic network and low spare parts inventories, such as more frequent emergency orders and occasional prolonged asset downtimes caused by waiting for the spare parts, were mitigated through more aggressive scheduling of PM operations and the implementation of inventory sharing[36].

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[35] Since the Nearest-MC network enables fastest possible deliveries of spare parts and, consequently, least aggressive PM scheduling, uptime performance ends up being better than in other networks, but at the increased costs of building and operating the SPL network.

[36] An asset could obtain necessary spare parts from several nearby maintenance centers.

Statistic	Proposed	No-MC	Nearest-MC
Number of active maintenance centers	2	0	9
Number of facility-asset connections	64	0	51
Total spare part inventory level	153	0	187
Average PM triggering usage level	29.56	21.43	48.02
System uptime (%)	92.35	83.31	92.58

Table 4: Comparison of performance statistics between three network designs

5.5.3 Sensitivity Analysis Regarding Network Construction Costs

In this section, influence of the network construction costs on the newly proposed network design will be evaluated through increasing/decreasing of the costs necessary for construction of the maintenance centers (F_i-s), costs associated with connecting the assets to the constructed maintenance centers ($C_{i,j}$-s) and fixed facility-operating costs for maintenance centers (O_i-s). To study these effects in a relatively tractable way, a construction cost scalar α is introduced to simultaneously magnify/diminish these costs in the baseline parameter set. This scalar takes values in the set $\alpha \in \{0,1,5\}$, with the baseline system corresponding to $\alpha = 1$.

It can be observed from Figure 36 that the unit-time overall cost under the newly proposed network design consistently increases as the scalar α grows. To offset negative effects of the increased construction costs, a relatively sparse network design with fewer maintenance centers and fewer facility-asset connections can be observed in the resulting networks for $\alpha = 0$ (Figure 37), $\alpha = 1$ (Figure 32) and $\alpha = 5$ (Figure 38).

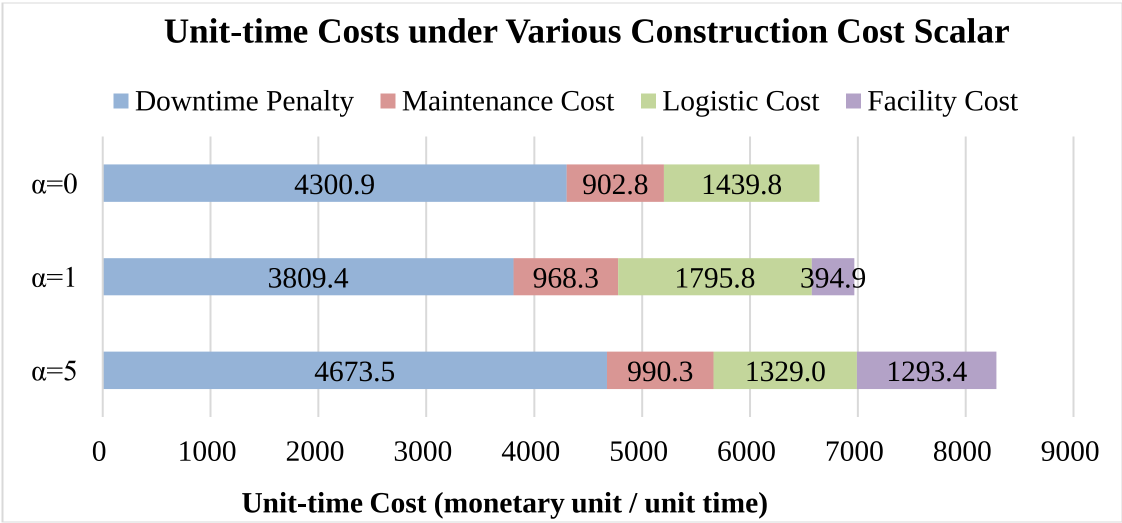

Figure 36: Cost comparison under the proposed SPL network design with various construction cost scalar

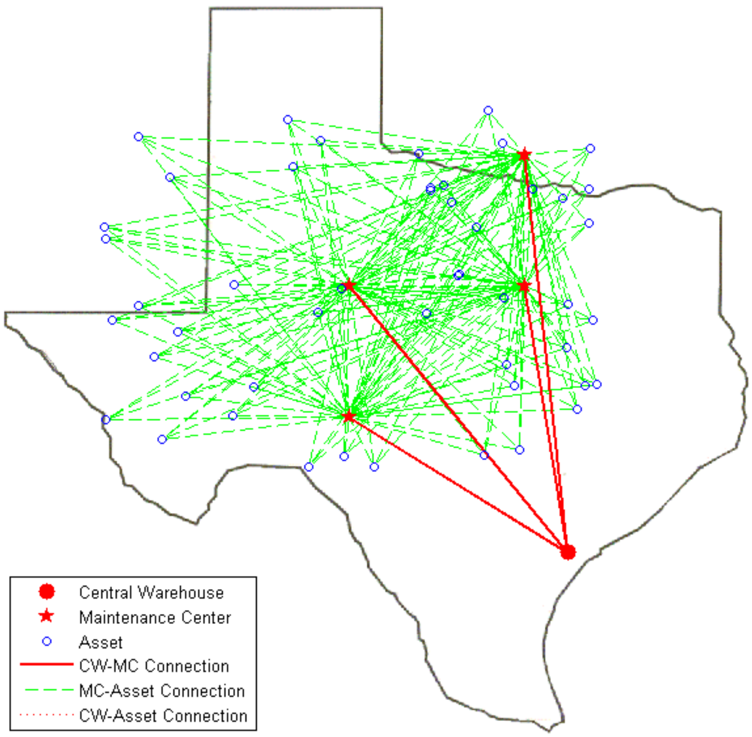

Figure 37: SPL network obtained by the proposed network design under $\boldsymbol{\alpha} = \mathbf{0}$

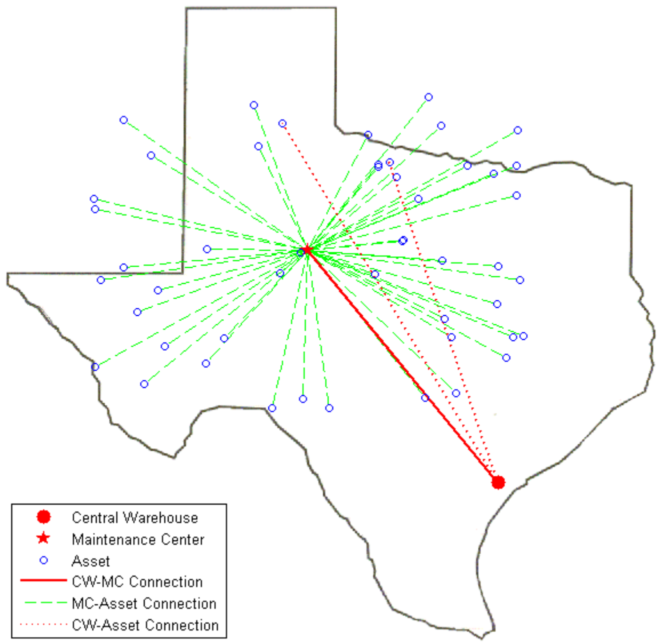

Figure 38: SPL network obtained by the proposed network design under $\boldsymbol{\alpha} = \mathbf{5}$

It is interesting to note that when the construction cost scalar α approaches zero, it seems intuitive that all 9 candidate maintenance centers can be built and connections can be established so that all 49 assets can be serviced by these centers (building them is free). However, as it can be seen from Figure 10 and Table 5, the newly proposed design methodology leads to the SPL network with only four maintenance centers providing the maintenance services[37]. Furthermore, one can also observe from Table 5 that, when $\alpha = 0$, the total spare part inventory levels are reduced by 11.7% compared to the baseline system setting ($\alpha = 1$), while at the same time, easier availability of spare parts caused by the larger number of maintenance centers enables the system to operate with a more

[37] The other five maintenance centers are not needed though they are free to build because if they stocked any spare parts, the non-negligible costs to hold/replenish the spare part would lead to losses. In other words, these five maintenance centers are not needed, though they are free to be built.

aggressive PM schedule (evidenced by the smaller average PM triggering level under $\alpha = 0$ than that under $\alpha = 1$).

On the other hand, when construction of the maintenance facilities costs five times as it does in the baseline system settings (when $\alpha = 5$), only one maintenance center is built and it is located close to the geographical center of the assets, providing 47 out of 49 assets with the necessary spare parts (the remaining 2 assets are serviced directly by the central warehouse). An added benefit of having only one maintenance center is the more efficient usage of logistic resources, which is reflected in the reduced total spare part inventory levels, as well as the savings in the SPL costs. The reason for this is the fact that the logistic resources are localized in a single maintenance center, instead of being spread out across multiple ones. As for maintenance operations, $\alpha = 5$ yielded the smallest average PM triggering usage level compared to $\alpha = 0$ and $\alpha = 1$. This is intuitive because, as only one maintenance center is built when $\alpha = 5$, the expected times for most assets to obtain spare parts are much longer compared to $\alpha = 0$ or $\alpha = 1$. Therefore, more aggressive PM scheduling is needed to ensure avoidance of lengthy RM interventions and timely deliveries of spare parts.

Scalar α	5	1	0
Number of active maintenance centers	1	2	4
Number of facility-asset connections	47	64	196
Total spare part inventory level	120	153	135
Average PM triggering usage level	32.38	29.56	24.72
System uptime (%)	90.08	92.35	90.98

Table 5: Summary statistics for optimized network design under various $\boldsymbol{\alpha}$

5.4.4 DOE Based Sensitivity Analysis for the Proposed Network Design

In this section, a two-way analysis of variance (ANOVA) [188] is used to study the effects of cost parameters associated with the facility construction, inventory management and maintenance scheduling on the unit-time overall costs, involving the network construction costs and operational costs obtained when the SPL network design is jointly optimized with the SPL and PM operations, as suggested in Section 3.1. Three input factors, labeled as F1, F2 and F3, are considered within this DOE. Factor F1 denotes a scalar for the cost parameters regarding logistic network construction, factor F2 is a scalar for inventory-related cost parameters, including inventory holding and replenishment costs, and factor F3 denotes a scalar for all maintenance-related cost parameters. Each factor (F1-F3) is varied at three levels (low, medium & high), resulting in 27 experimental levels.

In Table 6, significance levels for the three main effects and three 2nd order interaction effects are shown as the result of ANOVA. The main effects of all 3 factors were found to have strong statistical significance and to be positively correlated with the unit-time overall cost of the entire system. Statistical significance of these effects is plausible, since changes in these factors directly affect decisions on the SPL network design, spare part inventory management and maintenance schedule, thus, inevitably affecting the overall system performance.

Furthermore, all three 2nd order interaction effects, F1×F2, F2×F3 and F2×F3, are also found to be statistically significant according to ANOVA analysis, with *p* values being less than 0.05. It confirms the main motivation of this chapter, which is the fact that, for the fairly generic system considered in this chapter, decisions regarding the SPL network construction, PM scheduling and spare parts inventory management must be considered and optimized jointly, as suggested in this chapter, rather than separately, which is the traditional approach.

Factor	**F value**	**Pr(>F)**	**Regression Coefficient**
F1	394.17	1.02e-8	1665.19
F2	16681.27	3.30e-15	741.47
F3	16206.47	3.71e-15	679.24
F1×F2	30.62	6.72e-5	-116.26
F1×F3	4.79	0.029	25.18
F2×F3	322.96	7.22e-9	36.12

Table 6: Result table of ANOVA for factors F1-F3

5.6 Conclusions and Future Work

This chapter introduces a new design method for joint optimization of a network of maintenance centes servicing a set of geographically distributed assets with the necessary spare parts, PM schedules for those assets and SPL inventory polices throughout the logistic network. From the side of network construction, the locations of the maintenance centers that stock the spare parts needed for maintenance activities and their links with the geographically dispersed assets are determined. From the side of system operations, this work considers usage-based PM operations for the degrading assets and (s,S) replenishment policies to manage the spare part inventories in the maintenance centers that are selected for building. The new SPL network design is pursued as a solution to a stochastic optimization problem in which maintenance locations and their connections to the assets are optimized jointly with the underlying PM and SPL operations, minimizing the total costs of the SPL network construction, maintenance and SPL operations. This solution is sought through a simulation-based optimization using a Genetic Algorithm-based heuristic.

Simulations were used to compare the newly proposed SPL network design to two more traditional benchmark network designs in which the networks are pre-built, while the PM and SPL operations are optimized for that pre-built SPL network (i.e. post-festum). The results showed that the newly proposed method consistently incurs lower overall costs of system construction and operations by enabling more efficient usage of the spare part inventories and better synchronization of maintenance and SPL operations.

Moreover, an elaborate sensitivity analysis was conducted to evaluate the influence of network construction costs on the proposed SPL network design. One can conclude that, lower facility construction costs always lead to more maintenance centers being built and a reduction in the overall system costs. Besides that, more maintenance facilities provide extra flexibility in the PM and SPL operations, so that more aggressive PM schedules can be pursued without overburdening the logistic resources.

Finally, a DOE based sensitivity study was used to quantitatively describe the main/interaction effects of cost parameters on the performance of SPL network designs obtained using the newly proposed methods. The DOE results showed that 1st order effects of facility-related, maintenance-related, as well as inventory-related cost parameters are all statistical significant factors to the expected overall cost. Furthermore, all 2nd order effects were also found to be statistically significant, which confirms the necessity to pursue joint rather than fragmented optimization across the network construction and operations domains, as suggested in this chapter.

As for possible future research that could extend the results presented in this chapter, several classical constraints associated with the SPL network design can be incorporated into the current optimization, including the budget constraints on the network construction and fill-rate constraints on the maintenance services. In addition, the newly proposed methodology for SPL network design can be further improved in the sense of robustness to model uncertainties due to, for example, inaccurate estimates of parameters describing the system operations, or potentially variable network topologies (assets moving, new assets appearing, or some assets disappearing from the network). Finally, real life implementation of the methods proposed in this chapter, with realistic model parameters and scales remains a challenge for the chapter.

Chapter 6

Summary of Accomplishments and Proposed Future Work

6.1 SUMMARY OF THE RESEARCH

This doctoral dissertation presents the research on a series of decision-making problems on jointly considering PM schedules, service parts logistics and network design in a SPL systems of geographically dispersed degrading multi-component assets and maintenance facilities providing spare parts to those assets. The goal was to develop decision-making framework and tools that concurrently pursue SPL network design and system operations that minimize a customizable cost function that rewards system uptimes and production, while penalizing utilization of maintenance and logistic resources.

In Chapter 2, a review of the research relevant to the optimization of maintenance strategies and spare parts logistics was presented. This review focuses on the maintenance strategies, service part logistics, logistics network design, the integrated models of the maintenance and service part logistics, as well as the commonly adopted methods for optimization of operation in maintenance/SPL systems.

Derived from a recent submitted publication, Chapter 3 presents a novel integrated decision-making policy consisting of the usage-based PM policies for degrading assets and (s,S) replenishment policies for management of spare part inventories locally stocked in the maintenance centers. The integrated decision-making is formulated as a stochastic optimization problem with the objective of minimizing a customizable cost function that penalizes the consumptions of maintenance/logistics resources and asset downtimes. Due to numerous stochastic effects in the system and the large-scale solution space to the optimization problem, the formulated stochastic optimization problem was solved via an elaborate simulation-based metaheuristic approach using a GA heuristic. The newly proposed policy was shown to consistently outperform the fragmented policy which separately optimizes the maintenance schedules, followed by the optimization of the spare parts inventory levels in the maintenance centers. In addition, sensitivity analysis demonstrated that the integrated policy yields increased benefits in systems with higher inventory-related costs, systems with more geographically dispersed assets and systems with higher penalties for asset downtime.

An extension of the research described in Chapter 3 was pursued in Chapter 4, where imperfect PM operations, expedited RM deliveries and flexible replenishment deliveries are considered as additional elements in the system operations. Moreover, a Design of Experiment (DOE) based factorial analysis was performed to conduct sensitivity studies, which showed consistent cost benefits of considering these additional elements in the joint decision-making process. This DOE-based analysis also showed that the integrated decision-making policies were sensitive with statistical significance to changes in geographical dispersion levels of the SPL system, maintenance/logistic cost parameters, as well as their interaction effects.

Chapter 5 focuses on the integration of the SPL network design with the decision-making in the domains of maintenance scheduling and spare part inventory management. Compared to the more traditional SPL network designs, where operational decisions are made independently from the network design, the overall system efficiency can be greatly improved through jointly optimizing strategic-level decisions of maintenance center allocations and their association with the assets, along with the decisions in the domains of PM scheduling and spare part inventory management.

6.2 SCIENTIFIC CONTRIBUTIONS

Each chapter of this doctoral thesis has certain scientific contributions which have already been elaborated in individual chapter and resulted in past/foreseen publications. This section will provide a summary of scientific contributions across this dissertation.

This entire doctoral research demonstrates the interactions between maintenance scheduling and spare part logistics management for geographically dispersed system consisting of degrading assets and maintenance facilities serving these assets. To capture such interactions between system operations, a novel decision-making framework is established to jointly optimize PM and SPL operations for multi-echelon SPL systems. Established on a discrete-event simulation-based optimization approach, the proposed integrated decision-making framework has a building flexibility in incorporating various cost functions, PM/SPL structures and different types of uncertain factors, which becomes a powerful paradigm to model real-world maintenance system having geographical dispersed assets/facilities. To the best of our knowledge, this is the first research that conduct systematic studies on joint PM and SPL optimization with focus on a geographically dispersed SPL network.

From the strategic-level point of view, maintenance activities are also influenced by network topology of the spare part system. Therefore, in this dissertation, a novel SPL network design is proposed that enables the joint optimization of PM and SPL operations, leading to a more efficient SPL system in providing maintenance services. This work is among the first few works that focus on the SPL network design and, to our best knowledge, is the only work that allows the maintenance optimization within a logistic network design. More importantly, this proposed network design provides a completely new perspective to improve the maintenance services in terms of timing and efficiency.

6.3 FUTURE WORKS

In Chapter 3 - Chapter 5, several possible avenues for future research specifically related to the work in those chapters have been identified. Generally speaking, the most critical future research would be the development of a robust version of the decision-making framework that enables joint PM and SPL optimization in the existence of uncertain system parameters, including inaccurate reliability parameter estimates, changing system environments and uncertain cost function parameters *etc*. Robust optimization should be able to handle such uncertainties, while maintain the flexibility of the methods presented in this thesis. The major challenge of developing a robust version of decision-making framework is to properly develop a modeling methodology that enables robust optimization approach to be applied on a system with various PM/SPL operations and uncertain factors. Besides the challenge in modeling methodology, concerns on computational efficiency of robust optimization approach will dramatically increase when a large number of decision variables are taken into considerations. Overcoming the aforementioned challenges will enable transform of the results of this doctoral research from simulation to decision-making in real-life logistic and maintenance scheduling problems in geographically distributed systems.

6.4 COMPLETED AND EXPECTED FUTURE PUBLICATION

This section provides a list of publications that have already been produced, or are anticipated to be finished based on this doctoral dissertation:

(1) C. Jin, D. Djurdjanovic, H.D. Ardakani, **K. Wang,** M. Buzza, B. Begheri, P. Brown and J. Lee, "A comprehensive framework of factory-to-factory dynamic fleet-level prognostics and operation management for geographically distributed assets", in

Proc. Of the IEEE conference on Automation Science and Engineering, August 24-28, 2015, Gothenburg, Sweden, pp. 225-230, 2015.

(2) A. UI Haq, **K. Wang** and D. Djurdjanovic, "Feature Construction for Dense Inline Data in Semiconductor Manufacturing Processes", *IFAC-PapersOnLine*, 49(28), pp.274-279, 2016.

(3) D. Djurjdanovic, A. Ul Haq and **K. Wang**, "System and Method for Feature Extraction for Sensor Data", Application Ref. 62/458,792, Application Date Feb. 14, 2017 (patent in application).

(4) **K. Wang** and D. Djurdjanovic, "Joint Optimization of Preventive Maintenance and Spare Part Inventory for Multi-echelon Geographically Dispersed Systems", in *Proc. of the 2017 World Congress on Engineering Asset Management (WCEAM)*, Brisbane, Queensland, Australia, August 2-4, 2017, Paper No. 143, 2017.

(5) **K. Wang** and D. Djurdjanovic, "Joint Optimization of Maintenance and Spare Parts Logistics for a System of Geographically Distributed, Multi-part Assets", submitted to the *Journal of Intelligent Manufacturing*, Paper No. JIMS-D-17-00416, 2017.

(6) **K. Wang** and D. Djurdjanovic, "Joint Optimization of Preventive Maintenance and Spare Part Inventory and Transportation Options for Systems of Geographically Distributed Assets", submitted to *Elsevier Journal of Computers and Industrial Engineering*, Paper No. CAIE-S-17-10392, 2017.

(7) **K. Wang** and D. Djurdjanovic, "Spare Part Logistic Network Design for Jointly Optimal Preventive Maintenance and Spare Part Logistic Operations", submitted to *European Journal of Operations Research*, Paper No. EJOR-S-17-03980, 2017.

Appendices

Appendix A: System Settings for Simulation Examples in Chapter 3

This appendix provides a detailed description of the baseline system in Section 3.4.1. Generally, the SPL system has 1 central warehouse, 3 maintenance centers and 49 assets (i.e. $n = 3$ and $J = 49$). Maintenance center specific parameters are given in Table 7, with the description of each term listed below.

- $\mathcal{RT}_i(\cdot)$: A symmetric triangular distribution for replenishment delivery time from the center warehouse to the maintenance center MC_i.
- $H_{i,h}$: Inventory holding cost per unit time for the spare part S_h at MC_i.
- $S_{i,h}$: Replenishment delivery cost per unit time for the spare part S_h at MC_i
- $\mathcal{MT}(\cdot)$: A symmetric triangular distribution for repair times during maintenance.

Maintenance center	$\mathcal{RT}_i(\cdot)$	$H_{i,h}$-s (monetary unit/unit time)	$S_{i,h}$-s (monetary unit/order)	$\mathcal{MT}(\cdot)$
MC_1	Tri(10.5,15,19.5)	30	450	Tri (0.35, 0.5, 0.65)
MC_2	Tri(13.6,18,23.4)	30	540	
MC_3	Tri(14.7,21,26.3)	30	630	

Table 7: Maintenance center specific parameters for the baseline system in Chapter 3

Parameters specifically related to an asset A_j are listed in Table 8, where

- L_j : Downtime penalty, penalty cost of unit downtime of the asset A_j.
- K_j : Number of working parts inside the asset A_j.
- $\mathcal{LT}_j^i(\cdot)$: A symmetric triangular distribution of lead time from MC_i to the asset A_j.
- $\mathcal{LT}_j^{cw}(\cdot)$: A symmetric triangular distribution of lead time from the central warehouse to the asset A_j.

Asset	L_j	K_j	Mapping of working part to spare part type	$\mathcal{LT}_j^1(\cdot)$	$\mathcal{LT}_j^2(\cdot)$	$\mathcal{LT}_j^3(\cdot)$	$\mathcal{LT}_j^{cw}(\cdot)$
$\boldsymbol{A_1}$	1000	4	$P_{1,1} = SP_1, P_{1,2} = SP_2, P_{1,3}$	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_2}$	1000	3	$P_{2,1} = SP_1\ , P_{2,2} = SP_2, P_{2,3} = SP_4$	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_3}$	1000	2	$P_{3,1} = SP_1, P_{3,2} = SP_3$	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_4}$	1000	2	$P_{4,1} = SP_1, P_{4,2} = SP_4$	Tri(1.4,2,2.6)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_5}$	1000	3	$P_{5,1} = SP_1, P_{5,2} = SP_3, P_{5,3} = SP_4$	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_6}$	1000	3	$P_{6,1} = SP_1, P_{6,2} = SP_4, P_{6,3} = SP_5$	Tri(1.75,2.5,3.25)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_7}$	1000	2	$P_{7,1} = SP_1, P_{7,2} = SP_5$	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_8}$	1000	3	$P_{8,1} = SP_1, P_{8,2} = SP_2, P_{8,3} = SP_3$	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_9}$	1000	2	$P_{9,1} = SP_1, P_{9,2} = SP_3$	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_{10}}$	1000	2	$P_{10,1} = SP_1, P_{10,2} = SP_4$	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(10.5,15,19.5)
$\boldsymbol{A_{11}}$	1000	4	$P_{11,1} = SP_1, P_{11,2} = SP_2, P_{11,3}$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{12}}$	1200	4	$P_{12,1} = SP_1, P_{12,2} = SP_2, P_{12,3}$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{13}}$	1000	2	$P_{13,1} = SP_1, P_{13,2} = SP_3$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{14}}$	1500	2	$P_{14,1} = SP_1, P_{14,2} = SP_4$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{15}}$	1000	3	$P_{15,1} = SP_1, P_{15,2} = SP_3, P_{15,3} = SP_4$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{16}}$	2000	3	$P_{16,1} = SP_1, P_{16,2} = SP_4, P_{16,3} = SP_5$	Tri(3.5,5,6.5)	Tri(1.4,2,2.6)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{17}}$	1000	2	$P_{17,1} = SP_1, P_{17,2} = SP_5$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{18}}$	1000	3	$P_{18,1} = SP_1, P_{18,2} = SP_2, P_{18,3} = SP_3$	Tri(3.5,5,6.5)	Tri(1.05,1.5,1.95)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{19}}$	500	2	$P_{19,1} = SP_2, P_{19,2} = SP_3$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{20}}$	1000	2	$P_{20,1} = SP_2, P_{20,2} = SP_5$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{21}}$	1000	3	$P_{21,1} = SP_1, P_{21,2} = SP_4, P_{21,3} = SP_5$	Tri(3.5,5,6.5)	Tri(1.4,2,2.6)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{22}}$	1500	2	$P_{22,1} = SP_1, P_{22,2} = SP_5$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{23}}$	500	3	$P_{23,1} = SP_3, P_{23,2} = SP_4, P_{23,3} = SP_5$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{24}}$	800	2	$P_{24,1} = SP_2, P_{24,2} = SP_3$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{25}}$	1000	2	$P_{25,1} = SP_2, P_{25,2} = SP_5$	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{26}}$	800	2	$P_{26,1} = SP_2, P_{26,2} = SP_3$	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(3.5,5,6.5)	Tri(13.6,18,23.5)
$\boldsymbol{A_{27}}$	1000	4	$P_{27,1} = SP_1, P_{27,2} = SP_2, P_{27,3}$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{28}}$	1200	4	$P_{28,1} = SP_1, P_{28,2} = SP_2, P_{28,3}$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{29}}$	1000	2	$P_{29,1} = SP_1, P_{29,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{30}}$	1500	2	$P_{30,1} = SP_1, P_{30,2} = SP_4$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{31}}$	1000	3	$P_{31,1} = SP_1, P_{31,2} = SP_3, P_{31,3} = SP_4$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{32}}$	2000	3	$P_{32,1} = SP_1, P_{32,2} = SP_4, P_{32,3} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(1.4,2,2.6)	Tri(14.7,21,27.3)
$\boldsymbol{A_{33}}$	1000	2	$P_{33,1} = SP_1, P_{33,2} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{34}}$	1000	3	$P_{34,1} = SP_1, P_{34,2} = SP_2, P_{34,3} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(1.05,1.5,1.95)	Tri(14.7,21,27.3)
$\boldsymbol{A_{35}}$	500	2	$P_{35,1} = SP_2, P_{35,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{36}}$	1000	2	$P_{36,1} = SP_2, P_{36,2} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{37}}$	1000	3	$P_{37,1} = SP_1, P_{37,2} = SP_4, P_{37,3} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(1.4,2,2.6)	Tri(14.7,21,27.3)
$\boldsymbol{A_{38}}$	1500	2	$P_{38,1} = SP_1, P_{38,2} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)

Table 8: Asset-specific parameters for the baseline system in Chapter 3

Table 8. Continued from previous page

$\boldsymbol{A_{39}}$	500	3	$P_{39,1} = SP_3, P_{39,2} = SP_4, P_{39,3} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{40}}$	800	2	$P_{40,1} = SP_2, P_{40,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{41}}$	1000	2	$P_{41,1} = SP_2, P_{41,2} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{42}}$	800	2	$P_{42,1} = SP_2, P_{42,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{43}}$	1000	2	$P_{43,1} = SP_2, P_{43,2} = SP_5$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)
$\boldsymbol{A_{44}}$	800	2	$P_{44,1} = SP_2, P_{44,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{45}}$	500	4	$P_{45,1} = SP_1, P_{45,2} = SP_2, P_{45,3} = SP_3, P_{45,4} = SP_4$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{46}}$	1200	4	$P_{46,1} = SP_1, P_{46,2} = SP_2, P_{46,3} = SP_3, P_{46,4} = SP_4$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.7,1,1.3)	Tri(14.7,21,27.3)
$\boldsymbol{A_{47}}$	500	1	$P_{47,1} = SP_1$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(1.05,1.5,1.95)	Tri(14.7,21,27.3)
$\boldsymbol{A_{48}}$	500	1	$P_{48,1} = SP_1$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(1.05,1.5,1.95)	Tri(14.7,21,27.3)
$\boldsymbol{A_{49}}$	1500	2	$P_{49,1} = SP_1, P_{49,2} = SP_3$	Tri(3.5,5,6.5)	Tri(3.5,5,6.5)	Tri(0.35,0.5,0.65)	Tri(14.7,21,27.3)

The spare parts that are needed to execute RM/PM on a working part $P_{j,k}$ can be obtained from any of the three maintenance centers, as well as the central warehouse, with the following cost terms (as explained in the body of Chapter 3):

- $M_{j,k}^{i}$: Cost to order a PM for the working part $P_{j,k}$ from the maintenance center MC_i.
- $R_{j,k}^{i}$: Cost to order a RM for the working part $P_{j,k}$ from the maintenance center MC_i.
- $M_{j,k}^{cw}$: Cost to order a PM for the working part $P_{j,k}$ from the central warehouse.
- $R_{j,k}^{cw}$: Cost to order a RM for the working part $P_{j,k}$ from the central warehouse.

Values of these parameters are listed in Table 9 below.

Asset	$M_{j,k}^{1}$	$R_{j,k}^{1}$	$M_{j,k}^{2}$	$R_{j,k}^{2}$	$M_{j,k}^{3}$	$R_{j,k}^{3}$	$M_{j,k}^{cw}$	$R_{j,k}^{cw}$
A_{1}	500	1000	700	1200	700	1200	500	1200
A_{2}	500	1000	700	1200	700	1200	500	1200
A_{3}	500	1000	700	1200	700	1200	500	1200
A_{4}	500	1000	700	1200	700	1200	500	1200
A_{5}	500	1000	700	1200	700	1200	500	1200
A_{6}	500	1000	700	1200	700	1200	500	1200
A_{7}	500	1000	700	1200	700	1200	500	1200
A_{8}	500	1000	700	1200	700	1200	500	1200
A_{9}	500	1000	700	1200	700	1200	500	1200
A_{10}	500	1000	700	1200	700	1200	500	1200
A_{11}	700	1200	500	800	700	1200	700	1200
A_{12}	700	1200	500	800	700	1200	700	1200
A_{13}	700	1200	500	800	700	1200	700	1200
A_{14}	700	1200	500	800	700	1200	700	1200
A_{15}	700	1200	500	800	700	1200	700	1200
A_{16}	700	1200	500	800	700	1200	700	1200
A_{17}	700	1200	500	800	700	1200	700	1200
A_{18}	700	1200	500	800	700	1200	700	1200
A_{19}	700	1200	500	800	700	1200	700	1200
A_{20}	700	1200	500	800	700	1200	700	1200
A_{21}	700	1200	500	800	700	1200	700	1200
A_{22}	700	1200	500	800	700	1200	700	1200
A_{23}	700	1200	500	800	700	1200	700	1200
A_{24}	700	1200	500	800	700	1200	700	1200
A_{25}	700	1200	500	800	700	1200	700	1200
A_{26}	700	1200	500	800	700	1200	700	1200
A_{27}	700	1200	700	1200	300	600	300	1200
A_{28}	700	1200	700	1200	300	600	300	1200
A_{29}	700	1200	700	1200	300	600	300	1200
A_{30}	700	1200	700	1200	300	600	300	1200
A_{31}	700	1200	700	1200	300	600	300	1200
A_{32}	700	1200	700	1200	300	600	300	1200
A_{33}	700	1200	700	1200	300	600	300	1200
A_{34}	700	1200	700	1200	300	600	300	1200
A_{35}	700	1200	700	1200	300	600	300	1200
A_{36}	700	1200	700	1200	300	600	300	1200
A_{37}	700	1200	700	1200	300	600	300	1200
A_{38}	700	1200	700	1200	300	600	300	1200
A_{39}	700	1200	700	1200	300	600	300	1200
A_{40}	700	1200	700	1200	300	600	300	1200
A_{41}	700	1200	700	1200	300	600	300	1200
A_{42}	700	1200	700	1200	300	600	300	1200
A_{43}	700	1200	700	1200	300	600	300	1200
A_{44}	700	1200	700	1200	300	600	300	1200
A_{45}	700	1200	700	1200	300	600	300	1200
A_{46}	700	1200	700	1200	300	600	300	1200
A_{47}	700	1200	700	1200	300	600	300	1200
A_{48}	700	1200	700	1200	300	600	300	1200
A_{49}	700	1200	700	1200	300	600	300	1200

Table 9: PM/RM costs for the baseline system in Chapter 3

For the convenience of illustration, the distribution for usage to failure of working parts, $\mathcal{T}_{j,k}(\cdot)$-s, are assumed to be spare-part specific and follows a Weibull distribution, as listed in Table 10.

Spare part type	$\mathcal{T}_{j,k}(\cdot)$	Expected time to failure
SP_1	$\text{Weibull}(3.0, 80)$	69.88
SP_2	$\text{Weibull}(4.0, 100)$	93.06
SP_3	$\text{Weibull}(3.5, 65)$	59.04
SP_4	$\text{Weibull}(3.5, 70)$	63.58
SP_5	$\text{Weibull}(2.7, 65)$	54.76

Table 10: Usage to failure distributions for working parts (k for shape, λ for scale)

As for the decision variables, there are 156 of them, 30 of which are related to spare part inventory management and the other 126 are the PM triggers. Each decision variable is assumed to take values in a discrete value set, as described in Table 11.

Symbol	**Description**	**Value set**
$X_{j,k}$ $(1 \leq j \leq 49, 1 \leq k \leq K_j)$	Discrete real-number set for PM trigger $x_{j,k}$	$\{5, 10, 15, \ldots, 150\}$
$Y_{i,h}$ $(1 \leq i \leq 3, 1 \leq h \leq 5)$	Discrete integer set for reorder level $y_{i,h}$	$\{-1, 0, 1, 2, \ldots, 30\}$
$Z_{i,h}$ $(1 \leq i \leq 3, 1 \leq h \leq 5)$	Discrete integer set for batch size $z_{i,h}$	$\{1, 2, 3, 4, 5\}$

Table 11: Candidate value sets for the decision variables in Chapter 3

In Table 12, a complete list of parameters for the GA based optimization metaheuristic, as well as the relevant computational times are given. These parameters were selected *ad hoc*, after a few trial and error runs, though more formal methods for selecting GA parameter can be found in the literature [181].

	Description	Value
General parameters	Time horizon, T	1825 time units
	Replication number	50
Parameters for GA	Population size	60
	Maximum iteration number	5000
	Maximum unchanged iteration	500
	Crossover rate	0.6
	Mutation rate	0.02
Computational time in baseline system	Each GA iteration	17.5 seconds
	Entire algorithm	$\leq$10 hours

Table 12: The algorithm-related parameters and computation cost for the proposed algorithm in Chapter 3

APPENDIX B: SYSTEM SETTINGS FOR SIMULATION EXAMPLES IN CHAPTER 4

For all the examples studied in Chapter 4, the relevant system settings and parameters, as well as detailed simulation results will be given in this appendix. Firstly, for the baseline example given in Section 4.4.1, the parameters that are uniform across the system are listed in Table 13.

Symbol	Description	Value
J	Number of assets	20
CT	Lead time of replenishment delivery	3 time units
H_i	Inventory holding cost per unit time	10 monetary unit/unit time
S_i^{fix}	Fixed replenishment handling cost per order	120 monetary unit/order
S_i^{add}	Additional cost to have one more spare part added to replenishment order	0 monetary unit/part
$R_{j,k}$	RM cost per order	1000 monetary unit/order
$RT_{j,k}^{RM}$	RM repair time per RM order	0.5 time unit/order
$M_{j,k}^{fix}$	Fixed PM cost per order	200 monetary unit/order
$M_{j,k}^{add}$	Additional PM cost to improve PM quality	800 monetary unit/order
$RT_{j,k}^{fix}$	Fixed PM repair time per order	0.4 time unit/order
$RT_{j,k}^{add}$	Additional repair time to improve PM quality	0.1 time unit
$E_{j,k}$	Additional charge of an emergency RM	0 monetary unit/order
T_j	Additional charge to accelerate RM delivery	500 monetary unit/order

Table 13: System-uniform parameters for the baseline system in Chapter 4

For the baseline system, parameters specifically related to an asset A_j are given in Table 14, with the description of each term listed below,

- $\mathcal{MT}_j(\cdot)$: Lead time distribution for the asset A_j to obtain new spare parts from the maintenance center.

- $\mathcal{CT}_j(\cdot)$: Lead time distribution for the asset A_j to obtain new spare parts from the central warehouse.
- L_j : Penalty per unit downtime of the asset A_j.
- K_j : Number of working parts inside the asset A_j.

Asset	$\boldsymbol{\mathcal{MT}_j(\cdot)}$	$\boldsymbol{\mathcal{CT}_j(\cdot)}$	$\boldsymbol{L_j}$ **(monetary unit/unit time)**	$\boldsymbol{K_j}$	**Mapping of working part to spare par type**
A_1	Weibull(1.1, 5)	Constant(3)	400	4	$P_{1,1} = SP_1, P_{1,2} = SP_2, P_{1,3} = SP_3, P_{1,4} = SP_4$
A_2	Weibull(1.1, 5)	Constant(3)	400	3	$P_{2,1} = SP_1$, $P_{2,2} = SP_2, P_{2,3} = SP_4$
A_3	Weibull(1.1, 5)	Constant(3)	400	2	$P_{3,1} = SP_1, P_{3,2} = SP_3$
A_4	Weibull(1.1, 5)	Constant(3)	400	2	$P_{4,1} = SP_1, P_{4,2} = SP_4$
A_5	Weibull(1.1, 5)	Constant(3)	400	3	$P_{5,1} = SP_1, P_{5,2} = SP_3, P_{5,3} = SP_4$
A_6	Weibull(1.1, 5)	Constant(3)	400	3	$P_{6,1} = SP_1, P_{6,2} = SP_4, P_{6,3} = SP_5$
A_7	Weibull(1.1, 5)	Constant(3)	400	2	$P_{7,1} = SP_1, P_{7,2} = SP_5$
A_8	Weibull(1.1, 5)	Constant(3)	400	3	$P_{8,1} = SP_1, P_{8,2} = SP_2, P_{8,3} = SP_3$
A_9	Weibull(1.1, 5)	Constant(3)	400	2	$P_{9,1} = SP_2, P_{9,2} = SP_3$
A_{10}	Weibull(1.1, 5)	Constant(3)	400	2	$P_{10,1} = SP_2, P_{10,2} = SP_5$
A_{11}	Weibull(2.2,	Constant(3)	800	4	$P_{11,1} = SP_1, P_{11,2} = SP_2, P_{11,3} = SP_3, P_{11,4}$
A_{12}	Weibull(2.2,	Constant(3)	800	3	$P_{12,1} = SP_1$, $P_{12,2} = SP_2, P_{12,3} = SP_4$
A_{13}	Weibull(2.2,	Constant(3)	800	2	$P_{13,1} = SP_1, P_{13,2} = SP_3$
A_{14}	Weibull(2.2,	Constant(3)	800	2	$P_{14,1} = SP_1, P_{14,2} = SP_4$
A_{15}	Weibull(2.2,	Constant(3)	800	3	$P_{15,1} = SP_1, P_{15,2} = SP_3, P_{15,3} = SP_4$
A_{16}	Weibull(2.2,	Constant(3)	800	3	$P_{16,1} = SP_1, P_{16,2} = SP_4, P_{16,3} = SP_5$
A_{17}	Weibull(2.2,	Constant(3)	800	2	$P_{17,1} = SP_1, P_{17,2} = SP_5$
A_{18}	Weibull(2.2,	Constant(3)	800	3	$P_{18,1} = SP_1, P_{18,2} = SP_2, P_{18,3} = SP_3$
A_{19}	Weibull(2.2,	Constant(3)	800	2	$P_{19,1} = SP_2, P_{19,2} = SP_3$
A_{20}	Weibull(2.2,	Constant(3)	800	2	$P_{20,1} = SP_2, P_{20,2} = SP_5$

Table 14: Asset-specific parameters for the baseline system in Chapter 4

The usage time to failure of a working part is assumed to be part type specific and follows a Weibull distribution. For each of the five spare part types, the distribution of its usage time to failure, along with its expected value and standard deviation, are listed in Table 15.

Spare part type	**Weibull distributed time to failure, $\mathbf{Weibull}(\boldsymbol{k},\boldsymbol{\lambda})$: $\boldsymbol{k}$ for shape, $\boldsymbol{\lambda}$ for scale**	**Expected time to failure, $\mathbb{E}(\boldsymbol{SP_h})$**	**Standard deviation of time to failure, $\mathbf{SD}(\boldsymbol{SP_h})$**
SP_1	$\mathrm{Weibull}(3.0, 80)$	69.88	26.00
SP_2	$\mathrm{Weibull}(4.0, 100)$	93.06	25.45
SP_3	$\mathrm{Weibull}(3.5, 65)$	59.04	18.53
SP_4	$\mathrm{Weibull}(3.5, 70)$	63.58	19.95
SP_5	$\mathrm{Weibull}(2.7, 65)$	54.76	23.13

Table 15: Spare part related parameters for the baseline system in Chapter 4

There are all together 102 decision variables in the baseline example, including 52 usage levels that trigger PM operations for the corresponding working parts ($x_{j,k}$-s), 5 inventory reorder levels that trigger replenishment from the central warehouse (y_i-s) and 5 replenishment batch sizes (z_i-s), 20 recovery rates (u_j-s) that represent the quality of PM operations and 20 acceleration rates (v_j-s) that denote shipping options of the spare part delivery service. Each decision variable is assumed to take value in a discrete value set, as described in Table 16,

Symbol	**Description**	**Value set**
$X_{j,k}$	A discrete real-number set for PM trigger $x_{j,k}$ (mapping to the spare part SP_h)	$\{\mathbb{E}(SP_h) + \beta \cdot \mathrm{SD}(SP_h)\}$ where $\beta \in \{-2.5, -2.0, -1.5, -1.0, -0.5, 0, 0.5, 1.0, 1.5, 2.0, 2.5\}$
Y_i	A discrete integer set for reorder level y_i	$\{-1, 0, 1, 2, \dots, 20\}$
Z_i	A discrete integer set for batch size z_i	$\{1, 2, 3\}$
U_j	A discrete real-number set for RM expedition rate u_j	$\{0, 0.5, 1\}$
V_j	A discrete real-number set for PM recovery rate v_j	$\{0, 0.5, 1.0, 1.5, 2.0\}$

Table 16: Value sets for the decision variables in Chapter 4

Table 17 gives a complete list of parameters for the GA based metaheuristic, as well as the relevant computational times of the algorithm for optimization of the baselines system operations. The stopping criteria for the genetic algorithm are either the maximum number of iterations being reached, or the solution not being improved over a number of successive iterations. The algorithm is implemented in Java, on a relatively standard personal computer (Intel Core i5-3570 CPU, 16 GB RAM, 64-bit Window 7 operating system).

	Description	**Value**
General parameters	Time horizon, T	1825 time units
	Replication number	100
Parameters for GA	Population size	60
	Maximum iteration number	500
	Maximum unchanged iteration	30
	Crossover rate	0.6
	Mutation rate	0.05
	GA runs	5
Computational time of baseline system	Each GA iteration	17.9 seconds
	Entire algorithm	$\leq$10 hours

Table 17: Parameters of the discrete event simulations, GA-related parameters and computational times for the proposed algorithm in Chapter 4

To quantitatively evaluate all examples presented in Section 4.4.1, a complete report of simulation results for the baseline system and restricted systems (R0-R6) is provided in Table 18.

System Index	R0	R1	R2	R3	R4	R5	R6	Baseline
I1: Indicator for multi-mode PM	1	0	1	1	0	0	1	0
I2: Indicator for RM expedition	1	1	0	1	0	1	0	0
I3: Indicator for flexible replenishment	1	1	1	0	1	0	0	0
System uptime (%)	94.40	94.91	95.29	94.54	95.71	94.85	95.18	95.66
Cumulative inventory holding times	12493.95	15910.15	15911.44	16226.56	16036.76	17208.50	16258.20	16288.49
Cumulative replenishment order	1311.20	1389.00	1388.72	614.71	1347.79	564.41	612.83	611.75
Cumulative number of PM orders	591.16	446.99	557.64	623.36	229.26	482.55	579.95	380.05
Cumulative number of RM orders	879.23	1012.68	903.93	859.42	1178.64	992.93	891.93	1084.70
Cumulative number of emergency orders	10.36	4.53	4.66	7.39	3.83	6.99	7.27	7.07
Unit-time fixed PM cost	64.78	48.99	61.11	68.31	25.12	52.88	63.56	41.65
Unit-time added PM cost	259.14	185.01	244.44	273.25	81.43	197.03	254.22	143.44
Unit-time RM cost	481.77	554.89	495.30	470.92	645.83	544.07	488.73	594.36
Unit-time inventory holding cost	68.46	87.18	87.19	88.91	87.87	94.29	89.09	89.25
Unit-time replenishment cost	86.22	91.33	91.31	40.42	88.62	37.11	40.30	40.22
Unit-time downtime penalty	673.98	643.59	546.06	659.11	510.60	645.00	556.99	516.64
Unit-time RM acceleration cost	0.00	0.00	84.14	0.00	138.32	0.00	77.62	109.50
Unit-time emergency RM cost	10.36	4.53	4.66	7.39	3.83	6.99	7.27	7.07

Table 18: Performance statistics of the baseline system and the restricted systems in Section 4.4

In Section 4.4.2, six factors are studied in the DOE analysis of the unit time operating costs under the integrated decision-making policy. A detailed description for each factor is listed in Table 19 and the unit time operating costs under the integrated policy with different system settings are provided in Table 20.

Factor	Description	Low vs. High Level	Relevant system parameters need to be scaled
F1	Geographical dispersion level	1.0 vs. 5.0	CT and $\mathcal{CT}_j(\cdot)$ for $1 \le j \le 20$
F2	Inventory holding cost per unit time	0.2 vs. 5.0	H_i for $1 \le i \le 5$
F3	Replenishment cost per order	1.0 vs. 5.0	S_i^{fix} and S_i^{add} for $1 \le i \le 5$
F4	PM quality improvement cost per order	0.2 vs. 5.0	$M_{j,k}^{add}$ for $1 \le j \le 20, 1 \le k \le K_j$
F5	Penalty cost per unit downtime	0.2 vs. 5.0	L_j for $1 \le j \le 20$
F6	RM acceleration cost per order	0.2 vs. 5.0	T_j for $1 \le j \le 20$

Table 19: Factors F1-F6 used for DOE study in Section 4.4.2

	F1	F2	F3	F4	F5	F6	Cost		F1	F2	F3	F4	F5	F6	Cost		F1	F2	F3	F4	F5	F6	Cost
1	L	L	L	L	L	L	709.1	**23**	H	L	L	L	H	H	3244.8	**45**	L	H	L	H	H	L	1570.5
2	L	L	H	L	L	L	822.9	**24**	H	L	H	L	H	H	3095.0	**46**	L	H	H	H	H	L	3060.4
3	H	L	L	L	L	L	718.0	**25**	L	L	L	H	L	H	3237.3	**47**	H	H	L	H	H	L	3274.2
4	H	L	H	L	L	L	815.2	**26**	L	L	H	H	L	H	954.7	**48**	H	H	H	H	H	L	3581.8
5	L	L	L	L	H	L	2339.5	**27**	H	L	L	H	L	H	985.0	**49**	L	H	L	L	L	H	3791.0
6	L	L	H	L	H	L	2439.8	**28**	H	L	H	H	L	H	941.2	**50**	L	H	H	L	L	H	795.7
7	H	L	L	L	H	L	2383.2	**29**	L	L	L	H	H	H	998.3	**51**	H	H	L	L	L	H	1242.3
8	H	L	H	L	H	L	2451.1	**30**	L	L	H	H	H	H	4104.7	**52**	H	H	H	L	L	H	874.3
9	L	L	L	H	L	L	916.7	**31**	H	L	L	H	H	H	4162.4	**53**	L	H	L	L	H	H	1368.6
10	L	L	H	H	L	L	979.9	**32**	H	L	H	H	H	H	4167.9	**54**	L	H	H	L	H	H	3637.7
11	H	L	L	H	L	L	932.9	**33**	L	H	L	L	L	L	4183.9	**55**	H	H	L	L	H	H	3989.6
12	H	L	H	H	L	L	993.2	**34**	L	H	H	L	L	L	798.1	**56**	H	H	H	L	H	H	4151.8
13	L	L	L	H	H	L	2422.6	**35**	H	H	L	L	L	L	1241.3	**57**	L	H	L	H	L	H	4541.4
14	L	L	H	H	H	L	2495.5	**36**	H	H	H	L	L	L	927.4	**58**	L	H	H	H	L	H	1006.8
15	H	L	L	H	H	L	2461.2	**37**	L	H	L	L	H	L	1360.7	**59**	H	H	L	H	L	H	1329.7
16	H	L	H	H	H	L	2527.5	**38**	L	H	H	L	H	L	3046.8	**60**	H	H	H	H	L	H	1387.9
17	L	L	L	L	L	H	789.9	**39**	H	H	L	L	H	L	3237.6	**61**	L	H	L	H	H	H	1615.5
18	L	L	H	L	L	H	837.3	**40**	H	H	H	L	H	L	3465.2	**62**	L	H	H	H	H	H	4705.4
19	H	L	L	L	L	H	725.6	**41**	L	H	L	H	L	L	3768.8	**63**	H	H	L	H	H	H	4895.1
20	H	L	H	L	L	H	843.7	**42**	L	H	H	H	L	L	1010.1	**64**	H	H	H	H	H	H	5329.6
21	L	L	L	L	H	H	3024.1	**43**	H	H	L	H	L	L	1329.5								
22	L	L	H	L	H	H	709.1	**44**	H	H	H	H	L	L	1353.4								

Table 20: Operating costs under different system settings, with "L" denoting low level and "H" denoting high level

APPENDIX C: SYSTEM SETTINGS FOR SIMULATION EXAMPLES IN CHAPTER 5

For the baseline example studied in Section 5.5., the system settings will be described in details in this appendix. In general, there are 9 candidate maintenance centers ($N = 9$) and 49 assets ($J = 49$). Moreover, facility-related parameters are listed in Table 21.

	Description	Central Warehouse	MC_1	MC_2	MC_3	MC_4	MC_5	MC_6	MC_7	MC_8	MC_9
(x, y)	Location Coordinate	(0,0)	(5,5)	(5,15)	(5,25)	(15,5)	(15,15)	(15,25)	(25,5)	(25,5)	(25,25)
$R^i_{j,k}$	RM cost per order from MC_i	3500	886	824	474	430	454	418	486	452	802
$M^i_{j,k}$	PM cost per order from MC_i	2000	443	412	237	215	227	209	243	226	401
F_i	Construction cost for MC_i	NA	1631073	1522228	696729	835716	870629	760027	673857	574999	1697354
O_i	Fixed facility-maintenance cost for MC_i per unit time	NA	97	87	95	93	89	80	106	121	123
$D_{i,h}$	Spare part inventory holding cost in MC_i per unit time	NA	30	30	30	30	30	30	30	30	30
$S_{i,h}$	Replenishment delivery cost per order to MC_i	NA	1290	1110	960	1110	870	690	960	690	450

Table 21: Facility-related parameters for the baseline system in Chapter 5

For the baseline system in Chapter 5.5, parameters specifically related to an asset A_j are shown in Table 22, with the description of each term listed below,

- K_j : Number of working parts in the asset A_j.
- L_j : Penalty per unit downtime of the asset A_j (monetary unit/unit time).
- $C_{i,j}$: Connection costs between maintenance center MC_i and the asset A_j (monetary unit).

Asset	L_j	K_j	Mapping of working part to spare part type	Location coordinate	$C_{1,j}$	$C_{2,j}$	$C_{3,j}$	$C_{4,j}$	$C_{5,j}$	$C_{6,j}$	$C_{7,j}$	$C_{8,j}$	$C_{9,j}$
A_1	1000	4	$P_{1,1} = SP_1, P_{1,2} = SP_2, P_{1,3} = SP_3, P_{1,4} = SP_4$	(11.4,28.9)	99851	61209	82623	80250	69363	57110	51257	71056	59206
A_2	1000	3	$P_{2,1} = SP_1\ , P_{2,2} = SP_2, P_{2,3} = SP_4$	(24.3,16.4)	86289	68519	92079	86712	78552	58843	97870	63267	96230
A_3	1000	2	$P_{3,1} = SP_1, P_{3,2} = SP_3$	(16,15.6)	61189	68679	54376	82006	59031	52253	86159	67372	83031
A_4	1000	2	$P_{4,1} = SP_1, P_{4,2} = SP_4$	(10.5,6.9)	69194	81368	51083	95529	90028	87293	90656	69166	80864
A_5	1000	3	$P_{5,1} = SP_1, P_{5,2} = SP_3, P_{5,3} = SP_4$	(28.2,14.7)	78775	76503	63754	62432	72582	61386	90223	99306	51500
A_6	1000	3	$P_{6,1} = SP_1, P_{6,2} = SP_4, P_{6,3} = SP_5$	(26.3,18.7)	76784	54354	90105	99458	53348	96970	50909	84192	89187
A_7	1000	2	$P_{7,1} = SP_1, P_{7,2} = SP_5$	(16.5,20.4)	76707	94268	94951	81297	56894	60891	59108	52091	55348
A_8	1000	3	$P_{8,1} = SP_1, P_{8,2} = SP_2, P_{8,3} = SP_3$	(18.7,11.9)	80823	96984	67723	70532	99218	97279	83833	99416	88342
A_9	1000	2	$P_{9,1} = SP_2, P_{9,2} = SP_3$	(17.6,11)	66835	83120	62209	64776	84009	76393	70580	80132	87527
A_{10}	1000	2	$P_{10,1} = SP_2, P_{10,2} = SP_5$	(6.2,29.6)	79177	77590	79179	75591	54130	85979	99808	67727	98563
A_{11}	1000	4	$P_{11,1} = SP_1, P_{11,2} = SP_2, P_{11,3} = SP_3, P_{11,4} = SP_4$	(9,1.1)	67323	94328	72735	70672	60887	56283	65446	86306	89144
A_{12}	1200	3	$P_{12,1} = SP_1\ , P_{12,2} = SP_2, P_{12,3} = SP_4$	(14.1,26.6)	84690	50491	92161	96117	88548	52133	68910	85217	86476
A_{13}	1000	2	$P_{13,1} = SP_1, P_{13,2} = SP_3$	(6.9,27.4)	61214	63453	83652	73875	81186	61823	58857	91483	88347
A_{14}	1500	2	$P_{14,1} = SP_1, P_{14,2} = SP_4$	(25.3,23.9)	96724	55395	59112	54955	74489	59663	94795	54955	52209
A_{15}	1000	3	$P_{15,1} = SP_1, P_{15,2} = SP_3, P_{15,3} = SP_4$	(5.8,3)	77865	88625	65598	58950	66948	60508	75508	95319	81447
A_{16}	2000	3	$P_{16,1} = SP_1, P_{16,2} = SP_4, P_{16,3} = SP_5$	(6.8,7.9)	55077	69543	52731	75065	71587	99879	90581	74283	94723
A_{17}	1000	2	$P_{17,1} = SP_1, P_{17,2} = SP_5$	(5.1,10.1)	56878	69501	96368	95875	85679	80917	67165	96802	56239
A_{18}	1000	3	$P_{18,1} = SP_1, P_{18,2} = SP_2, P_{18,3} = SP_3$	(6.8,20.4)	86530	82324	91658	69915	87492	91762	66124	77614	98957
A_{19}	500	2	$P_{19,1} = SP_2, P_{19,2} = SP_3$	(13.1,4.1)	77466	66522	80974	68032	87826	70696	74618	84738	98637
A_{20}	1000	2	$P_{20,1} = SP_2, P_{20,2} = SP_5$	(9.3,21.6)	66388	91891	86954	97709	51597	67844	83133	64076	61520
A_{21}	1000	3	$P_{21,1} = SP_1, P_{21,2} = SP_4, P_{21,3} = SP_5$	(27.7,3.2)	85557	81229	79531	83022	52378	67440	72568	62046	85753
A_{22}	1500	2	$P_{22,1} = SP_1, P_{22,2} = SP_5$	(12.9,19.6)	92810	64076	86553	56889	91837	56931	79411	68308	90338
A_{23}	500	3	$P_{23,1} = SP_3, P_{23,2} = SP_4, P_{23,3} = SP_5$	(5.5,14.8)	75190	74480	93853	67658	72473	98177	52115	98648	59461
A_{24}	800	2	$P_{24,1} = SP_2, P_{24,2} = SP_3$	(27.1,23.4)	83357	79322	83756	68052	81014	90558	50963	54194	98741
A_{25}	1000	2	$P_{25,1} = SP_2, P_{25,2} = SP_5$	(29.4,21.5)	82568	61562	70175	56102	63422	62893	66584	57612	67401

Table 22: Asset-specific parameters for the baseline example in Chapter 5

Table 22. Continued from previous page

A_{26}	800	2	$P_{26,1} = SP_2, P_{26,2} = SP_3$	(13.2,27.1)	56083	94208	54714	96503	69951	52371	67119	86799	89735
A_{27}	1000	4	$P_{27,1} = SP_1, P_{27,2} = SP_2, P_{27,3} = SP_3, P_{27,4} = SP_4$	(3.3,26.7)	77246	84312	94682	52740	65184	52310	59774	86009	86088
A_{28}	1200	4	$P_{28,1} = SP_1, P_{28,2} = SP_2, P_{28,3} = SP_3, P_{28,4} = SP_4$	(7.7,10)	93890	79122	53535	96138	90019	64298	77184	99239	85784
A_{29}	1000	2	$P_{29,1} = SP_1, P_{29,2} = SP_3$	(12.3,21)	91949	71664	73532	78036	63455	87451	75195	82341	65388
A_{30}	1500	2	$P_{30,1} = SP_1, P_{30,2} = SP_4$	(17.8,5.9)	56937	73779	68123	89406	89015	83426	56676	51078	77993
A_{31}	1000	3	$P_{31,1} = SP_1, P_{31,2} = SP_3, P_{31,3} = SP_4$	(7.9,0.9)	65041	96971	99046	64332	90042	94806	79877	94201	97187
A_{32}	2000	3	$P_{32,1} = SP_1, P_{32,2} = SP_4, P_{32,3} = SP_5$	(18.1,22.3)	77458	86420	78838	51293	72327	82316	76061	68616	96857
A_{33}	1000	2	$P_{33,1} = SP_1, P_{33,2} = SP_5$	(21.3,15)	91477	92455	68627	79660	93628	96676	83424	60339	82693
A_{34}	1000	3	$P_{34,1} = SP_1, P_{34,2} = SP_2, P_{34,3} = SP_3$	(6.7,14.4)	53603	70337	83347	96687	90548	74228	87838	70853	98590
A_{35}	500	2	$P_{35,1} = SP_2, P_{35,2} = SP_3$	(3.5,27.1)	99399	93208	69445	72738	62335	89222	94142	95686	77915
A_{36}	1000	2	$P_{36,1} = SP_2, P_{36,2} = SP_5$	(8.9,18.3)	79944	57444	94986	72520	60284	94983	88130	94125	64248
A_{37}	1000	3	$P_{37,1} = SP_1, P_{37,2} = SP_4, P_{37,3} = SP_5$	(9.6,18.5)	83662	83214	56141	70366	63765	85834	64170	94810	91329
A_{38}	1500	2	$P_{38,1} = SP_1, P_{38,2} = SP_5$	(12.7,25.8)	69502	74896	84741	91719	80482	78737	66303	72822	85690
A_{39}	500	3	$P_{39,1} = SP_3, P_{39,2} = SP_4, P_{39,3} = SP_5$	(15.2,24.2)	94221	86043	50931	83739	71926	71892	55852	90735	66243
A_{40}	800	2	$P_{40,1} = SP_2, P_{40,2} = SP_3$	(2.6,17.3)	62312	67136	68785	77328	78097	69792	69907	75769	82877
A_{41}	1000	2	$P_{41,1} = SP_2, P_{41,2} = SP_5$	(7.9,5.5)	97546	86118	70004	91594	56717	53024	54213	58195	66211
A_{42}	800	2	$P_{42,1} = SP_2, P_{42,2} = SP_3$	(24,7.2)	65087	50585	76996	54769	57326	81558	92967	98712	78542
A_{43}	1000	2	$P_{43,1} = SP_2, P_{43,2} = SP_5$	(0.9,26.6)	99843	77678	75773	66535	71501	74591	53552	94387	53232
A_{44}	800	2	$P_{44,1} = SP_2, P_{44,2} = SP_3$	(27.9,0.9)	71810	91332	69727	80674	90933	94312	96556	59540	62930
A_{45}	500	5	$P_{45,1} = SP_1, P_{45,2} = SP_2, P_{45,3} = SP_3, P_{45,4} = SP_4, P_{45,5} = SP_5$	(21.9,14.7)	94894	79669	75193	80641	90972	76595	60104	72695	71396
A_{46}	1200	5	$P_{46,1} = SP_1, P_{46,2} = SP_2, P_{46,3} = SP_3, P_{46,4} = SP_4 , P_{46,4} = SP_5$	(14.7,5)	98303	81003	84770	86009	67345	75850	77835	57825	78103
A_{47}	500	1	$P_{47,1} = SP_1$	(17.4,29.4)	84741	71323	91814	86570	68002	72711	69320	88778	86714
A_{48}	500	1	$P_{48,1} = SP_1$	(7.1,21.4)	71514	84688	97261	89212	85279	55467	69497	79546	72970
A_{49}	1500	2	$P_{49,1} = SP_1, P_{49,2} = SP_3$	(13.8,15)	52517	61435	91710	50783	93186	53904	83453	75011	60900

Given the location coordinates of central warehouse, maintenance centers and assets, the lead time distribution between two entities, with coordinates (x_1, y_1) and (x_2, y_2), is given by a symmetric triangular distribution as,

$$\mathcal{LT} \sim \text{Triangle}\left(0.9\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, 1.1\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\right).$$

The usage time to failure of a working part is assumed to be type-specific and follows a Weibull distribution. For each of the five spare part types, the distribution of its usage time to failure, along with its expected value and standard deviation, are listed in Table 23.

Spare part type	**Weibull distributed time to failure, $\mathbf{Weibull}(\boldsymbol{k}, \boldsymbol{\lambda})$: $\boldsymbol{k}$ for shape, $\boldsymbol{\lambda}$ for scale**	**Expected time to failure, $\mathbb{E}(\boldsymbol{SP_h})$**	**Standard deviation of time to failure, $\mathbf{Std}(\boldsymbol{SP_h})$**
SP_1	$\text{Weibull}(3.0, 80)$	69.88	26.00
SP_2	$\text{Weibull}(4.0, 100)$	93.06	25.45
SP_3	$\text{Weibull}(3.5, 65)$	59.04	18.53
SP_4	$\text{Weibull}(3.5, 70)$	63.58	19.95
SP_5	$\text{Weibull}(2.7, 65)$	54.76	23.13

Table 23: Spare part specific parameters for the baseline example in Chapter 5

From the view of decision variable, there are 666 decision variables in the baseline example. Each decision variable is assumed to take value in a discrete value set, which is described as follows,

	Description	Number of Decision Variables	Value set for decision variable
$x_{j,k}$	PM triggering usage level	126	A discrete real-number set: $\{15,20,25,\ldots,120\}$
$y_{i,h}$	Spare part inventory level	45	A discrete integer set: $\{-1,0,1,2,\ldots,20\}$
$z_{i,h}$	Replenish batch size	45	A discrete integer set: $\{1,2,3,4,5\}$
u_i	Maintenance center construction indicator	9	A binary set: {0, 1}
$v_{i,j}$	Facility-asset connection indicator	441	A binary set: {0, 1}

Table 24: Value sets for the decision variables in Chapter 5

In Table 25, a complete list of parameters for the GA based metaheuristic, as well as relevant computational times of the algorithm for the baselines system are given. The algorithm is implemented in Java, on a PC (Intel Core i5-3570 CPU, 16 GB RAM, 64-bit Window 7).

	Description	Value
General parameters	Time horizon, T	3650 time units
	Replication number	40
Parameters for GA	Population size	50
	Crossover rate	0.6
	Mutation rate	0.02
	GA runs	5
Stop criteria	Maximum iteration number	3000
	Maximum unchanged iteration	200
Computational time of baseline system	Evaluation of each GA iteration	42 seconds
	Entire algorithm for 5 GA runs	132 hours

Table 25: The algorithm-related parameters and computation cost for the baseline system in Chapter 5

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