THESIS - TI185401

JOINT OPTIMIZATION MODEL OF SPARE PARTS INVENTORY AND PLANNED MAINTENANCE UNDER UNCERTAIN FAILURES

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MODEL OPTIMASI GABUNGAN PADA MANAJEMEN PERSEDIAAN SUKU CADANG DAN PERENCANAAN PERAWATAN DENGAN MEMPERTIMBANGKAN KETIDAKPASTIAN KEGAGALAN

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JOINT OPTIMIZATION MODEL OF SPARE PARTS INVENTORY AND PLANNED MAINTENANCE UNDER UNCERTAIN FAILURES

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ABSTRACT

Spare parts are often considered as Class C items, because of their low cost and low demand among the stocked items, but the availability of spare parts is essential to support maintenance requirements. Optimizing inventory parameters is the main problem of spare parts management to maintain a small number of SKUs kept in a store, and optimization techniques are commonly used to balance inventory cost and spare parts availability. Thus, this research proposes a joint optimization model of single-item multi-period spare parts inventory management and planned maintenance under uncertain failures. We present a Mixed Integer Nonlinear Programming (MINLP) formulation of the inventory optimization model under (s, S) policy with T periods of the order interval. Second, we combine this formulation with the predictive maintenance interval, representing the uncertain failures under predefined distribution. Since the model is nonlinear and stochastic, it is difficult to use exact methods to tackle it. Therefore, we combine the previously introduced MINLP formulation with a metaheuristic approach to solve the problem. Lastly, we perform a computational study on some instances and a real case study to demonstrate the proposed approach's effectiveness and efficiency. Based on the numerical experiment results, the proposed GA performs efficiently in large scale problem and the total cost of the real case study decreased by 17.9% compared to the current policy.

Keywords: Inventory management, metaheuristics, stochastic programming

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MODEL OPTIMASI GABUNGAN PADA MANAJEMEN PERSEDIAAN SUKU CADANG DAN PERENCANAAN PERAWATAN DENGAN MEMPERTIMBANGKAN KETIDAKPASTIAN KEGAGALAN

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ABSTRAK

Suku cadang pada umumnya termasuk dalam kelompok barang kelas C, hal ini disebabkan karena biaya dan permintaan yang rendah dibandingkan dengan barang-barang lainnya. Tetapi, ketersediaan suku cadang sangat penting untuk mendukung perawatan. Salah satu masalah utama dalam manajemen persediaan suku cadang adalah meminimalkan jumlah barang yang tersimpan dalam gudang dengan mengoptimalkan parameter persediaan. Teknik optimasi pada umumnya digunakan untuk menyeimbangkan biaya persediaan dan ketersediaan suku cadang. Penelitian ini mengusulkan model optimasi gabungan dari manajemen persediaan suku cadang multi-periode multi-item dan perencanaan perawatan dengan mempertimbangkan ketidakpastian kegagalan. Pertama, model *Mixed Integer Nonlinear Programing* (MINLP) persediaan suku cadang diformulasikan dengan kebijakan (s, S) dengan tinjauan berkala setiap T periode. Kedua, model persediaan suku cadang ini kemudian digabungkan dengan model perencanaan pemeliharaan berkala. Ketidakpastian kegagalan dimodelkan berdasarkan distribusi probabilitas normal. Pendekatan optimasi eksak akan membutuhkan waktu komputasi yang lama untuk menyelesaikan model gabungan ini dalam skala besar. Sehingga, pendekatan metaheuristik dengan *Genetic Algorithm* (GA) dikembangkan untuk menyelesaikan permasalahan ini dalam skala besar. Ketiga, analisis komputasi dilakukan pada beberapa contoh dan studi kasus untuk mengevaluasi efektivitas dan efisiensi pendekatan GA yang diusulkan. Berdasarkan hasil simulasi, GA dapat menyelesaikan permasalahan berskala besar. Total biaya pada contoh studi kasus dapat menurun hingga 17,9% dibandingkan dengan kebijakan awal.

Kata kunci: Manajemen persediaan, meta-heuristik, pemrograman stokhastik

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“Which, then, of your Lord’s blessings do you both deny?” (QS. 55)
“For indeed, with hardship [will be] ease.” (QS. 94:5)

Praise to Allah SWT Almighty God for His grace, *taufiq*, and *hidayah*, the writing of the final project carried out by the author with the title "Joint Optimization Model of Spare Parts Inventory and Planned Maintenance under Uncertain Failures" can be completed on time and running smoothly. During the implementation and writing of this final project report, I have received a lot of help, direction, and support from relevant parties. Therefore, on this occasion, I want to express my blessings that have been given in order to complete this thesis project research, to my parents, Mrs. Rachmawati and Mr. Wahyu Dewanto, and my siblings, Sarah Ahya Kahirunnisa and Javier Firaz Darwisy provided support, motivation, and all prayers for the smooth process of my college life. As the chief of the NTUST Industrial Management Department and my advisor, Professor Vincent F. Yu, allows me to be a part of Global Logistics and Supply Chain Management laboratory, who has guided with great patience, support, assistance, and advice during the completion of this thesis. As my co-advisor and my lecturer during the inventory and stochastic course, Professor Po-Hsun Kuo shared new knowledge and insights about the inventory and stochastic course. Mr. Nurhadi Siswanto, Ph.D., as the Head of the ITS Industrial Engineering Department and my supervisor, who has given me a lot of advice and supports during the completion of this thesis. Prof. Iwan Vanany, as the coordinator of the graduate study program of Industrial and System Engineering Department of ITS. And also Ms. Rahayu, as the graduate study academic, who have helped me to complete the graduation administration. The committee members, Prof. Vincent F. Yu, Prof. Po-Hsun Kuo, and Prof. Cheng-Hung Wu from National Taiwan University, have provided advice and recommendations that can significantly improve my research. My colleagues from ITS, the lab members, and all of my friends who have shared their most excellent company and supports in this whole year in Taipei. Thank you for all the support.

Surabaya, August 2020
Nabila Yuraisyah Salsabila

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CHAPTER 1
INTRODUCTION

Chapter 1 contains the description of the thesis background, problem formulation, thesis objectives, scopes and assumptions, and also the thesis organization.

1.1 Background

Indonesia is currently targeting the industrial sector as the primary driver of national economic development. Several developed countries are currently competing on economic growth. The economic growth in developing Asian countries is projected to 5.6% in 2020 (Asian Development Bank, 2019). Furthermore, Indonesia's economic growth is projected to remain above 5% in 2020 (OECD, 2018). This economic growth will lead to high demand for various products in Indonesia. Several actions have been made to support these demands, including importing various products. In 2019, the total import value in Indonesia reached a value of 156 Billion in US $. This value is very high compared to Indonesia's export value, which amounts to 153 Billion in US $ (Indonesian Central Bureau of Statistics, 2019). Indonesia can reduce the dependence on these import activities by increasing the industries' capability to meet domestic demands (Salsabila et al., 2019). Increasing the capacity and developing the technology of the manufacturing system can be done to increase production performances. Equipment availability becomes essential to support the development of manufacturing technologies.

Spare parts inventories exist for serving the need for the maintenance and replacement of operating plant items (Wang, 2012). Spare parts are often considered the class C item since they contribute to low demand and cost, among other stock items. However, the unavailability of the spare parts will lead to unsatisfied production performances, which will affect the financial performances, especially for the high manufacturing technologies. According to Gallagher et al. (2005) in Hu et al. (2018), machinery which might have a useful life up to 30 years, annually consumes spare parts amounting to as much as 2.5 percent of the purchase price. Many researchers are interested in studying this research area in the past few decades. The spare parts inventory management has different characteristics compared to other stock items. Kennedy et al. (2002) in Wang (2012) mentioned two main differences between spare parts inventory management and other manufacturing inventories, such as work-in-process and finished products, namely the functionality and the policy for managing the inventory. Spare parts demands are hard to forecast because most of the demand has irregular patterns. Equipment could require a significant value of spare parts at a time, but no spare parts are needed for a sequence of periods afterward.

Furthermore, most plants consist of a large variety and number of spare parts that are hard to manage. The most critical characteristic is the unavailable spare parts can extend the machine downtime. On the other hand, maintaining unnecessary spare parts leads to high holding costs and obsolescence risks. However, although the spare parts management differs from other stock items, the critical question is still the same, namely deciding the optimal stocking level of the spare parts (Wang, 2012).

Four standard stocking policies are commonly used in spare parts management:

1. (Q, R) inventory policy: continuous review, with fixed reorder point (r) and fixed order quantity (Q)
2. (s, S) inventory policy: continuous review, with fixed reorder point (s) and order-up-to level (S)
3. (T, R) inventory policy: periodic review, with fixed review interval (T) and order-up-to-level (R)
4. (S-1, S) inventory policy: continuous review, with order-up-to-level (S) in one-for-one replenishment mode.

Combining several standard stocking policies is also possible to increase the parameter performances. Scarf (1960) has proven the optimality of (T, s, S) policy, which gave the minimum total cost than the other systems under general assumptions of demand and cost factors. The (T, s, S) is a combination of periodic review control policy with fixed reorder point (*s*) and order-up-to level (*S*). . Furthermore, this policy is commonly implemented in practice.

Inventory replenishment based on forecasting under (*T*, *R*) and (*S*, *S*) policy has been done before by Syntetos and Boylan (2006) and Zhou and Viswanathan (2011). Syntetos and Boylan (2006) assessed the empirical stock control performance of intermittent demand estimation procedures under periodic order-up-to-level (*T*, *R*) policy. Zhou and Viswanathan (2011) addressed forecasting and managing the inventory of service parts where the demand patterns are highly intermittent under (*s*, *S*) policy. Based on these studies, they suggested that the order-up-to level's decision by taking into account that the demand for that period triggers the order in a period.

Many optimization problems assume that the demands and parameters are already known. However, in reality, the machine utilization to meet the production parameters causes the failures' uncertainty. The uncertain failures will result in the variability of the spare parts requirements. Thus, the allocation of spare parts more complicated. Several studies have been done to solve the uncertain behavior of spare parts requirements. Simulation studies are standard techniques to tackle the uncertain behavior of the spare parts requirements (Lee et al., 2008; Marseguerra et al., 2005; Salsabila and Siswanto, 2019). Lee et al. (2008) developed a multi-objective simulation-optimization framework. In this study, they integrated simulation, multi-objective evolutionary algorithms, and multi-objective computing budget allocation methods. Marseguerra et al., (2005) proposed an approach to the multi-objective optimization of the spare part allocation by combining the Genetic Algorithm and Monte Carlo simulation. A discrete event simulation study was done by Salsabila and Siswanto (2019) to model the equipment' configuration of a manufacturing system. They model each equipment's failure, which triggered the spare parts requirements. Other than the simulation study, other modeling techniques also have been done in several studies (Wen et al., 2017; Xiang et al., 2018). Wen et al. (2017), instead of utilizing the probability theory that requires massive historical data, proposed a new method to measure uncertainty based on the belief degree of decision-makers. They also utilized a Genetic Algorithm procedure to search for the optimal solution. In Xiang et al. (2018), they present a mixed-integer nonlinear programming (MINLP) formulation for determining near-optimal (*s*, *S*) policy parameters. To tackle more significant instances, they combine the previously introduced MINLP formulation with a Binary Search approach. They also linearized these models into mixed-integer linear programming (MILP) by utilizing a piecewise function.

Preventive maintenance is commonly implemented in some companies to maintain their equipment. Scheduling the regular interval period for preventive maintenance is practically universal in some companies. A longer interval will result in more spare parts during failures. On the other hand, a shorter interval will require more spare parts during PM. Thus, the spare parts inventory management and maintenance schedule should be managed jointly (Wang, 2012). Joint spare parts inventory management and maintenance optimization model have been done in several studies (Bousdekis et al., 2017; Olde Keizer et al., 2017; Wang, 2012). Bousdekis et al. (2017) proposed a proactive event-driven decision model for joint predictive maintenance and spare parts inventory optimization, which can be embedded in an Event-Driven Architecture (EDA) for real-time processing in the frame of e-maintenance concept. In Wang (2012), joint optimization of the spare parts and PM was done by utilizing the stochastic dynamic programming model. This model follows a periodic review inventory policy with the demand generated based on the spare parts requirement due to maintenance. Furthermore, the preventive maintenance schedule was determined based on the optimal multiplication of the review interval.

In this research, we develop a joint optimization model of spare parts inventory management and preventive maintenance under uncertain failures. The joint optimization model consists of MINLP formulation of spare parts optimization under periodic review of *s*, *S* policy and periodic preventive maintenance, which to the best to our knowledge has never been done before in the previous studies. Furthermore, we also consider the uncertainty of the failures that will cause the variability of the spare parts requirements. The Monte Carlo simulation provides a flexible simulation that can be implemented for many realistic issues (Marseguerra et al., 2005). We perform a Monte Carlo simulation to generate the random spare parts requirements under a predetermined probability distribution. Therefore, based on this random number generation, we determine the periodic s, S parameters. Furthermore, we determine the periodic preventive maintenance based on the multiplication of the periodic review.

This problem's objective is to minimize the total relevant cost, which consists of fixed ordering cost, purchasing cost, holding cost, penalty cost, and maintenance cost. The fixed ordering cost is incurred when there is an order issued. The purchasing cost incurs based on the variable unit cost of the spare parts requirements. The holding cost is the variable cost of the stocking cost. The penalty cost is incurred when there are no spare parts available during the downtime machine.

Furthermore, we breakdown the maintenance cost into two costs, namely corrective maintenance cost and preventive maintenance cost. The corrective maintenance is incurred when the failure occurs during the preventive maintenance interval. On the other side, the preventive maintenance cost incurs when preventive maintenance is performed. Both preventive maintenance and corrective maintenance are mutually exclusive since they cannot be conducted at the same time.

This study proposes the Genetic Algorithm (GA) to be implemented in the real problem. The implementation of GA of spare parts inventory management has been done by Marseguerra et al. (2005) and Wen et al. (2017). Marseguerra et al. (2005) utilized GA to determine the optimal spare parts allocation concerning different objectives. Wen et al. (2017) implemented GA to solve nonlinear discrete programming models. GA is a search heuristic that can efficiently reach global optimal and can flexibly adjust its search direction without determining rules (Wen et al., 2017). GA is numerical search tools which operate according to procedures that resemble the principles of natural selection and genetics (Marseguerra et al., 2005). The procedure of searching optimal stock levels of spare parts is implemented by the representation of the initial population, fitness evaluation, genetic operation (selection, crossover, and mutation) (Wen et al., 2017).

We present numerical analysis to some instances and a real case problem of the chemical process industry in Gresik, Indonesia. This chemical process industry is currently working on 70,000 Ton of production capacity. However, the equipment breakdown causes a decreasing availability to 88%, and the manufacturing system cannot perform effectively. Furthermore, 40% of the production shutdown causes are related to the machine breakdown. Therefore, optimizing the spare parts inventory management and planned maintenance is essential to minimize the shutdown risks.

This study provides theoretical and practical contributions. The theoretical contribution is developing a new joint optimization model of spare parts inventory and planned maintenance under uncertain failures. Based on this case, we consider periodic s, S inventory policy, which has never been done in the previous research. We also implement this proposed model to some instances and a real case problem to evaluate the performance.

1.2 Problem Formulation

This study focuses on developing a new joint optimization model of spare parts inventory management and planned maintenance under uncertain failures. This study also presents a numerical analysis to demonstrate this model to some instances and a real case study on a chemical process plant in Gresik, Indonesia.

1.3 Research Objectives

The research objectives are listed as follows:

1. Develop a new joint optimization model of spare parts inventory management and planned maintenance under uncertain failures with periodic *s, S* policy.
2. Propose a Genetic Algorithm to solve the optimum policy parameters.
3. Implement the proposed model to solve the real case study on a chemical process plant in Gresik, Indonesia.

1.4 Research Scopes and Assumptions

Scopes and assumptions of this research follow:

1. The demand is generated based on the normal distribution with the given average as the expected value.

2. The replacement is done when failed items occur, and preventive maintenance takes place.
3. If there is no stock available, the items are backordered, and very high penalty costs occur.
4. The delay-time of the replacement process is neglected.
5. The proposed model only considers the inventory and maintenance system.

1.5 Thesis Organization

This thesis is divided into seven chapters. Chapter 1 is the introduction section, which presents the background and the objective of this research. Chapter 2 is the literature review that presents the related studies and the overview of the terminologies related to our research. Chapter 3 describes the problem and the developed mathematical model. Chapter 4 describes the solution methodology, which consists of the solution representation and the explanation of the proposed algorithm operations. Chapter 5 presents the computational analysis, which evaluates the computing performance and implementation of the real case study. Chapter 6 summarizes this thesis and suggestion for future research.

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CHAPTER 2
LITERATURE REVIEW

Chapter 2 contains the literature review which is related to this research. In this chapter, we describe some theoretical review, which are consist of spare parts inventory management, planned maintenance, spare parts inventory management under uncertainty, and some solution methods that have been done in the previous research. Other related previous studies also reviewed in this chapter.

2.1 Spare Parts Inventory Management

Spare parts inventories are used to serve the maintenance requirements of operating plant items (Wang, 2012). The spare parts inventory management has the different characteristics of inventory management, aiming to achieve the desired equipment availability at a minimum cost. The following are the particular characteristics of the spare part inventory management (Hu et al., 2018):

1. The spare parts' demand is commonly intermittent. Therefore, the spare parts demand is complicated to forecast.
2. The spare parts are usually hard to manage because of the large number and various types. Thus, it is hard to determine the parameters of each spare part.
3. It is important to minimize stocks, with only a small quantity per Stock Keeping Unit (SKU) to reduce the risk of spare parts' obsolescence.
4. The consumption of the spare parts is closely related to maintenance. A spare part is needed when the corresponding part of the equipment fails, damaged, or wears out. The dependences of equipment usage become a critical decision to support the whole production system.

Although the spare parts inventory management has different characteristics from other stock items, the critical decision variable is the same, deciding the optimal stocking level of the spare parts (Wang, 2012). Special characteristics of spare parts management challenge many researchers to tackle this problem. Operational Research (OR) models and many solutions methods have been proposed in the past decades. Hu et al. (2018) have created a framework for OR in spare parts management in academic researches.

Figure 2.1 describes the OR spare parts management framework, which consists of three layers: i) objectives of spare parts management, ii) main tasks based on the equipment life-cycle phase, iii) OR disciplines for supporting spare parts management. The critical question of the spare parts management is deciding which items to be stocked, when, and how many items to (re)order. The objectives mostly consist of minimizing downtime by maximizing spare parts' availability and minimizing economic costs. The economic costs are the total of holding cost, stock-out penalty cost, and the ordering cost. The second layer describes the spare parts management's main tasks at each phase of the equipment life-cycle. Hu et al. (2018) categorize the equipment life-cycle into four phases: i) phase 0: pre-life phase, ii) phase 1: initial procurement, iii) phase 2: normal operation, and iv) phase 3: end-of-life. The third layer describes many techniques to facilitate the spare parts management. Hu et al. (2018) classify four main technical approaches of OR, namely multi-criteria classification, forecasting, optimization, and simulation.

The optimization techniques are considered to be challenging in inventory management since it has been used by many researchers to achieve high system availability with minimal inventory. Hu et al. (2018) divided the relevant contributions into three groups: i) optimization of the system parameters, ii) optimization of the replenishment quantities, and iii) end-of-life orders and reuse supply chain design.

The optimization of the system parameters is related to the first phase of the spare part management. In this phase, the managers will have two main choices: to stock the initial spare parts or place an order when demand occurs. After optimizing the system parameters, then the next main task is to optimize the replenishment quantities. There are four standard stocking policies commonly used in spare parts management (Hu et al., 2018):

1. (Q, R) inventory policy: continuous review, with fixed reorder point (r) and fixed order quantity (Q);
2. (s, S) inventory policy: continuous review, with fixed reorder point (s) and order-up-to level (S);

3. (*T*, *R*) inventory policy: periodic review, with fixed review interval (*T*) and order-up-to-level (*R*); and
4. (*S-1*, *S*) inventory policy: continuous review, with order-up-to-level (*S*) in one-for-one replenishment mode.

Combining several standard stocking policies is also possible to increase the optimization performances. Scarf (1960) has proven the optimality of (*T*, *s*, *S*) policy which gave the minimum total cost than the other systems under general assumptions of demand and cost factors. The (*T*, *s*, *S*) is a periodic review control policy with fixed re-order point (*s*) and order-up-to level (*S*).

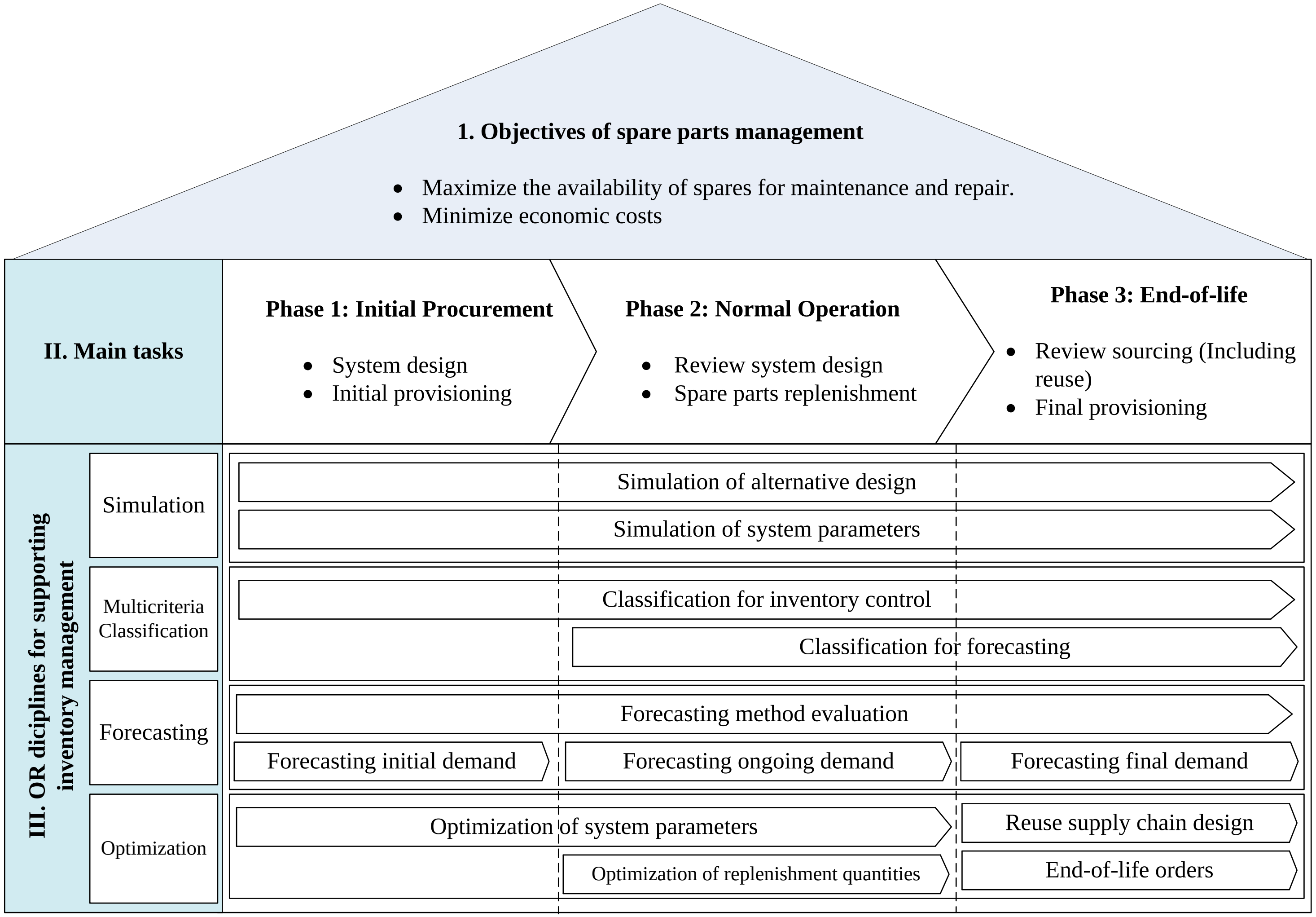

Figure 2.1 Framework for OR in spare parts management (Hu et al., 2018)

2.2 Planned Maintenance

There are several types of maintenance policies have been implemented in practice and extensively studied, namely corrective, periodic, age-based, and condition-based maintenance.

1. Corrective maintenance is a maintenance action that is done when the machine breakdown. Sometimes this maintenance action requires equipment replacement. In practice, this maintenance action could be more expensive than preventive maintenance because an equipment failure can damage other equipment (Olde Keizer et al., 2017).
2. Periodic maintenance is preventive maintenance (PM) at a regular interval. This maintenance policy is commonly implemented in practice. The lumpy demand for the spare parts is usually the result of the periodic maintenance actions because several defective but still working parts may be identified and replaced at PM. Thus, the interdependency between the PM interval and spare parts inventory could occur (Wang, 2012). A periodic maintenance policy is determined by an optimal scheduling plan for servicing a set of machines over a planning horizon while minimizing the total costs (Mjirda et al., 2016).
3. Age-based maintenance is a maintenance policy that considers the degradation phenomena. If the degradation level of a component reaches a given critical size, it is replaced by a new one, and other components undergo a PM action. Degradation failure can result in substantial costs of repair or replacement. Furthermore, significant losses of production and catastrophic safety hazards also can be happened. An age-based preventive maintenance policy is implemented to maintain machine reliability (Shafiee and Finkelstein, 2015).
4. Condition-based maintenance is the maintenance action that is based on the actual system state (Olde Keizer et al., 2017). This maintenance policy is also known as a just-in-time maintenance policy since it’s done at the appropriate time based on information based on inspection and monitoring (Zhang and Zeng, 2017).

Figure 2.2 illustrates the relationship between the number of failures and the PM interval (Wang, 2012). Defective item's arrival is represented by ○ and failure is represented by ●. An arc linking ○ and ● represents the delay-time. An arc linking ○ and * represents the censored delay-time due to preventive replacement. Four defective items are preventively replaced, and seven potential failures reduced into three due to PM inspections. If the PM interval is shortened by half of the current interval, then one more defective item could be identified and replaced. Thus, the PM interval influences the number of failures, and if no inspection is performed, all seven defective items will lead to failures.

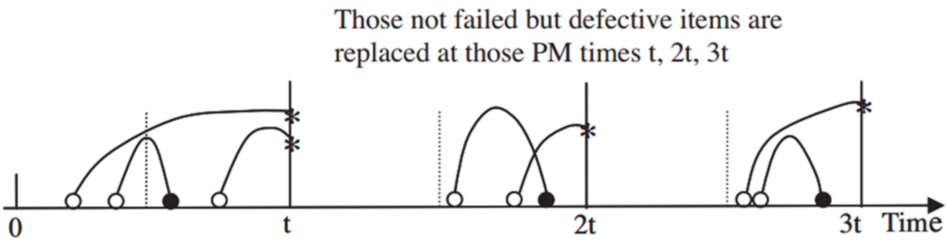

Figure 2.2 The process of defective and failed items (Wang, 2012)

2.3 Spare Parts Inventory Management under Uncertainty

Many spare parts inventory management studies have implemented several techniques to cope with uncertain failures. Robust dynamic programming was implemented by Qiu et al. (2017). They used two types of uncertainty sets, i.e., box and ellipsoid, to model demand distribution uncertainty. This method is useful when the assumption of the distribution function is unknown and nonstationary. Based on the result of their numerical study, the (s, S) policy is different from the optimal policy when the actual distribution is known. The objective values of the optimal (s, S) are higher than when the actual distribution is known. However, the solution found is close to the actual optimal solution. This solution implies that the proposed models are robust, and the corresponding solution approaches are powerful for solving inventory management problems.

Another technique was developed by Wen et al. (2017). They focused on developing an uncertainty theory-based method to model the demand uncertainty with a lack of statistical data. They used the uncertainty theory to describe the belief degree of decision-makers, which presents the likelihood that an uncertain event happens. The availability and effectiveness of these models were proven through the numerical example. However, the optimality and the computational time of the solution were not further analyzed.

These two studies are effective in solving the lack of knowledge of the demand distribution problem. Thus, the solution is hardly reaching the optimal solution. However, these techniques are unnecessary to be implemented if the demand distribution has already given, and the historic data were provided. Other methods such as Markov Decision Process, Stochastic dynamic programming, and simulation techniques relax the assumption of unknown distribution probability and lack of historical data.

An exact method for a multi-component system by formulating the problem as Markov Decision Process was firstly implemented by Olde Keizer et al. (2017). The state space is used to keep track of the state of each component, the status of each order, and the number of spares on hand. The transition probabilities summarize the probabilities of the component state changes based on the replacement decision. Each probability was generated based on Poisson distribution. Based on the numerical analysis, the main results are robust for a variety of parameter settings.

Other than Markov Decision Process, Stochastic dynamic programming also implemented by Wang (2012) to deal with uncertain failures. They provide a probability tree showing all scenarios of the possible numbers of replacements over an order interval. Furthermore, this probability tree results in an expected value, which will be further analyzed through the dynamic programming model. An enumeration procedure was also provided to find the optimal parameter of order interval and planned maintenance interval. Based on the numerical analysis, an optimal joint solution was found. However, the dimensionality could be a problem if the arrival of defective items is large, which will substantially increase the computational time, mainly if the enumeration is also used to determine other decision variables. In the numerical example presented, it requires about 20 minutes to find the optimal solution.

The common method to solve a stochastic problem is simulation modeling. There were various kinds of simulation techniques done by previous researches (Marseguerra et al., 2005; Salsabila and Siswanto, 2019). Salsabila and Siswanto (2019) utilized the Discrete Event Simulation (DES) to determine the spare parts inventory parameter by considering the equipment failures. DES is commonly utilized to model the stochastic queue system. However, it is hard to combine DES with other optimization techniques. This method mostly involves an experimental design to find a better solution. Therefore, the solution provided by the DES technique is hardly reaching the optimal solution.

Marseguerra et al. (2005) firstly developed the Monte Carlo simulation with a Genetic Algorithm to optimize the order quantity by a multi-component system. The modeling of the system repair, failure, and stochastic replacement processes is done by Monte Carlo simulation, which they claimed it could achieve more realistic system modeling. The Monte Carlo provides a flexible simulation tool capable of evaluating all the fitness of interest while accounting for many practical issues (Marseguerra et al., 2005). Three probability density functions (PDFs) were involved in this research: the failure time distribution of the component, the replacement time distribution, and the recycling time distribution. In this research, they assume that the repair facility starts the repair process as soon as it receives the failed component, which means the repair queues are not modeled.

Based on the above literature review, the most suitable method to model the uncertain failure in our case is the Monte Carlo Simulation. This method is flexible, which can be combined with other optimization techniques but still can achieve realistic system modeling. Furthermore, the queue system is not necessarily modeled in this case. Thus, we can assume that all the equipment can be repaired as soon as the components available.

2.4 Solution Method

Various solution methods to solve *s*, *S* inventory policy was presented in the previous researches. An exact evaluation was done by Topan et al. (2017). They develop a hybrid approach based on applying *Lagrangian* decomposition and column generation to obtain a lower bound and then using a two-step greedy algorithm to generate feasible policy parameters from that lower bound. Based on the numerical studies, the solution generated is asymptotically optimal in the number of parts. In line with this finding, the lower bound obtained by the *Lagrangian* decomposition and column generation method is asymptotically tight. This result means that their solution method can solve with large numbers of items optimally.

Two approaches were presented by Xiang et al. (2018). First, they introduce an MINLP and solve it by the Binary Search algorithm. Furthermore, they linearized previously formulated MINLP to become a MILP model by piecewise function. The off-shelf software can solve the advantage of this linearized MILP model. Based on their computational experiments, the linearized MILP can provide shorter computational time than the Binary Search algorithm approach. However, this approach cannot solve a larger size problem. Furthermore, the smaller optimality gap was provided by the Binary Search approach.

Some researchers have implemented the genetic algorithm to solve spare parts inventory management (Marseguerra et al., 2005; Wen et al., 2017). GA is numerical search tools which operate according to procedures that resemble the principles of natural selection and genetics (Marseguerra et al., 2005). The procedure of searching optimal stock levels of spare parts is implemented by the representation of the initial population, fitness evaluation, genetic operation (selection, crossover, and mutation) (Wen et al., 2017). The advantage of GA is the global optimization, and it can flexibly adjust its search direction. In this research, we develop an MINLP model that is solved by the GA approach, which can provide efficient nonlinear and discrete problem solutions.

According to Wen et al. (2017), the GA procedure can be illustrated as follows:

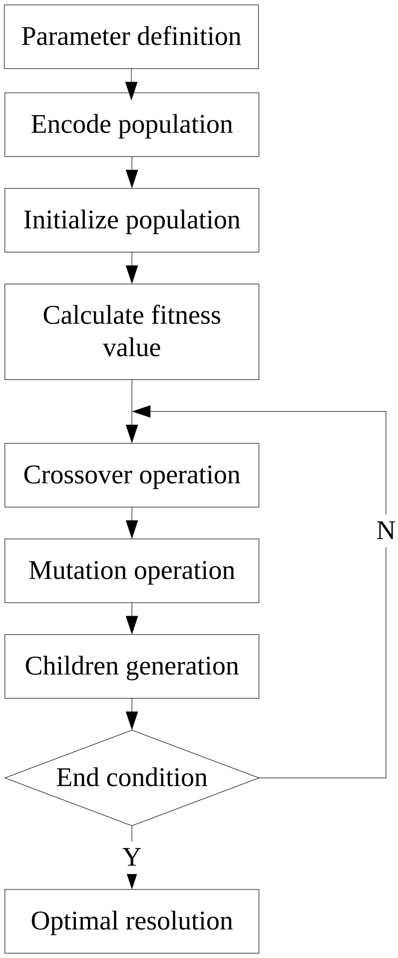

Figure 2.3 GA Procedures (Wen et al., 2017)

GA procedure starts with defining the parameters, Such as the population size of each chromosome, the crossover probability, and the mutation probability. An initial population can be generated through a random seed approach. The fitness calculation is done by calculating the objective function of the initial population. The crossover operation is rearranging the chromosomes of each population according to their fitness from big to small, and the first chromosome passes on directly to the next generation. Other chromosomes are selected from generation based on spinning roulette wheel characterized by fitness for population size times. Each time a single chromosome is selected. The parents are selected based on the crossover probability. Before accepting the selected parents, the feasibility must be evaluated. If both children are feasible, the children replace their parents. Otherwise, the existing feasible solution must be kept. The crossover operation is repeated until two feasible children are obtained. The mutation operation is based on the probability of mutation. The mutation result can be selected if it is feasible. A new approach is proposed Santosa and Ai (2017), which is elitism operation. This operation aims to maintain the best solution in each generation.

Table 2.1 The Summary of Literature Review on the Related Researches

No	Title	Authors	Year	Journal Name	Consideration: Spare Parts Inventory Management	Consideration: Maintenance Policy	Consideration: Stochastic/ Deterministic	Consideration: Inventory Control Policy	Solving Algorithm
1	Optimizing (*s*, *S*) policies for multi-period inventory models with demand distribution uncertainty: Robust dynamic programming approaches	Ruozhen Qiu, Minghe Sun, Yun Fong Lim	2017	European Journal of Operational Research	-	-	Stochastic	(*T*, *s*, *S*)	Robust dynamic programming
2	Computing non-stationary (*s*, *S*) policies using mixed integer linear programming	Mengyuan Xiang, Roberto Rossi, Belen Martin-Barragan, *S*. Armagan Tarim	2018	European Journal of Operational Research	-	-	Stochastic	(*s*, *S*)	Mixed integer linear programming & Binary Search Algorithm
3	Multiobjective spare part allocation by means of Genetic Algorithms and Monte Carlo simulation	Marzio Marseguerra, Enrico Zio, Luca Podofillini	2005	Reliability Engineering and System Safety	✓	-	Stochastic	(*S*-1, *S*)	Genetic Algorithm & Monte Carlo simulation

No	Title	Authors	Year	Journal Name	Consideration				Solving Algorithm
					Spare Parts Inventory Management	Maintenance Policy	Stochastic/ Deterministic	Inventory Control Policy	
4	Multi-objective simulation-based evolutionary algorithm for an aircraft spare parts allocation problem	Loo Hay Lee, Ek Peng Chew, Suyan Teng, Yankai Chen	2008	European Journal of Operational Research	✓	-	Stochastic	(*Q*, *R*)	Simulation-based evolutionary algorithm
5	Comparison of a new bootstrapping method with parameteric approaches for safety stock determination in service parts inventory systems	Chenxi Zhou, *S.* Viswanathan	2011	International Journal of Production Economics	✓	-	Intermittent Demand	(*s*, *S*)	Bootstrapping Forecasting Method
6	Uncertain Optimization Model for Multi-echelon spare parts supply system	Meilin Wen, Qiao Han, Yi Yang, Rui Kang	2017	Applied Soft Computing	✓	-	Stochastic	(*S*-1, *S*)	Uncertainty Theory, Genetic Algorithm
7	Heuristics for multi-item two-echelon spare parts inventory	Engin Topan, Z. Pelin Bayindir, Tarkan Tan	2017	European Journal of Operational Research	✓	-	Deterministic	(*Q*, *R*) and (*S*-1, *S*)	*Lagrangian* heuristics, two-step greedy

No	Title	Authors	Year	Journal Name	Consideration				Solving Algorithm
					Spare Parts Inventory Management	Maintenance Policy	Stochastic/ Deterministic	Inventory Control Policy	
	control subject to aggregate & individual service measure								algorithm, sequential heuristics
8	An Inventory Location Modeling Structure for Spare parts Supply Chain Network	Tapia-Ubeda, Fransisco J., Miranda Pablo A., Roda Irene, Macchi Marco, Durán Orlando	2018	IFAC PapersOnLine	✓	-	Deterministic	Provided all inventory policy model	Exact Optimization
9	A Simulation study of availability analysis on a chemical process industry considering spare part inventory	Nabila Yuraisyah Salsabila & Nurhadi Siswanto	2019	IOP Conference Series: Materials Science and Engineering	✓	-	Stochastic	(s, S)	Discrete Event Simulation
10	A stochastic model for joint spare parts inventory and planned maintenance optimisation	Wenbin Wang	2012	European Journal of Operational Research	✓	✓	Stochastic	(T, R)	Stochastic Dynamic Programming

No	Title	Authors	Year	Journal Name	Consideration				Solving Algorithm
					Spare Parts Inventory Management	Maintenance Policy	Stochastic/ Deterministic	Inventory Control Policy	
11	On the joint optimization of the periodic preventive maintenance and the spare parts inventory problem	Anis Mjirda, Rachid Benmansour, Hamid Allaoui, Gilles Goncalves	2016	IFAC PapersOnLine	✓	✓	Deterministic	(*Q*, *R*)	Mixed Integer Programming
12	Joint optimization of condition-based opportunistic maintenance and spare parts provisioning policy in multiunit systems	Xiaohong Zhang, Jianchao Zeng	2017	European Journal of Operational Research	✓	✓	Deterministic	(*Q*, *R*)	Deterioration state-space partitioning
13	A proactive event-driven decision model for joint equipment predictive maintenance anc spare parts inventory optimization	Alexandros Bousdekis, Nikos Papageorgiou, Babis Magoutas, Dimitris Apostolou, Gregoris Mentzas	2017	Proceedia CIRP	✓	✓	Deterministic & Probabilistic	(*S*-1, *S*)	Exact Optimization

No	Title	Authors	Year	Journal Name	Consideration				Solving Algorithm
					Spare Parts Inventory Management	Maintenance Policy	Stochastic/ Deterministic	Inventory Control Policy	
14	Joint condition-based maintenance and inventory optimization for systems with multiple components	Minou C.A. Olde Keizer, Ruud H. Teunter, Jasper Veldman	2017	European Journal of Operational Research	✓	✓	Probabilistics	(s, S)	Markov Decision Process
15	Stochastic Joint Optimization Model of Spare Parts Inventory and Planned Maintenance				✓	✓	Stochastic	(T, s, S)	Mixed integer non-linear programming with Genetic Algorithm

CHAPTER 3
RESEARCH METHODOLOGY AND MODEL DEVELOPMENT

The research methodology of this study is described as follows.

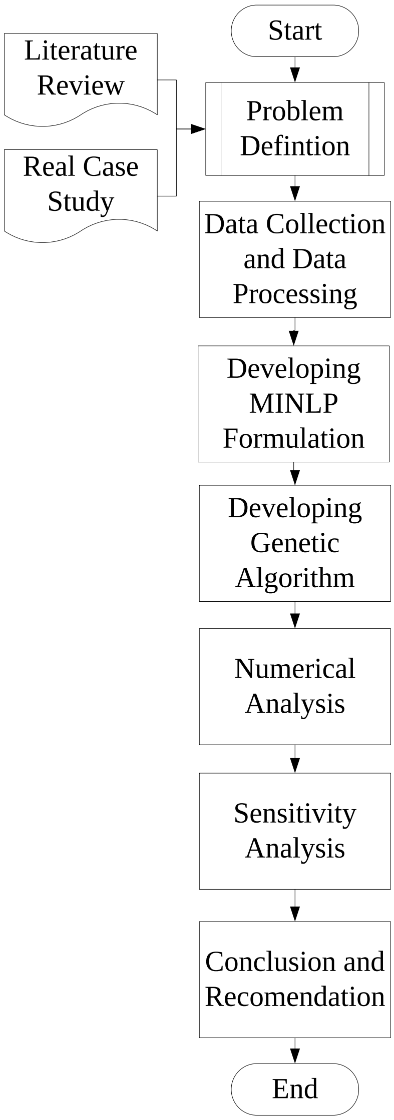

Figure 3.1 Research Methodology

The research is started with the problem definition. The problem is determined based on the literature review on the previous research and the real case study. The second stage is the data collection and data processing. The data are taken from the real case study and used as the input parameter in the numerical analysis. Next, we develop a Mixed-Integer Non-linear Programming formulation. We can develop this model by modifying the model in previous research. The next step is developing a Genetic Algorithm (GA) to be implemented to a large scale problem. In the numerical analysis, we test the MINLP model and GA to some instances and a real case study. In this stage, we evaluate the optimality and the computational efficiency of both approaches. Lastly, we provide a conclusion and recommendation, which also includes possible future research.

3.1 Problem Description

In this problem, we consider a significant key identical component in a petrochemical manufacturing system. In this system, components such as bearing and gasket with identical type and size significantly influence the cost. We assume the preventive maintenance (PM) is the inspection of the equipment. If during the inspection, a defective or failed component is found, a replacement takes place. In this problem, we do not consider repairing the defective component. Here we implement the regular PM policy, in which the inspection of each item takes place at a regular time interval, such as every three months or four months. Random failures may occur during the PM interval. If this failure occurs, corrective maintenance (CM) takes place.

A single warehouse stocks the components for replacing the failed and defective items. The review ordering of the spare parts is done periodically, which usually implemented in practice. An order will be issued if the inventory level is less than the reorder point (s). The amount of order will be the order-up-to level (S) minus the current inventory level. In this research, the uncertain variable is the spare parts requirement of each period. The Monte Carlo simulation generates the random spare parts requirement.

Figure 3.2 illustrates the inventory profile modified from Wang (2012). Unlike the previously described inventory profile, instead of implementing (Q, R) policy, we implement the periodic (s, S) policy. We assume that the PM interval is an integer multiple of the review interval, thus $t_m = kt_o$. The random number of failures from the ordering point to the next order arrival is represented by d, and the random number of items found faulty during PM inspection is represented by *dpm*. If the available spare parts are less than the requirements, the backorders (B_t) will be issued, which will be fulfilled in the next ordering period. Therefore, to avoid backorders at the current period, the previous inventory level (I_{t-1}) and the issued order quantity (Q_t) must fulfill the current failed items (d_t), the defective item (dpm_t) if there is a PM inspection, and the previously backordered items (B_{t-1}). Otherwise, the items will be backordered based on the number of failed items (d_t), the defective item (dpm_t) if there is a PM inspection, and the previously backordered items (B_{t-1}) which can not be satisfied by the the previous inventory level (I_{t-1}) and the issued order quantity (Q_t). Equation (1) and (2) is the formulation of inventory on hand and backordered items, where the order quantity is formualated as Equation (3).

$$I_t = Q_t + I_{t-1} - d_t - dpm_t - B_{t-1} \tag{1}$$

$$B_t = d_t + dpm_t + B_{t-1} - Q_t - I_{t-1} \tag{2}$$

where,

$$Q_t = S - I_{t-1} \tag{3}$$

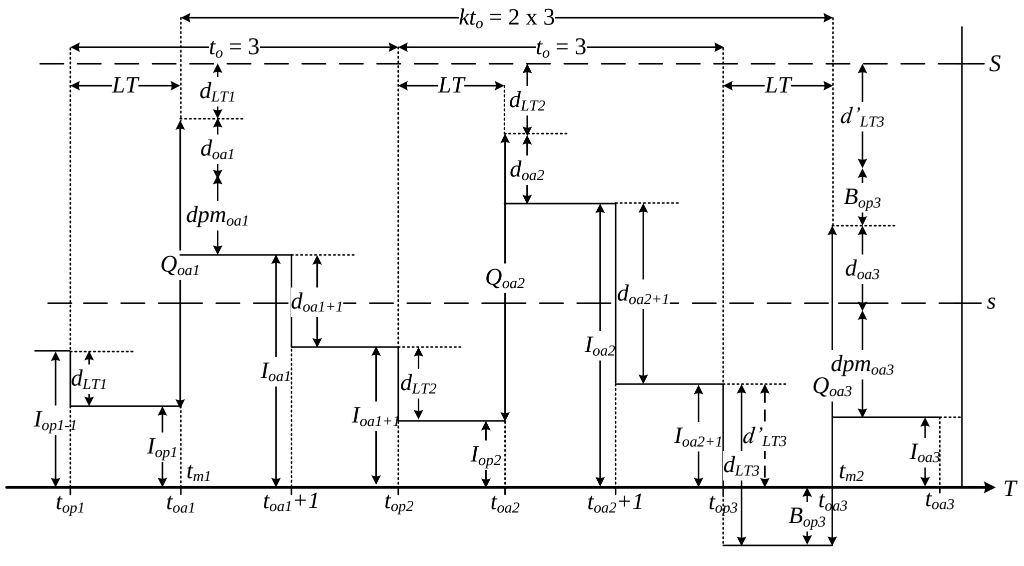

Figure 3.2 Spare Parts Inventory Profile if t_o = 3 and k = 2

where:

T	planning horizon
LT	ordering lead time
t_o	review interval
t_{opi}	the $i \in \frac{T}{t_o}$ ordering period, where $t_{opi} = t_{op1} + it_o$
t_{oai}	the $i \in \frac{T}{t_o}$ ordering arrival, where $t_{oai} = t_{op1} + LT$
kt_o	PM interval
t_{mj}	the $j \in \frac{T}{kt_o}$ preventive maintenance period, where $t_{mj} = t_{m1} + jkt_o$
Q_t	order quantity at period t
d_t	random number of failures at period t
d'_t	satisfied random number of failures at period t
dpm_t	random number of defective items at period t
I_t	inventory on hand at period t
B_t	backordered items at period t
S	order-up-to level
s	reorder point

According to Xiang et al., (2018), to model the stochastic behavior, the inventory and backorders will be estimated by utilizing the order loss function which is formulated as follows:

$$L(x, \omega) = E[\max(\omega - x, 0)] \tag{4}$$

where E denotes the expected value with respect to the random variable ω and scalar variable x. In our model, the spare parts requirements are the random variable and the order quantity, inventory, and the backordered items are the scalar variables. Therefore, if we want to model the non-linear holding and penalty units, the equations will be:

$$I_t = L(Q_t + I_{t-1} - B_{t-1}, d_t + dpm_t) \tag{5}$$

$$B_t = L(-Q_t - I_{t-1} + B_{t-1}, -(d_t + dpm_t)) \tag{6}$$

or

$$I_t = E[\max(Q_t + I_{t-1} - B_{t-1} - d_t - dpm_t 0)] \tag{7}$$

$$B_t = E[\max(B_{t-1} + d_t + dpm - Q_t - I_{t-1t} 0)] \tag{8}$$

Therefore, equation (7) and (8) can be formulated as follows:

$$E[Q_t + I_{t-1} - B_{t-1} - d_t - dpm_t] \leq I_t \tag{9}$$

$$E[-Q_t - I_{t-1} + B_{t-1} + d_t + dpm_t] \leq B_t \tag{10}$$

These equations will be used to calculate non-linear inventory and penalty units.

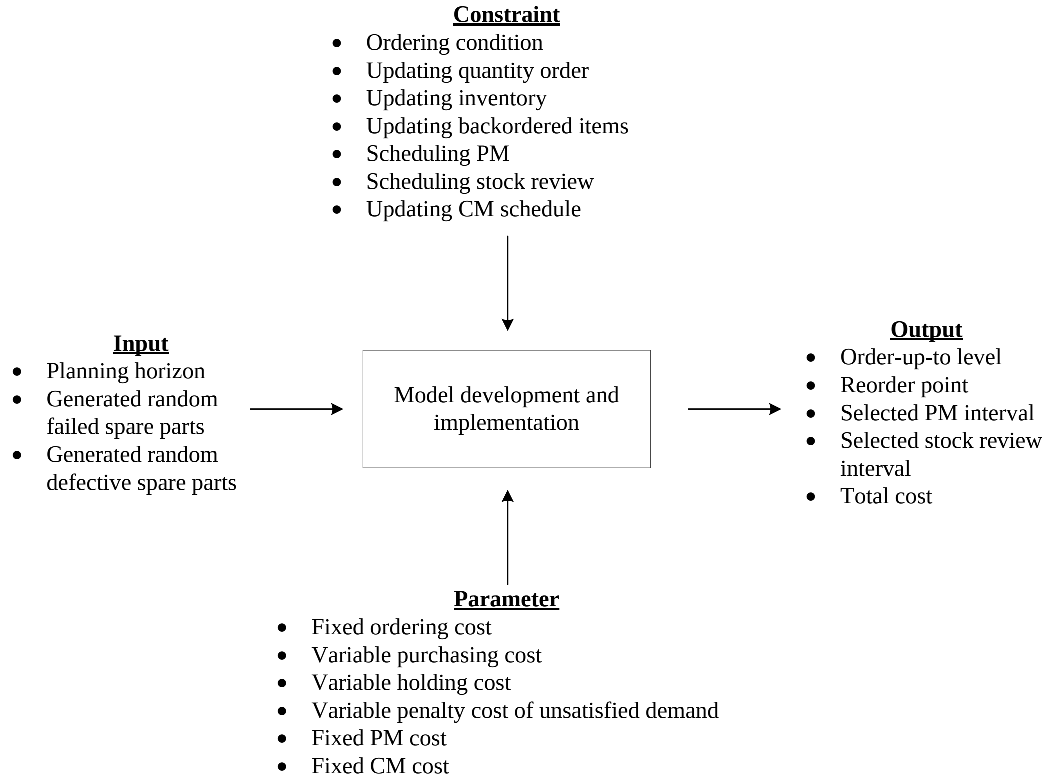

Figure 3.3 System Characterization

3.2 System Characterization

We use an Integer non-Linear Programing (INLP) to deal with the spare parts inventory problem under *S*, *s* policy. The uncertain spare parts requirement will be modeled by the Monte Carlo Simulation. Since the spare parts requirement is stochastic, the simulation requires a number of replications. Each replication will generates the required spare parts and will be solved by the INLP formulation. The objective function will be the average total cost and the decision variables will be the average of *S*, *s* parameters which are resulted by a set of replications. To find the optimal t_o and *k*, each schedule is generated and solved by this INLP formulation. The best solution is the t_o and *k* that give the minimum cost. The Figure 3.3 illustrates the system characterization of this research.

3.3 Problem Assumptions

The following are the assumptions of this problem:

1. The order lead time is assumed one period. Therefore, the ordered item will be arrived at one period after an order is issued.
2. A CM action takes place once a failed item is detected while operating, while a PM action takes place once a defective item or failed item is detected while a PM inspection is done.
3. The failure and PM replacements time are assumed less than one period, therefore the replacement processes do not influence the order and PM interval.
4. Once a defective or failed item are detected, a replacement takes place through PM or CM actions instead of repairing it.
5. The PM and CM action are assumed to be perfect, means that the replacement of the defective and failed spare parts is as good as new.
6. The penalty costs of unavailable spare parts at failures and PM inspections are included in the backordering cost.
7. The review interval is constant at t_o times of single period.
8. The PM inspection interval is constant at *k* times of the review interval, where $k \in \frac{T}{t_o}$

3.4 Mathematical Model

The following formulation is the MINLP model of the uncertain spare parts inventory management with planned maintenance. To find the optimal review interval (t_o) and PM interval (kt_o), we solve all possible combinations of t_o and *k* which will be generated as the stock review and PM schedule. To model the stochastic behavior, we generate random spare parts requirements in some scenarios under normal distribution. Since we do not have any detailed information about the *pdf*, thus, we assume that the expected value of the total cost is the average total cost of all scenarios.

Sets:

T Set of periods

U Set of items

S Set of schedule candidates

Ω Set of spare part requirements scenarios

Parameters:

K Fixed ordering cost for placing an order

c_u Variable purchasing cost of item $u \in U$ for each unit

h_u Variable holding cost of the item $u \in U$ for each unit carried at the end of each time period

b Variable penalty cost for each unmet demand at the end of each time period

PC Predictive maintenance cost

CC Corrective maintenance cost

$d_{\omega ut}$ Generated random failed items $u \in U$ at period $t \in T$ of scenario $\omega \in \Omega$

$dpm_{s\omega t}$ Generated random defective items at period $t \in T$ if schedule $\omega \in \Omega$ is implemented on the scenario $s \in S$

R_{st} Binary variable equal to 1 if stock review of schedule $s \in S$ is done at $t \in T$, and 0 otherwise

P_{st} Binary variable equal to 1 if PM of schedule $s \in S$ is done at $t \in T$, and 0 otherwise

LT Order lead time

Decision Variables:

O_{ut}	Binary variable equal to 1 if order item $u \in U$ is done at $t \in T$, and 0 otherwise
B_{ut}	Expected unsatisfied demand item $u \in U$ at the end of period $t \in T$
I_{ut}	Expected closing inventory level item $u \in U$ at the end of period $t \in T$
Q_{ut}	Order quantity level of item $u \in U$ at the beginning of period $t \in T$
C_{ut}	Binary variable equal to 1 if CM of item $u \in U$ is done at $t \in T$, and 0 otherwise
z_s	Binary variable equal to 1 if schedule $s \in S$ is selected, and 0 otherwise
M	Big number
S_u	Order-up-to level of item $u \in U$
s_u	Reorder point of item $u \in U$

Objective Function

$$\text{Min} \sum_{s \in S} E[TC_s] z_s \tag{12}$$

s. t

$$\sum_{s \in S} z_s = 1 \tag{13}$$

$$E[TC_s] = \frac{\sum_{\omega \in \Omega} TC_s(\omega)}{\Omega}, \qquad \forall s \tag{14}$$

where:

$TC_s(\omega) =$

$$\text{Min} \sum_{u \in U} \sum_{t \in T} (O_{ut} K(\omega) + I_{ut} h_u(\omega) + B_{ut} b(\omega) + Q_{ut} c_u(\omega) + P_t PC + C_{ut} CC(\omega)) \tag{15}$$

s. t

$$I_{u0}(\omega) = 0, \qquad \forall u \tag{16}$$

$$B_{u0}(\omega) = 0, \qquad \forall u \tag{17}$$

$$Q_{u0}(\omega) = 0, \qquad \forall u \tag{18}$$

$$I_{u,t-1}(\omega) - s_u(\omega) \le M(1 - O_{ut}(\omega)), \qquad \forall u, \forall t \tag{19}$$

$$R_{st}(s_u(\omega) - I_{u,t-1}(\omega) + 1) \le M O_{ut}(\omega), \qquad \forall u, \forall t \tag{20}$$

$$O_{u,t-LT}(\omega)(S_u(\omega) - I_{u,t-1}(\omega)) = Q_{ut}(\omega), \qquad \forall u, \forall t \tag{21}$$

$$I_{u,t-1}(\omega)+Q_{ut}(\omega)-B_{u,t-1}(\omega)-d_{ut}(\omega)-dpm_{st}(\omega)P_{st}\le I_{ut}(\omega), \qquad \forall u, \forall t \qquad (22)$$

$$-(I_{u,t-1}(\omega)+Q_{ut}(\omega)-B_{u,t-1}(\omega)-d_{ut}(\omega)-dpm_{st}(\omega)P_{st})\le B_{ut}(\omega), \qquad \forall u, \forall t \qquad (23)$$

$$\begin{aligned}&I_{u,t-1}(\omega)+Q_{ut}(\omega)-B_{u,t-1}(\omega)-d_{ut}(\omega)-dpm_{st}(\omega)P_{st}\\&=\left|I_{ut}(\omega)+B_{ut}(\omega)\right|\end{aligned}, \qquad \forall u, \forall t \qquad (24)$$

$$d_{ut}(\omega)(1-P_{st})\le MC_{ut}(\omega), \qquad \forall u, \forall t \qquad (25)$$

$$O_{ut}(\omega), C_{ut}(\omega)\in\{0,1\}, \qquad \forall u, \forall t \qquad (26)$$

$$I_{ut}(\omega), B_{ut}(\omega), Q_{ut}(\omega), S_u(\omega), s_u(\omega), M\in Z^{+} \qquad \forall u, \forall t \qquad (27)$$

The objective function of this model is shown in the Equation (12) which is to minimize the expected total cost of the selected schedule. Equation (13) ensures only one schedule can be selected. Equation (14) calculates the expected total cost which is the average of the total cost of each scenario. Here we minimize the total cost of each scenario by using Equation (15), which consist of the total purchasing cost, holding cost, penalty cost, ordering cost, PM cost, and CM cost. Equation (16), (17), and (18) ensure that there is no inventory, backordered items, and the quantity order at the beginning of the planning horizon. Equation (19) ensures that an order should not be issued if the inventory on hand (*I*) is more than the reorder point (*s*). Otherwise, in Equation (20), an order should be issued if a stock review is performed at period *t* and the inventory on hand (*I*) is less than equal to the reorder point (*s*). Equation (21) generates the order quantity. If an order is issued, the order quantity is the difference between the order-up-to level (*S*) and the inventory on hand (*I*). Equation (22) calculates the amount of inventory on hand (*I*) at the end of period *t*. The inventory on hand (*I*), is calculated based on the difference between inventory on hand (*I*) at the end of the previous period and the order quantity (*Q*) at the current period with the backordered items (*B*) at the previous period, the failed spare parts of the current period (*d*), and the defective spare parts if a PM is performed (*dpm*). Otherwise, if this value is negative, it will be calculated as the backordered items (*B*), which is shown in the Equation (23). Equation (24) ensures that both inventory on hand (*I*) and backordered items (*B*) are mutually exclusive. Equation (25) ensures that a CM (*C*) must be performed if there is a failed item (*d*) and no PM (*P*) is performed. Equation (26) is the binary constraint of the variable order (O) and CM (C). Equation (27) is the nonnegative integer constraint for variable inventory on hand (I), backordered items (B), order quantity (Q), or-der-up-to level (S), and the reorder point (s).

CHAPTER 4
SOLUTION METHODOLOGY

We propose a Genetic Algorithm (GA) to solve a near optimal solution of a larger size problem in a larger replication. Previously, a set of review interval (t_o) and the PM interval (k) combination are predetermined and then the optimal (S, s) inventory policies are solved through an MINLP model. Meanwhile in this algorithm, we also provide a joint optimization between the inventory management and the maintenance planning. Figure 4.3 describes the whole solution methodology. We propose two stages of GA. First, we solve the inventory policy parameters, the review interval, and the PM interval of each replication. The output of the first stage GA is the best solutions of each replication. Second, from this solution, we try to solve the best inventory policy parameters based on the best review interval and PM interval resulted from the first stage GA. The detailed operations will be explained further in this chapter. We develop our GA based on the GA framework on Wen et al. (2017); Santosa and Ai (2017). The GA procedure of each generation is illustrated in Figure 4.4.

4.1 Solution Representation

The notations that will be used for GA are shown as follow:

Sets:

re = 1, 2, 3, ..., Rep	Set of replications
n = 1, 2, 3, ..., N	Set of chromosomes
it = 1, 2, 3, ..., maxit	Set of iterations
itm = 1, 2, 3, ..., item	Set of items
t =1, 2, 3, ..., P	Set of periods

Input parameters:

N	Number of chromosomes
g	Number of genes

$maxit_1$	Maximum iteration of GA stage 1
$maxit_2$	Maximum iteration of GA stage 2
K	Fixed ordering cost for placing an order
v_{itm}	Variable purchasing cost
h_{itm}	Variable holding cost for each unit carried at the end of period t
b	Variable penalty cost for each unmet demand at the end of period t
$Repd_{re,itm,t}$	Generated demand of replication *re* failed items *itm* at period t
$Repdpm_{re,itm,t}$	Generated demand of defective items of replication *re itm* at period t
x_LsS_{itm}	Lower limit of s and S of each item
x_UsS_{itm}	Upper limit of s and S of each item
$Pcross$	Probability of crossover
Mut	Percentage of mutation

Output:

$S_{re,itm}$	Order-up-to level item *itm* of replication *re*
$s_{re,itm}$	Reorder point item *itm* of replication *re*
to_{re}	Ordering interval of replication *re*
$R_{re,itm,t}$	Binary variable equal to 1 if a stock review of item *itm* is done at replication *re* period t, and 0 is otherwise
$O_{re,itm,t}$	Binary variable equal to 1 if an order of item *itm* is done at replication *re* period t, and 0 is otherwise
$B_{re,itm,t}$	Unsatisfied demand of replication *re* at period t
$I_{re,itm,t}$	Closing inventory level of replication *re* at period t
$Q_{re,itm,t}$	Order quantity level of replication *re* at period t
$PM_{re,t}$	Binary variable equal to 1 if a PM is done at replication *re* period t, and 0 is otherwise
$CM_{re,itm,t}$	Binary variable equal to 1 if a CM of item *itm* is done at replication *re* period t, and 0 is otherwise

TC_{re}	Total cost of replication *re*
Elapsed time	Computing time
it	Required iteration to reach optimal solution

Since our model is considered as a continuous problem, the solution representation consists of the decision variables (s_{itm}, S_{itm}, t_o, and k). To deal with the uncertain spare parts requirement, we generate some replications of the demand based on the predetermined distribution function. Each replication will be solved independently and results a near optimal solution. The solution structure for this problem is illustrated as follows:

s_1	S_1	s_2	S_2	s_3	S_3	...	s_{item}	S_{item}	t_o	k

Figure 4.1 Solution Structure

Based on the above solution structure, the number of genes can be formulated as follows:

$$g = 2 \times item + 2 \tag{28}$$

4.2 1st Stage Genetic Algorithm Procedure

This first stage of GA solves the inventory policies, review interval, and the PM interval of each replication. After the solution of these variables have already found, the mode of the best review interval and PM interval found are selected as the best review interval, and the PM interval.

4.2.1 Population initialization

A population of *N* rows of chromosomes and *g-2* columns of genes is generated randomly as the initial solution. Each chromosome is generated based on the following formulation:

$$x = x_L + r \times (x_U - x_L) \tag{29}$$

Where x_L is the lower limit of each gene, x_U is the upper limit of each gene, *r* is a random value between (0, 1). Since our solution structure consists of the decision variables, each x_L and x_U consist of four values. The x_L and x_U of s and S are entered as the input of the GA function. The x_L of t_o and k is 1 and the x_U of t_o is T-2 since we want to define the review interval. While x_U of k is dependent to t_o. Therefore, three genes (s, S, and t_o) are generated first, then, the x_U of k will be $\frac{T}{t_o}$. Then the value of k is generated randomly between x_L and x_U of k.

4.2.2 Updating Variables and Evaluating the Population

Each variable is updated based on the generated population in each chromosome. After updating variables, the total cost of each chromosome is calculated. The pseudo code for updating each variable is shown in Figure 5.5. The following are the procedure to update the variables.

1. Stock review schedule ($R_{n,t}$)

   This variable is illustrated as a binary matrix of N rows, P columns. R_{nt} = 1 means a stock review is performed at chromosome n period t, if R_{nt} = 0, no review is performed. R_{nt} is changed to 1 at every t = 1+at_{on}, where $a \in \frac{T}{t_{on}}$.

2. Preventive maintenance schedule (PM_{nt})

   Variable PM_{nt} is illustrated as a binary matrix of N rows x P columns. PM_{nt} = 1 means a predictive maintenance is performed at chromosome n period t, if PM_{nt} = 0, no preventive maintenance is performed. PM_{nt} is changed to 1 at every t = 1+bk_nt_{on}, where $b \in \frac{T}{k_n t_{on}}$.

3. Order ($O_{n,itm,t}$)

   Variable $O_{n,itm,t}$ is illustrated as a binary matrix of N rows x P x *item* columns. $O_{n,itm,t}$ = 1 means an order of item *itm* is issued at chromosome n period t, if $O_{n,itm,t}$ = 0, no order is issued. If R_{nt} = 1 and $I_{n,itm,t-1} \leq s_{n,itm}$, then $O_{n,itm,t}$ = 1, otherwise $O_{n,itm,t}$ = 0.

4. Quantity order ($Q_{n,itm,t}$)

Variable $Q_{n,itm,t}$ is the quantity order of item *itm* at chromosome *n* period *t*. This variable is illustrated as an integer matrix of *N* rows x *P* columns. Each $Q_{n,itm,t}$ is formulated as follows:

$$Q_{n,itm,t} = (S_{n,itm,t} - S_{n,itm,t-1}) \times O_{n,itm,t} \tag{30}$$

5. Inventory on hand ($I_{n,itm,t}$)

   Variable $I_{n,itm,t}$ is the inventory on hand of item *itm* at chromosome *n* period *t*. This variable is illustrated as an integer matrix of *N* rows x *P* x *item* columns. Each $I_{n,itm,t}$ is formulated as follows:

$$I_{n,itm,t} = \max(I_{n,itm,t-1} + Q_{n,itm,t} - Repd_{re,itm,t} - (Repdm_{re,t} PM_{nt}) - B_{n,itm,t-1}, 0) \tag{31}$$

6. Backordered items ($B_{n,itm,t}$)

   Variable $B_{n,itm,t}$ is the backordered number of item *itm* at chromosome *n* period *t*. This variable is illustrated as an integer matrix of *N* rows x *P* x *item* columns. Each $B_{n,itm,t}$ is formulated as follows:

$$\begin{aligned} &B_{n,itm,t} \\ &= \max(-(I_{n,itm,t-1} + Q_{n,itm,t} - Repd_{re,itm,t} - (Repdm_{re,t} PM_{nt}) - B_{n,itm,t-1}), 0) \end{aligned} \tag{32}$$

7. Corrective maintenance ($CM_{n,itm,t}$)

   Variable $CM_{n,itm,t}$ is illustrated as a binary matrix of *N* rows x *P* x *item* columns. $CM_{n,itm,t}$ = 1 means a corrective maintenance of item *itm* is performed at *t*, if $CM_{n,itm,t}$ = 0, no corrective maintenance is performed. If $Repd_{re,itm,t} \times (1 - PM_{nt}) > 0$, then $CM_{n,itm,t}$ = 1, otherwise $CM_{n,itm,t}$ = 0.

8. Total cost (TC_n)

   Variable TC_n is the total cost of each chromosome. This variable is illustrated as an array of *N* rows. TC_n is formulated as follows:

$$\begin{aligned} &TC_n \\ &= \sum_{itm \in item} \sum_{t \in P} (Q_{n,itm,t} v_{itm} + I_{n,itm,t} h_{itm} + B_{n,itm,t} b + O_{n,itm,t} K + PM_{nt} PC + CM_{n,itm,t} CC) \end{aligned} \tag{33}$$

9. *Fitness*$_n$

   Variable $Fitness_n$ is illustrated as an array of *N* rows. Since our objective is minimizing the cost, $Fitness_n$ is formulated as follows:

$$Fitness_n = \frac{1}{TC_n} \tag{34}$$

The *BestX* is the best chromosome which result the biggest value of *Fitness*.

4.2.3 Elitism Operation

The elitism operation maintains the best chromosome which resulted from each iteration. So that this chromosome will stay appear in the population of the next iteration (Santosa and Ai, 2017). We perform this operation by copying the best chromosome into four times if N value is even or three times if N value is odd.

4.2.4 Crossover Operation

This operation consists of the selection of parents and the crossing procedure. Two parents are selected randomly through the roulette wheel selection. In this procedure, the chromosomes with larger fitness have a larger probability to be selected. After two parents are selected, a random value r is generated. In this procedure, we use two condition so that the chromosome is performed. First, if r value is less than *Pcross* and second, if the crossover results satisfiy the feasibility. If both of these conditions are satisfied, then two new children are generated by crossing both parents. Otherwise, both parents are selected as two new children without crossing them. The crossover results are considered feasible if $s < S$ and if $k \le \frac{T-1}{t_o}$. We use a simple crossover which is illustrated in Figure 4.2. Two different crossover points are selected randomly and then crossing the chromosome between these crossover points.

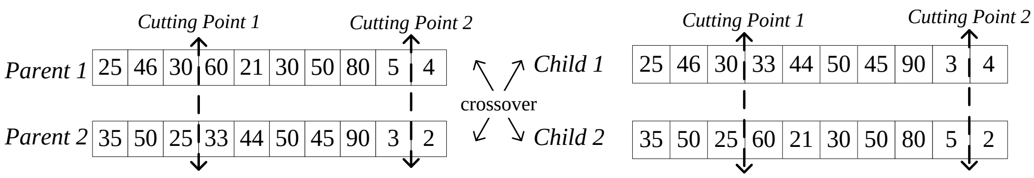

Figure 4.2 The Process of Crossover with Two Cutting Points

4.2.5 Mutation Operation

The mutation procedure enables the new chromosomes other than the crossover procedure (Santosa and Ai, 2017). Here we generate $Mut \times N$ of chromosomes randomly as the same procedure as the population initialization in the Section 4.2.1.

4.2.6 Evaluating the Terminating Condition

Here we evaluate the terminating condition based on the maximum iteration (*$maxit_1$*) and the non-improvement within a certain percentage (*maxter*) of iterations. If $it \geq maxit_1$ or $TC_{it} = TC_{it-(maxit_1 \times maxter)}$, the iteration breaks, otherwise, update iteration $it = it + 1$ and the iteration continues.

4.2.7 Final Solution

In this stage, the variables and the total cost are updated based on *BestX*. If some replications are performed and multiple items are considered, therefore each of $R_{re,itm,t}$, $PM_{re,itm,t}$, $O_{re,itm,t}$, $Q_{re,itm,t}$, $I_{re,itm,t}$, $B_{re,itm,t}$, and $CM_{re,itm,t}$ are formed in a matrix of *Rep* rows and *P* x *item* columns. Furthermore, each $s_{re,itm}$, $S_{re,itm}$, are formed in a matrix of *Rep* rows x *item* columns. Meanwhile each to_{re}, k_{re}, and TC_{re} are formed in an array of *Rep* rows.

4.3 2nd Stage GA Procedure

After resulting the initial solution based on GA in the first stage, then we select the best t_o and k. Here we use *mode* function to find the most appear t_o and k in the whole replications. Both t_o and k will be used as the input parameter in GA in the second stage. Meanwhile the inventory policies (s_{itm}, S_{itm}) will be used as the initial solution in GA in the second stage. Therefore, number of genes in this second stage of GA is g-2.

4.3.1 Population initialization

A population of *N-1* rows of chromosomes and g columns of genes is generated randomly as the initial solution. The first chromosome is the result of the 1st stage of GA. The next each chromosome is generated based on the following formulation:

$$x = x_L + r \times (x_U - x_L), \qquad n > 1 \tag{35}$$

Where x_L is the lower limit of each gene, x_U is the upper limit of each gene, r is a random value between (0, 1). Since this solution structure only consists of the inventory policy, we generate the initial solution within the x_L and x_U of s and S.

4.3.2 Updating Variables and Evaluating the Population

Each variable is updated based on the generated population in each chromosome. After updating variables, the total cost of each chromosome is calculated. The pseudo code for updating each variable is shown in Figure 5.5. The following are the procedure to update the variables.

1. Stock review schedule (R_t)

   This variable is illustrated as a binary array of P columns. R_t = 1 means a stock review is performed at period t, if R_t = 0, no review is performed. R_t is changed to 1 at every $t = 1+at_o$ where $a \in \frac{T}{t_{o\,n}}$.

2. Preventive maintenance schedule (PM_t)

   Variable PM_t is illustrated as a binary array of P columns. PM_t = 1 means a predictive maintenance is performed at chromosome n period t, if PM_t = 0, no preventive maintenance is performed. PM_t is changed to 1 at every $t = 1+bkt_o$ where $b \in \frac{T}{k_n t_{o\,n}}$.

3. Order ($O_{n,itm,t}$)

   Variable $O_{n,itm,t}$ is illustrated as a binary matrix of N rows x P x *item* columns. $O_{n,itm,t}$ = 1 means an order of item *itm* is issued at chromosome n period t, if $O_{n,itm,t}$ = 0, no order is issued. If R_{nt} = 1 and $I_{n,itm,t-1} \leq s_{n,itm}$, then $O_{n,itm,t}$ = 1, otherwise $O_{n,itm,t}$ = 0.

4. Quantity order ($Q_{n,itm,t}$)

   Variable $Q_{n,itm,t}$ is the quantity order of item *itm* at chromosome n period t. This variable is illustrated as an integer matrix of N rows x P columns. Each $Q_{n,itm,t}$ is formulated as follows:

   $$Q_{n,itm,t} = (S_{n,itm,t} - S_{n,itm,t-1}) \times O_{n,itm,t} \qquad (36)$$

5. Inventory on hand ($I_{n,itm,t}$)

Variable $I_{n,itm,t}$ is the inventory on hand of item *itm* at chromosome *n* period *t*. This variable is illustrated as an integer matrix of *N* rows x *P* x *item* columns. Each $I_{n,itm,t}$ is formulated as follows:

$$I_{n,itm,t} = \max(I_{n,itm,t-1} + Q_{n,itm,t} - Repd_{re,itm,t} - (Repdm_{re,t} PM_{nt}) - B_{n,itm,t-1}, 0) \quad (37)$$

6. Backordered items ($B_{n,itm,t}$)

Variable $B_{n,itm,t}$ is the backordered number of item *itm* at chromosome *n* period *t*. This variable is illustrated as an integer matrix of *N* rows x *P* x *item* columns. Each $B_{n,itm,t}$ is formulated as follows:

$$B_{n,itm,t} = \max(-(I_{n,itm,t-1} + Q_{n,itm,t} - Repd_{re,itm,t} - (Repdm_{re,t} PM_{nt}) - B_{n,itm,t-1}), 0) \quad (38)$$

7. Corrective maintenance ($CM_{n,itm,t}$)

Variable $CM_{n,itm,t}$ is illustrated as a binary matrix of *N* rows x *P* x *item* columns. $CM_{n,itm,t}$ = 1 means a corrective maintenance of item *itm* is performed at *t*, if $CM_{n,itm,t}$ = 0, no corrective maintenance is performed. If $Repd_{re,itm,t} \times (1 - PM_{nt}) > 0$, then $CM_{n,itm,t}$ = 1, otherwise $CM_{n,itm,t}$ = 0.

10. Total cost (TC_n)

Variable TC_n is the total cost of each chromosome. This variable is illustrated as an array of *N* rows. TC_n is formulated as follows:

$$TC_n = \sum_{itm \in item} \sum_{t \in P} (Q_{n,itm,t} v_{itm} + I_{n,itm,t} h_{itm} + B_{n,itm,t} b + O_{n,itm,t} K + PM_{nt} PC + CM_{n,itm,t} CC) \quad (39)$$

11. $Fitness_n$

Variable $Fitness_n$ is illustrated as an array of *N* rows. Since our objective is minimizing the cost, $Fitness_n$ is formulated as follows:

$$Fitness_n = \frac{1}{TC_n} \quad (40)$$

The *BestX* is the best chromosome which result the biggest value of *Fitness*.

4.3.3 Elitism Operation

The elitism operation maintains the best chromosome which resulted from each iteration. So that this chromosome will stay appear in the population of the next iteration (Santosa and Ai, 2017). We perform this operation by copying the best chromosome into four times if N value is even or three times if N value is odd.

4.3.4 Crossover Operation

This operation consists of the selection of parents and the crossing procedure. Two parents are selected randomly through the roulette wheel selection. In this procedure, the chromosomes with larger fitness have a larger probability to be selected. After two parents are selected, a random value r is generated. In this procedure, we use two conditions so that the chromosome is performed. First, if r value is less than *Pcross* and second, if the crossover results satisfy the feasibility. If both of these conditions are satisfied, then two new children are generated by crossing both parents. Otherwise, both parents are selected as two new children without crossing them. The crossover results are considered feasible if $s < S$ and if $k \le \frac{T-1}{t_o}$. Here we use two options of simple crossover. If *item* > 1, two different crossover points are selected randomly and then crossing the chromosome between these crossover points. Otherwise, a crossover between s and S are directly performed since there are only two genes.

4.3.5 Mutation Operation

The mutation procedure enables the new chromosomes other than the crossover procedure (Santosa and Ai, 2017). Here we generate $Mut \times N$ of chromosomes randomly as the same procedure as the population initialization in the Section 4.3.1.

4.3.6 Evaluating the Terminating Condition

Here we evaluate the terminating condition based on the maximum iteration ($maxit_2$) and the non-improvement within a certain percentage (*maxter*) of iterations. If $it \ge maxit_2$ or $TC_{it} = TC_{it-(maxit_2 \times maxter)}$, the iteration breaks, otherwise, update iteration $it = it + 1$ and the iteration continues.

4.3.7 Final Solution

In this stage, the variables and the total cost are updated based on *BestX*. If some replications are performed and multiple items are considered, therefore each of $R_{re,itm,t}$, $PM_{re,itm,t}$, $O_{re,itm,t}$, $Q_{re,itm,t}$, $I_{re,itm,t}$, $B_{re,itm,t}$, and $CM_{re,itm,t}$ are formed in a matrix of *Rep* rows and *P* x *item* columns. Furthermore, each $s_{re,itm}$, $S_{re,itm}$, are formed in a matrix of *Rep* rows x *item* columns. Meanwhile TC_{re} are formed in an array of *Rep* rows.

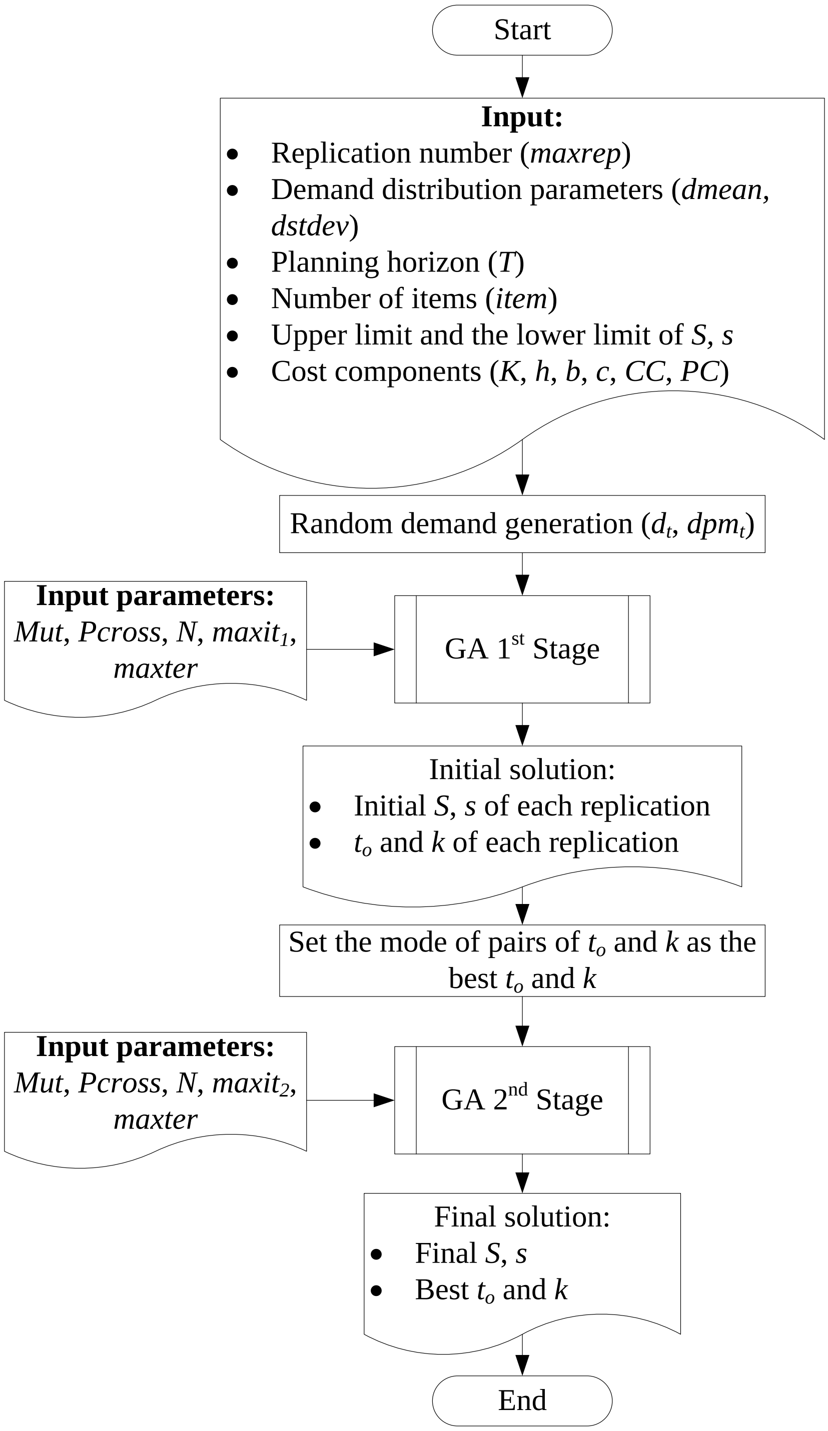

Figure 4.3 Solution Methodology

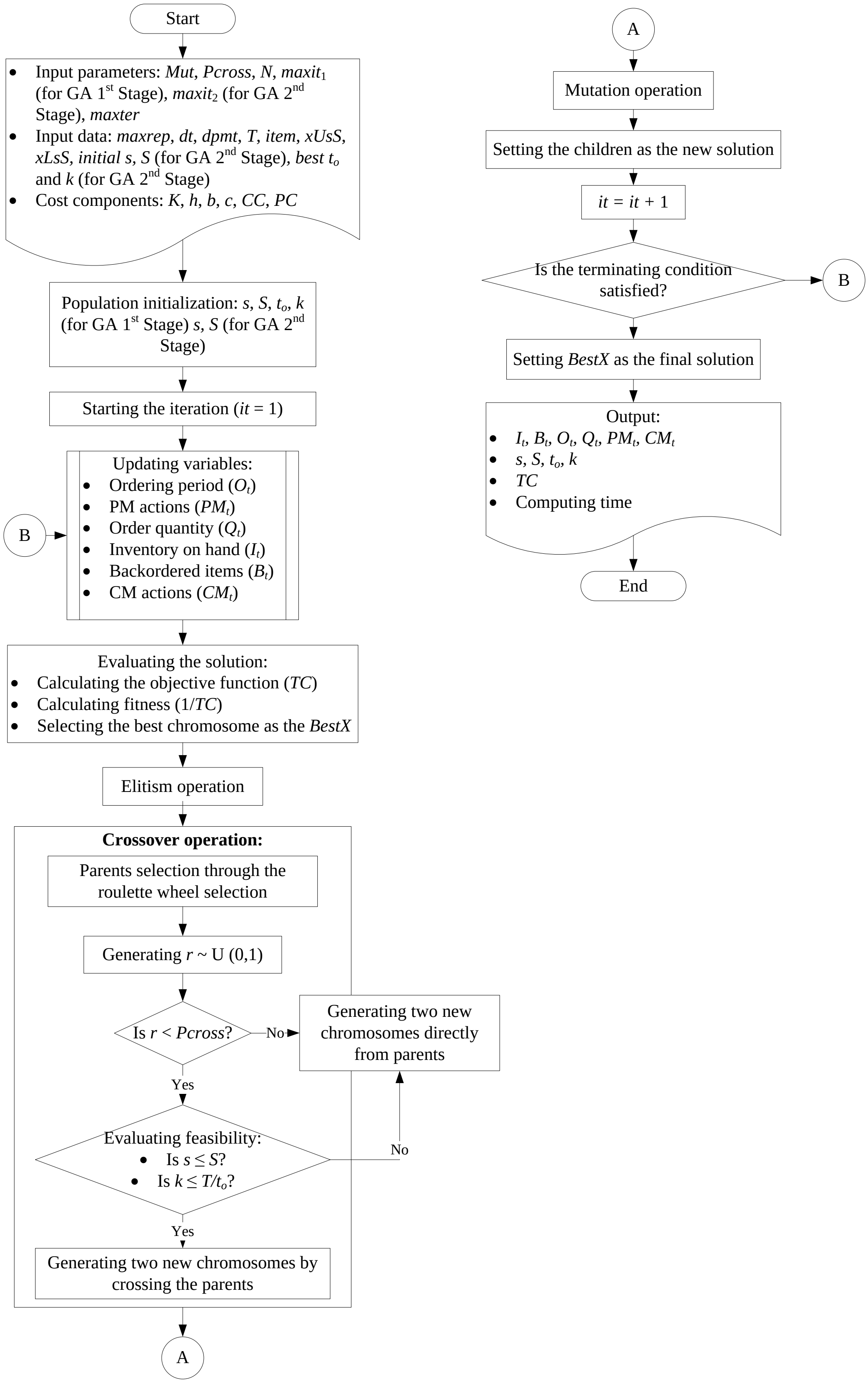

Figure 4.4 GA Procedure

Data: *maxrep*, *dt*, *dpmt*, *T*, *item*, cost (K, h, b, c, CC, PC), solutions (s, S, t_o, k)
Results: O, R, I, B, PM, CM

for $t = 1$ to T **do**
  for $a = 1$ to $\frac{T}{t_o}$ **do**
    if $t = 1 + at_o$ **then**
      $R_t = 1$;
    end
  end
  for $b = 1$ to $\frac{T}{kt_o}$ **do**
    if $t = 1 + bkt_o$ **then**
      $PM_t = 1$;
    end
  end
  for $itm = 1$ to $item$
    if $R_t = 1$ **and** $I_{n,itm,t-1} \leq s_{itm}$ **then**
      $O_{n,itm,t} = 1$;
    else
      $O_{n,itm,t} = 0$;
    end
    $Q_{n,itm,t} = (S_{itm} - I_{n,itm,t-1}) \times O_{t-1}$;
    $I_{n,itm,t} = \max(I_{n,itm,t-1} + Q_{n,itm,t} - d_{itm,t} - (dpm_{itm,t} \times PM_t) - B_{n,itm,t-1}, 0)$;
    $B_{n,itm,t} = \max(-(I_{n,itm,t-1} + Q_{n,itm,t} - d_{itm,t} - (dpm_{itm,t} \times PM_t) - B_{n,itm,t-1}), 0)$;
    if $d_{itm,t} \times (1 - PM_t) > 0$ **then**
      $CM_{itm,t} = 1$;
    end
  end
end

Figure 4.5 Algorithm for Updating Variables

CHAPTER 5
RESULTS AND DISCUSSION

The proposed GA is implemented in Matlab 2015 and run on a computer with an Intel® Core i7-6700 CPU at 3.40 GHz and 8 GB of RAM under Windows 10 Professional. The INLP model is implemented in LINGO 11. To evaluate the performance of our policy, we compare the result of our model with other policies such as (*Q*, *R*) and continuous (*s*, *S*). We also compare our GA solution result with the INLP result to evaluate the performance of our proposed GA. Furthermore, we will implement the proposed GA to a real case study. We present numerical analysis to a real case problem of the chemical process industry in Gresik, Indonesia.

5.1 Parameter Setting

The experimental design is created to determine the parameter setting in our proposed GA. We use 5 parameters in this study. The following list is the parameters which will be used in this experiment:

1. Mutation percentage (*Mut*) = 0.2, 0.4, 0.6, 0.8.
2. Crossover probability (*Pcross*) = 0.2, 0.4, 0.6, 0.8.
3. Number of chromosomes (*N*) = 100, 300, 500, 700.
4. Maximum iteration of the 1st stage GA ($maxit_1$) = 10000, 30000, 50000, 70000.
5. Maximum iteration of the 2nd stage GA ($maxit_2$) = 1000, 3000, 5000, 7000.
6. Non improvement within a certain percentage of iterations (*maxter*) = 0.05, 0.1, 0.2, 0.25.

First, we perform an OFAT (One Factor at Time) experiment to our parameter to determine the high and low level of these parameters. We use the instances from Xiang et al. (2018) to perform this experiment. They provide the datasets of demand distribution parameters ($\tilde{d}_t$) of a time series. They provide two instances, which are 8 periods and 25 periods of demand distribution parameters. Each instance has different demand pattern depends on the characteristic of the item. In this experiment, we use the life cycle (LCY) demand pattern to generate the random failed items of each period. The demand patterns are normal distribution characterized by means and coefficient of variation (c_v = 0.1); note that $\sigma_t = c_v \tilde{d}_t$. Appendix 1 shows the parameters of these datasets.

Based on this dataset, we use three instances for the experimental design. First, we consider 8 periods of horizon planning of three items in 15 replications. Second, 25 periods of horizon planning of single item in 15 replications. Third, 25 periods of horizon planning of three items in 15 replications. The detailed OFAT result is shown in the Appendix 2. Table 5.1 shows the selected of high and low level based for the 2^k design of experiment.

Table 5.1 Selected Parameters for 2^k Factorial Design

Parameter	**Level 1**	**Level 2**
Mut	0.60	0.80
Pcross	0.20	0.80
N	300	700
Maxit1	10,000	50,000
Maxit2	3,000	7,000
Maxter	0.20	0.25

All the selected level parameters are tested through a 2^k full factorial design. Here we have 64 combinations of paremeters. The best parameter setting is chosen based on the best total cost by considering the computing time. Table 5.2 shows the selected parameters for the proposed GA.

Table 5.2 Selected Parameters for the Proposed GA

Parameter	**Value**
Mut	0.60
Pcross	0.80
N	700
Maxit1	50,000
Maxit2	7,000
Maxter	0.20

We also perform a sensitivity analysis to evaluate the trade-off between the effectiveness and efficiency of our proposed GA. We consider the increasing rate of the computing time and the decreasing rate of the total cost to determine the setting parameters (Yu and Lin, 2015). The sensitivity analysis of the parameters to the total cost and the computational time are illustrated in Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4, Figure 5.5, and Figure 5.6.. Figure 5.1 illustrates the sensitivity analysis to the mutation percentage (*Mut*). Based on the graph, the changes of *Mut* do not significantly influence the total cost. The computing time decreases until *Mut* = 0.6. However, in a larger value, the computing time increases. Therefore, we can conclude that the most preferable value of *Mut* is 0.6.

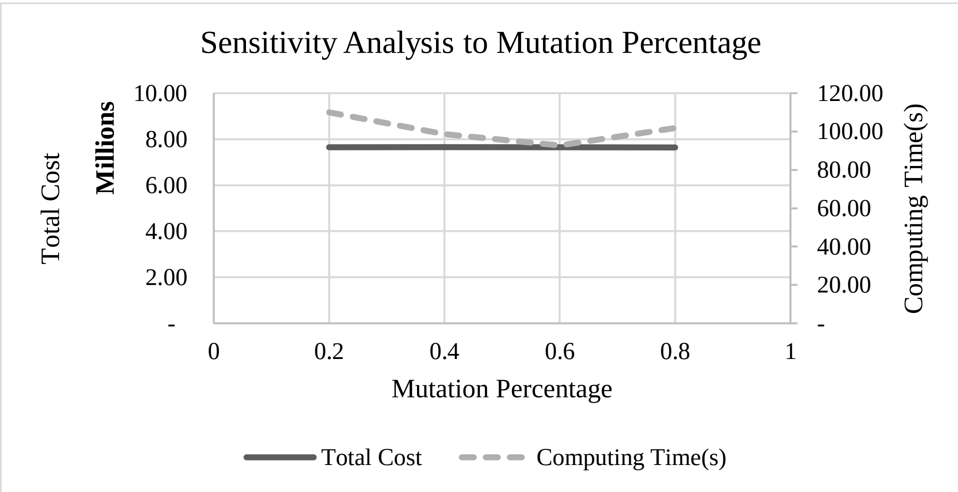

Figure 5.1 Sensitivity Analysis on the Mutation Percentage

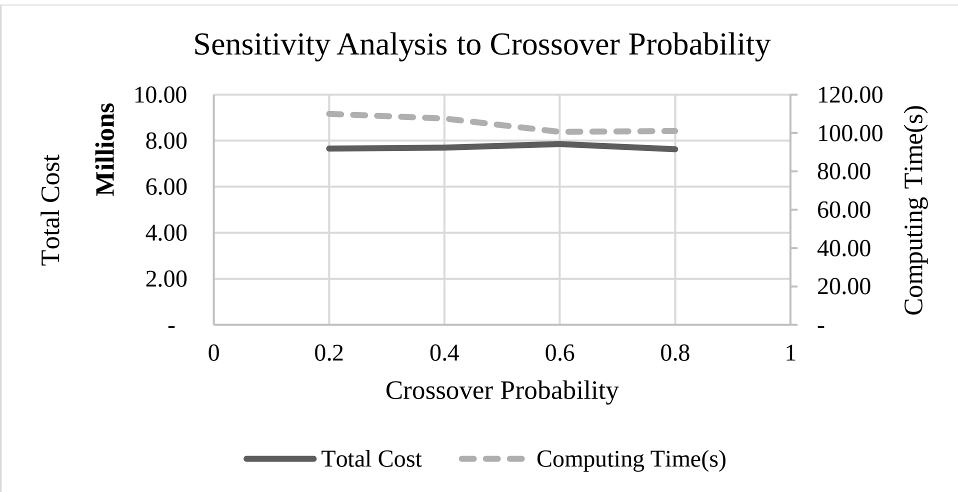

Figure 5.2 Sensitivity Analysis on the Crossover Probability

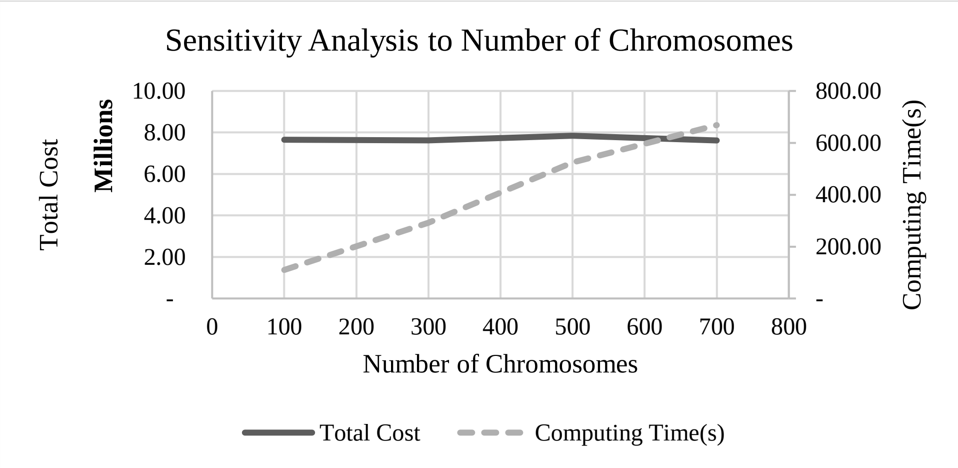

Figure 5.3 Sensitivity Analysis on the Number of Chromosomes

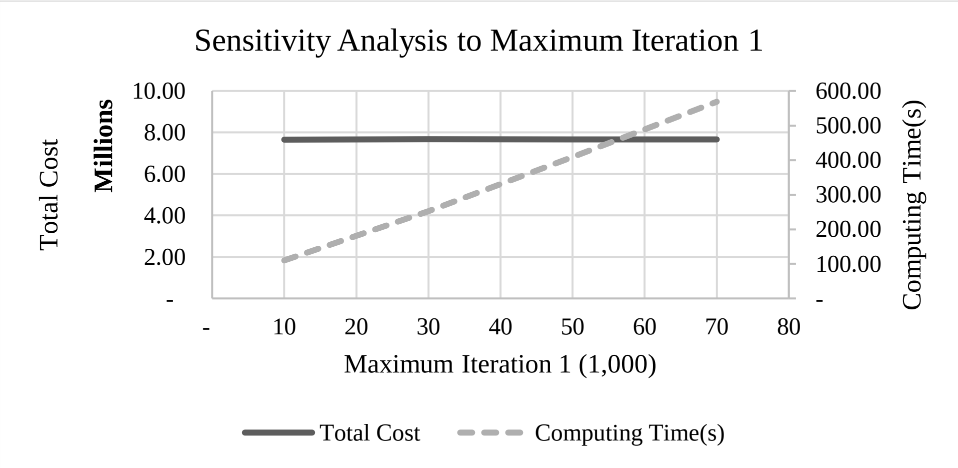

Figure 5.4 Sensitivity Analysis on the Maximum Iteration 1

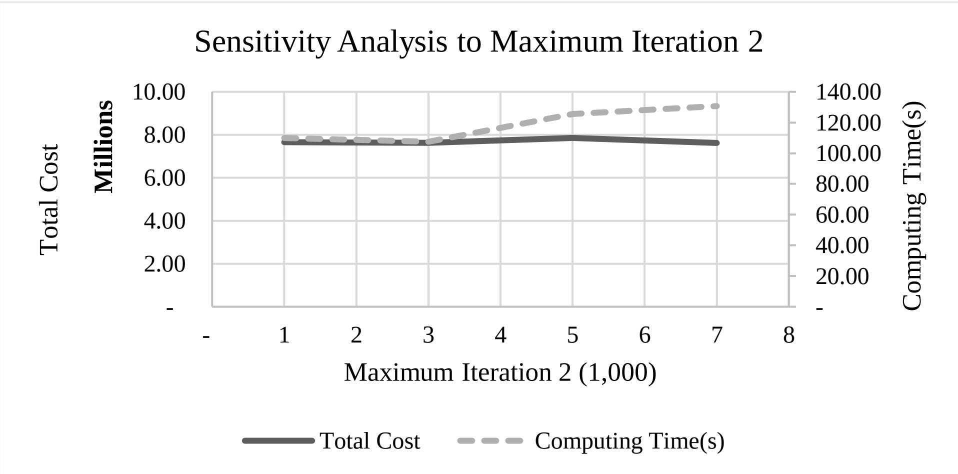

Figure 5.5 Sensitivity Analysis on the Maximum Iteration 2

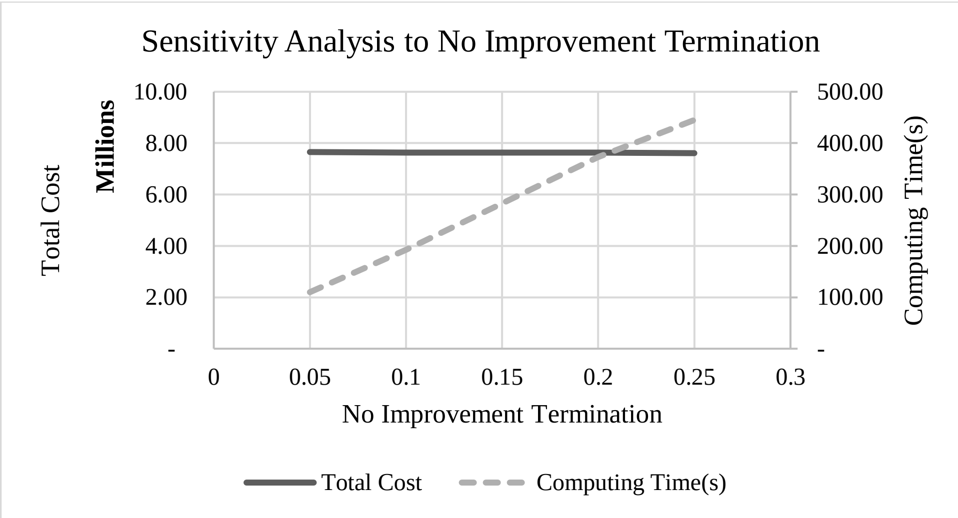

Figure 5.6 Sensitivity Analysis to Non-improvement Termination

Figure 5.2 illustrates the sensitivity analysis of the crossover probabiliry. The total cost increases in *Pcross* = 0.6 then decreases at *Pcross* = 0.8 which is the lowest point. The computing time decreases at *Pcross* = 0.6 and remains until *Pcross* = 0.8. Therefore, the most preferable value of *Pcross* is 0.8. The sensitivity analysis of the number of chromosomes is shown in Figure 5.3. Based on this figure, the lower total cost is resulted at value N = 300 and N = 700. However, the computing time increases significantly as the computing time increases. Based on Figure 5.4, the maximum iteration of the first stage GA ($Maxit_1$) does not significantly influence the total cost. However, the total cost is highly sensitive to $Maxit_1$. The maximum iteration of the second stage of GA ($Maxit_2$) results the lower value of the total cost at $Maxit_2$ = 3,000 and $Maxit_2$ = 7,000. The increasing rate of $Maxit_2$, is high at value $Maxit_2$ = 500. The non improvement termination (*maxter*) does not significantly influence the total cost. However, the computing time is significantly increases as this parameter increases.

5.2 Generating Stock Review and PM Schedule

In our model, the stock review and PM are scheduled on a regular basis based on a set of combinations of stock review and PM intervals. These interval combinations depend on the planning horizon. The longer the planning horizon, the larger the combinations. This leads to a larger solution space which will affect to the computing efficiency. We introduce a procedure to generate the combinations of stock review interval and PM interval as well as stock review schedule and PM schedule based on a given planning horizon in Figure 5.7.

Data: Planning horizon (T)
Result: A list of stock review and PM interval (*combinations*), a matrix of stock review schedule (*review schedule*), a matrix of PM schedule (*PM schedule*).
1 *com* = 1;
2 **for** t_o = 1 to T-2 **do**
3   **for** k = 1 to $\frac{T-2}{t_o}$ **do**
4   *combinations* (*com*, 1) = *com*;
5   *combinations* (*com*, 2) = t_o;
6   *combinations* (*com*, 3) = k;
7   **for** $t = 1 : t_o : T$ **do**
8   *review schedule* (*com*, t) = 1;
9   **end**
10   **for** $t = 2 : t_o \times k : T$ **do**
11   *PM schedule* (*com*, t) = 1;
12   **end**
13   *com = com+1*;
14   **end**
16 **end**

Figure 5.7 Algorithm for Generating Stock Review Schedule and PM Schedule

First, we enumerate all the possible t_o and k, then we record this combination in a matrix. The generation of *combinations* matrix is done in line 4-6, which consists of the number of combination in the first column, t_o in the second column, and k in the third column. Second, the matrix of *review schedule* is generated in line 7-9. This procedure results a matrix of number of combinations rows × T columns. Third, the matrix of *PM schedule* is generated in line 10-12, which results in a matrix of combinations rows × T columns.

5.3 Modeling Random Components

According to Altiok and Melamed (2007), the activity of modeling random components involves four stages of modeling activity as follows:

5.3.1 Data Collection

In this stage, the observations of system characteristics over time are gathered to avoid the paucity of the available data, or from irrelevant, outdated, or simply erroneous data. The data should be correct and relevant and the sample size collected should be representative and large enough.

5.3.2 Data analysis

After the data collection, a preliminary analysis of the data is done to assist the next stage of fitting distribution. Such analysis of this stage includes the statistics related to moments (mean, standard deviation, etc.), statistics related to distributions (histograms), and statistics related to temporal dependences (autocorrelations within an empirical time series, or cross-relations among two or more distinct time series).

5.3.3 Time series data modeling

In this stage, a stochastic process is fitted to empirical time series data, which are pairs of time and corresponding observations collected in the data collection stage. There are two main approaches to model this time series data. The simplest approach is to construct a histogram from the empirical data, and then normalize it to a step probability density function (*pdf*) or a probability mass function (*pmf*) is then declared to be the fitted distribution. The second approach is try to determine a probability function based on the histogram which forms a particular functional distribution. Two common methods that can be implemented to this approach are the method of moments and the maximum likelihood estimation (MLE) method.

5.3.4 Goodness-of-fit testing

The goodness of fit tests for distribution is assessed by a statistical test, where the null hypothesis states that the candidate distribution is sufficiently good fit to the data, while the alternative hypothesis states that is not. The mostly used tests for the goodness-of-fit of a distribution to sample data are the *chi-square test* and the *Kolmogorov-Smirnov test*.

5.4 Generating Random Spare Parts Requirements

Random spare parts requirements are generated based on the predetermined distribution function and parameters. In this model we have two spare parts requirements, which are the random failed items and the random defective items. Figure 5.8 shows the algorithm for generating random failed items and the random defective items.

First, we generate random failed items of each item and each period based on the predetermined distribution function in line 2-6. This procedure results a matrix with replication number of rows and planning horizon × number of items of columns. Second, random defective items will be generated based on the predetermined distribution parameters in line 7-18. If a PM is performed in a period, therefore the number of defective items will be decreased to be the number of defective item of the first period. Otherwise, the number of defective items will be increased. We generate this random defective item based on each combination of stock review interval and PM interval, which results in a matrix of with replication number of rows and planning horizon × number of combinations of columns.

```
Data: distribution parameters of failed items (d mean, d standard deviation),
      distribution parameters of defective items (dpm mean, dpm standard
      deviation), combination matrix, replication number.
Results: a matrix of generated random failed items (Repd), a matrix of generated
         random defective items (Repdpm).
for rep = 1 to replication number do
    for t = 2 to T do
        for itm = 1 to number of items do
            Repd(rep, ((itm-1) × T) + t) = round(d mean(((itm-1) × T) + t) +
            d standard deviation(((itm-1) × T) + t) × random number, 0);
        end
    end
    for j = 1 to number of combinations do
        t_o = combinations(j, 2);
        k = combinations(j, 3);
        m=t_o × k;
        a = 1;
        for t = 2 to T do
            Repdpm (rep, ((j-1) × T) + t) = round(dpm mean(t – 1 – m × (a - 1))
            + npmstdev(t – 1 – m × (a - 1)) × random number, 0);
            if t > a × m+1 do
                a = a+1;
            end
        end
    end
end
```

Figure 5.8 Algorithm for Generating Random Spare Parts Requirements

5.5 Algorithm Testing

We implement our proposed GA and MINLP model in some instances to evaluate the computing performance. We test our proposed GA to 8 different instances which varies in the planning horizon (*P*), number of items (*I*), and number of replications (*R*). Here we also consider a deterministic case (*Det*) which does not need replications. Table 5.4 shows the ordering cost (*K*), the penalty cost (*b*), the fixed PM cost (*PC*) , and the fixed CM cost (*CM*). Table 5.5 shows the variable holding cost (*h*) and the variable purchasing cost (*v*).

Table 5.3 Instances for Algorithm Testing

Instances	Planning Horizon	Number of Items	Number of Replications
8P-1I -1R	8	1	1
25P-1I-1R	25	1	1

Instances	Planning Horizon	Number of Items	Number of Replications
8P-3I-1R	8	3	1
25P-3I-1R	25	3	1
8P-1I-15R	8	1	15
25P-1I-15R	25	1	15
8P-3I-15R	8	3	15
25P-3I-15R	25	3	15

Table 5.4 Ordering Cost, Penalty Cost, PM Cost, and CM Cost

K	100.00
b	25,000.00
PC	4,360.00
CC	9,810.00

Table 5.5 Variable Purchasing Cost and Variable Holding Cost

Item	1	2	3
v	1,500.00	1,000.00	2,000.00
h	15	10	20

Table 5.6 shows the average total cost and the CPU of our computational study. Most of the result obtain good performances, which is less than 1%. However, both instances 8P-3I-Det and 8P-3I-15R results pretty much gap on the total cost. The decision variables of both proposed MINLP and proposed GA are obtained in the Table 5.7 and Table 5.8 to find the root cause of this problem. Based on the MINLP result, the review interval and the PM interval are t_o = 1 and k =4. Meanwhile, based on the GA result, the review interval and the PM interval are t_o = 4 and k =1. Based on this result, we can conclude that our solution could stuck in a local optimal, specifically for the ordering interval and the PM intervals.

Based on Table 5.6, it shows that the CPU relies heavily to the planning horizon, the number of items, and number of replications. The increasing of the planning horizon increases the solution space of the problem. As we described previously, the possible solution of t_o and k depends on the planning horizon. Therefore, as the planning horizon increases, the solution space increases. As the number of items increase, the decision variables are also increase. This also may cause an increasing to the CPU. Adding more replications also requires more computational time. This is because each replication need to be solved in some iterations. At a lower scale problem, our proposed GA doesn't work efficiently compared to the MINLP. However, in a larger scale problem such as in a larger planning horizon and multi-items, our proposed GA solves the problem efficiently compared to the MINLP approach.

Table 5.6 Algorithm Testing on The Proposed MINLP and GA

Instances	Proposed MINLP		Proposed GA		Gap
	Total Cost	CPU (s)	Total Cost	CPU (s)	
8P-1I -1R	451,855	13	451,855	139.89	0.00%
25P-1I-1R	4,317,685	348	4,317,685	171.07	0.00%
8P-3I-1R	1,356,465	67	1,373,195	273.94	1.23%
25P-3I-1R	17,276,605	40,702	17,276,605	463.61	0.00%
8P-1I-15R	451,242	124	451,242	2182.14	0.00%
25P-1I-15R	4,295,400	5,220	4,295,400	2726.38	0.00%
8P-3I-15R	1,374,191	1,037	1,389,678.7	4,545.25	1.13%
25P-3I-15R	17,107,019	670,540	17,107,019	7,098.19	0.00%

Table 5.7 The Decision Variables of The Proposed MINLP

Instances	Proposed MINLP							
	to	k	S1	s1	S2	s2	S3	s3
8P-1I -Det	1	4	224	9				
25P-1I-Det	13	1	1,293	1,293				
8P-3I-Det	1	4	224	0	263	29	206	47
25P-3I-Det	13	1	1293	1293	1410	1410	2277	2277
8P-1I-15R	1	4	237.80	23.47				
25P-1I-15R	13	1	1285.8	1285.8				
8P-3I-15R	1	4	223.07	6.67	279.73	28.20	199.87	47.27
25P-3I-15R	13	1	1285.9	1172.5	1333.6	1225.1	2675.5	1797.3

Table 5.8 The Decision Variables of The Proposed GA

Instances	Proposed GA							
	to	k	S1	s1	S2	s2	S3	s3
8P-1I -Det	1	4	224	4				
25P-1I-Det	13	1	1,293	591				
8P-3I-Det	4	1	143	84	181	127	179	153
25P-3I-Det	13	1	1293	1239	1410	783	2277	1319
8P-1I-15R	1	4	223.07	810.53				
25P-1I-15R	13	1	1285.8	771.4				

8P-3I-15R	4	1	144.33	116.87	188.33	151.07	177.33	157.40
25P-3I-15R	13	1	1,285.80	762.53	1,336.47	785.07	2,806.87	1,566.53

Since in our algorithm the computation could terminate when there is no improvement in a certain percentage of iterations, here we also obtain a further analysis of the number of iterations of each instance. Figure 5.9, Figure 5.10, Figure 5.11, Figure 5.12, Figure 5.13, Figure 5.14, Figure 5.15, and Figure 5.16 illustrates the improvement of the total cost at every iteration. Furthermore, the termination of the computation is also shown by a vertical line in the figure. Based on these figures, all the computation terminates before the $Maxit_1$ and $Maxit_2$ have reached. This means that the computation has already converged at a local optimal or global optimum value before reaching its maximum iteration.

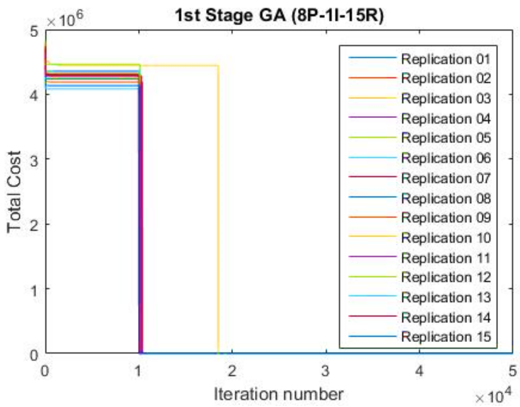

Figure 5.9 Iteration of 1st Stage of GA on 8P-1I-15R

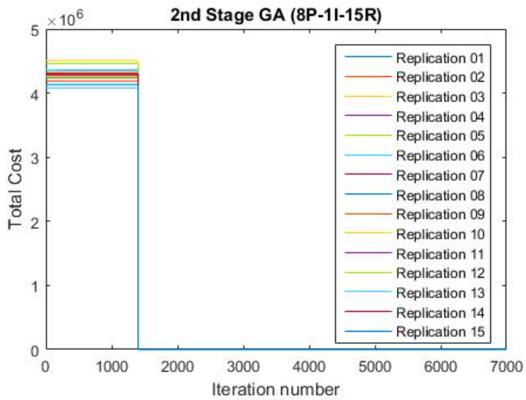

Figure 5.10 Iteration of 2nd Stage of GA on 8P-1I-15R

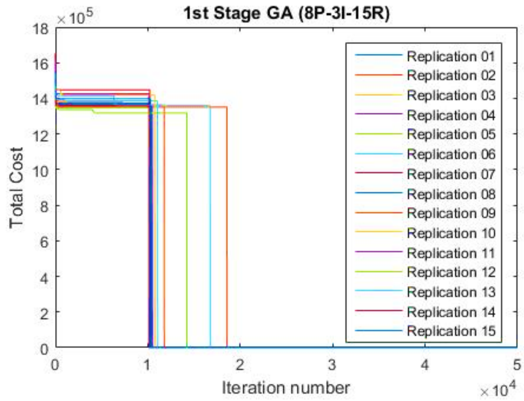

Figure 5.11 Iteration of 1st Stage of GA on 8P-3I-15R

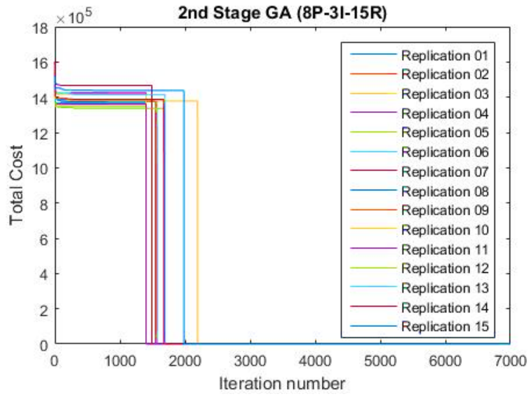

Figure 5.12 Iteration of 2nd Stage of GA on 8P-3I-15R

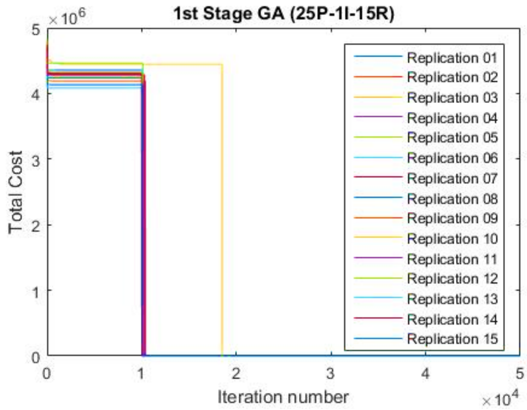

Figure 5.13 Iteration of 1st Stage of GA on 25P-1I-15R

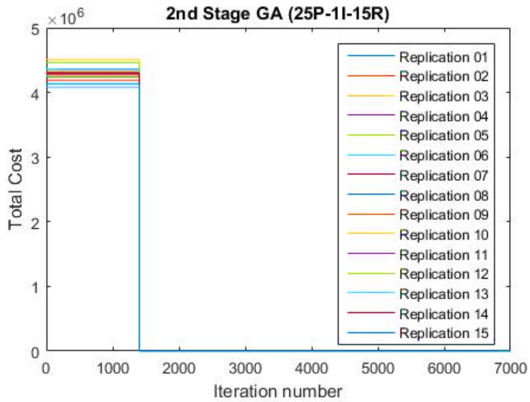

Figure 5.14 Iteration of 2nd Stage of GA on 25P-1I-15

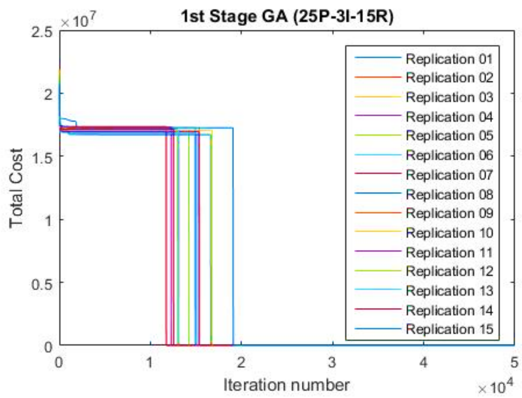

Figure 5.15 Iteration of 1st Stage of GA on 25P-3I-15R

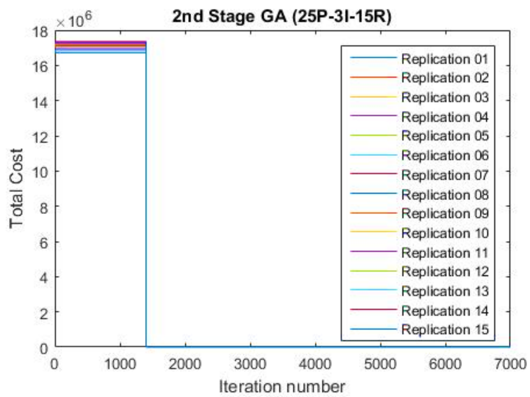

Figure 5.16 Iteration of 2st Stage of GA on 25P-3I-15R

5.6 Evaluation on Inventory Policies and PM Policies

In this study, we propose the (T, s, S) inventory policy. Scarf (1960) has proven the optimality of (T, s, S) policy which gave the minimum total cost than the other systems under general assumptions of demand and cost factors. Furthermore, we also evaluate our policy with other policy (Q, R) and continuous (s, S). Note that (T, s, S) policy will be equivalent with (Q, R) policy if $s = 0$ and (T, s, S) policy will be equivalent with (s, S) if $T = 1$.

Table 5.9 Comparing Inventory Policies

Instances	(*S*, *s*, *R*)	(*Q*, *R*)		(*S*, *s*)	
	Average Total Cost	**Average Total Cost**	**Gap**	**Average Total Cost**	**Gap**
8P-1I -Det	451,855.00	456,795.00	1.09%	451,855.00	0.00%
25P-1I-Det	4,317,685.00	4,502,700.00	4.29%	4,405,880.00	2.04%
8P-3I-Det	1,356,465.00	1,477,290.00	8.91%	1,356,465.00	0.00%
25P-3I-Det	17,272,560.00	18,075,290.00	4.65%	17,272,560.00	0.00%
8P-1I-15R	451,242.00	511,392.67	13.33%	451,242.00	0.00%
25P-1I-15R	4,295,400.00	4,545,798.00	5.83%	4,473,793.00	4.15%
8P-3I-15R	1,374,191.33	1,541,850.67	12.20%	1,374,191.33	0.00%
25P-3I-15R	17,107,019.33	17,787,733.33	3.98%	17,419,226.33	1.83%

Based on the Table 5.9, the (S, s, R) policy is much better compared to the (Q, R) policy. In some problem, the best decision is to review the stock continuously, which is equivalent to the continuous (S, s) policy. Therefore, there is no gap between the costs in some problems. In conclusion, the (S, s, R) policy could be considered as a flexible policy which could obtain an optimal solution at any condition of the stock-review intervals and the re-order point value.

The proposed PM policy is to perform an overhaul inspection in a regular basis. Here we also evaluate our proposed PM policy compared to performing PM policy at every period and when there is no PM performed until the end of the planning horizon.

Table 5.10 Comparing PM Policies

Instances	Regular PM Interval at *k*to*	PM at Every Period		No PM until the last period	
	Average Total Cost	**Average Total Cost**	**Gap**	**Average Total Cost**	**Gap**
8P-1I -Det	451,855.00	700,135.00	54.95 %	471,560.00	4.36%

Instances	Regular PM Interval at ***k*to***	PM at Every Period		No PM until the last period	
	Average Total Cost	Average Total Cost	Gap	Average Total Cost	Gap
25P-1I-Det	4,317,685.00	5,478,590.00	26.89 %	4,639,080.00	7.44%
8P-3I-Det	1,356,465.00	2,015,155.00	48.56 %	1,413,170.00	4.18%
25P-3I-Det	17,276,605.00	20,522,970.00	18.79 %	17,978,190.00	4.06%
8P-1I-15R	451,242.00	705,060.00	56.25 %	501,270.67	11.09%
25P-1I-15R	4,295,400.00	5,372,588.50	25.08 %	4,694,131.50	9.28%
8P-3I-15R	1,374,191.33	2,059,496.33	49.87 %	1,524,574.33	10.94%
25P-3I-15R	17,107,019.33	19,965,739.67	16.71 %	17,742,648.00	3.72%

Based on the Table 5.10, conducting PM at every period is not preferable since the total cost increases because it requires more items to be replaced. Furthermore, not performing PM is also not preferable since the number of defective items could increase if we do not replace it as soon as possible.

5.7 Evaluation on the Modeling Accuracy

We also evaluate the modeling accuracy (%) to evaluate the gap between the expected total cost and the simulation result. The expected total cost is obtained by calculating the optimal cost when the stochastic variables (*d*, *dpm*) are assumed to be the expected values. The manual calculation of these expected values are shown in the Appendix 4. The formula for evaluating the simulation result is shown as follows Xiang et al. (2018):

$$\text{model accuracy} = \left| \frac{\text{model result} - \text{simulation result}}{\text{simulation result}} \right| \times 100\% \tag{41}$$

To ensure that this simulation result has already represented the expected value, we can perform a hypothesis testing by conducting a *t-test* between our simulation result and the expected total cost.

H_0 : There is no significant difference between the simulation results and the expected total cost.

H_1 : There is a significant difference between the simulation results and the expected total cost.

Table 5.11 Modeling Accuracy

Instances	Replications	Expected Total Cost	Simulation Result	Model Accuracy	P-value
8P-1I	1	453,680	451,855.00	0.40%	N/A
	15		451,242.00	0.54%	0.517
8P-3I	1	1,387,770	1,373,195.00	1.05%	N/A
	15		1,389,678.67	0.14%	0.841
25P-1I	1	4,261,375	4,317,685.00	1.32%	N/A
	15		4,295,400.00	0.80%	0.25
25P-3I	1	17,206,545	17,276,605.00	0.41%	N/A
	15		17,107,019.33	0.58%	0.056

From the Table 6.11, the simulation result is still within the acceptable range of model accuracy (5%), and all of the p-value is larger than 0.05. This means that our simulation results in 15 replications have represented the expected total cost. Larger number of replications will be more representative. However, by considering the computing time, adding more replication will be less efficient.

5.8 Application: A Petrochemical Company in Gresik, Indonesia

We implement our proposed GA to a chemical process industry which currently working on 70,000 Ton of production capacity. However, the equipment breakdown cause a decreasing availability to 88% and the manufacturing system cannot perform effectively. Furthermore, 40% of the production shutdown causes are related to the machine breakdown. Therefore, optimizing the spare parts inventory management and planned maintenance is important to minimize the shutdown risks. In this case study, we will consider 48 periods of planning horizon. Each period represents a month of operational time. Since a petrochemical company operates continuously in 24 hours, therefore, our planning horizon is in 4 years' operational time. This company currently conducts a periodic planned maintenance once in every four years. Furthermore, the ordering review is done in every month, if the current stock is less than the reoder point (*s*), the company will order the spare part in amount of order-up-to-level (*S*) minus the current stock level (*I*). By implementing this policy, the expected cost during four years is IDR 7,469,607,000.-. The manual calculation of this expected cost is shown in the Appendix 5. Here we assume that the ordering lead time is one month. So that the ordered spare parts will arrive one month after it was issued.

We evaluate our proposed GA to six independent items of spare parts of the critical units in the production system. Appendix 3 shows the detailed information about the expected number of required items for CM and PM in every period of each item. Table 5.12 and Table 5.13 shows the information about the cost components, which consist of the fixed ordering cost (*K*), variable purchasing cost (*v*), variable penalty cost (*b*), variable holding cost (*h*), fixed PM cost (*PC*), and fixed CM cost (*CM*).

Table 5.12 Odering Cost, Penalty Cost, PM Cost, and CM Cost (IDR)

Ordering Cost	*K*	100,000
Penalty Cost	*b*	25,000,000
PMCost	*PC*	4,360,000
CMCost	*CC*	4,905,000

Table 5.13 Variable Purchasing Cost and Variable Holding Cost (IDR)

Item	**1**	**2**	**3**	**4**	**5**	**6**
v	200,000	600,000	1,800,000	3,000,000	2,000,000	2,500,000
h	2,000	6,000	18,000	30,000	20,000	25,000

First, we try to simulate the current policy by using our algorithm, where the review interval and the PM interval have already given (t_o = 1 and k = 47). Table 5.14 shows the total cost and the computing time in 15 replications of simulations.

Table 5.14 The Simulation Result of The Case Study (Existing Policy)

Replication	**Total Cost (1,000 IDR)**	**Computing Time 1st GA**	**Computing Time 2nd GA**	**Total Computing Time (s)**
1	7,384,062.00	1,838.24	412.75	2,250.99
2	7,698,289.00	1,365.24	400.07	1,765.31
3	6,956,427.00	1,555.31	154.35	1,709.65
4	7,229,323.00	1,861.92	491.64	2,353.56
5	7,085,226.00	1,786.04	172.04	1,958.08
6	7,346,577.00	2,468.17	377.23	2,845.41
7	7,771,944.00	1,486.20	381.16	1,867.36

Replication	Total Cost (1,000 IDR)	Computing Time 1st GA	Computing Time 2nd GA	Total Computing Time (s)
8	7,430,853.00	1,284.67	196.02	1,480.69
9	7,189,318.00	1,410.89	354.91	1,765.80
10	7,767,978.00	1,356.30	293.36	1,649.66
11	7,762,308.00	4,104.06	266.11	4,370.17
12	7,668,146.00	2,008.96	445.11	2,454.07
13	7,193,381.00	1,836.13	217.08	2,053.20
14	7,610,101.00	2,696.51	443.91	3,140.43
15	7,688,093.00	1,925.27	472.46	2,397.73
Average	7,452,135.67	1,932.26	338.55	2,270.81

To ensure that this simulation result has already represented the expected value, we can perform a hypothesis testing by conducting a *t-test* between our simulation result and the expected total cost.

H_0 : There is no significant difference between the simulation results and the expected total cost.

H_1 : There is a significant difference between the simulation results and the expected total cost.

Based on the Minitab result, the *p-value* is 0.797, which is greater than $\alpha = 0.05$, therefore, we can conclude that there is no significant difference between our simulation results and the expected value.

Next, we conduct the simulation in 15 replications through our proposed GA, the summary of the total cost and the computing time is shown in the Table 5.15, and the decision variables are shown in the Table 5.16 and Table 5.17.

Table 5.15 The Simulation Result of the Case Study (New Policy)

Replication	Total Cost (1000 IDR)	Computing Time 1st GA	Computing Time 2nd GA	Total Computing Time (s)
1	6,237,254.00	1,838.24	425.3	2,263.50
2	6,319,034.00	1,365.24	422.7	1,787.93
3	6,014,973.00	1,555.31	424.6	1,979.86
4	5,967,961.00	1,861.92	379.3	2,241.22
5	6,033,882.00	1,786.04	213	1,999.01
6	5,965,438.00	2,468.17	85.75	2,553.93
7	6,346,303.00	1,486.20	334.3	1,820.50
8	6,170,137.00	1,284.67	329.2	1,613.87

Replicatio n	Total Cost (1000 IDR)	Computing Time 1st GA	Computing Time 2nd GA	Total Computing Time (s)
9	6,184,319.00	1,410.89	325.3	1,736.16
10	6,026,296.00	1,356.30	364.1	1,720.45
11	6,154,276.00	4,104.06	492.6	4,596.62
12	6,134,891.00	2,008.96	437.5	2,446.50
13	6,379,230.00	1,836.13	184.4	2,020.56
14	5,762,803.00	2,696.51	105.1	2,801.60
15	6,081,209.00	1,925.27	269.9	2,195.21
Average	6,118,534.33	1,932.26	319.53	2,251.79

Table 5.16 Decision Variables (t_o, k)

t_o	k	m
1	25	25

Table 5.17 Average Decision Variables (S, s)

S_1	S_2	S_3	S_4	S_5	S_6
260.80	163.80	188.73	175.20	191.07	154.20
s_1	s_2	s_3	s_4	s_5	s_6
182.67	80.07	31.87	1.53	16.87	13.47

Table 5.18 Rounded Up Decision Variables (S, s)

S_1	S_2	S_3	S_4	S_5	S_6
261	164	189	176	192	155
s_1	s_2	s_3	s_4	s_5	s_6
183	81	32	2	17	14

Based on the simulation results, the total cost incurred for the maintenance is IDR 6,118,533,733.33 in four years. This simulation requires 33,776.92 seconds in total or 2,251.79 in average. This calculation can be considered efficient for the long-term planning in our case study. Based on our simulation result, the best ordering review is in every month and the PM interval is in every 25 months. Table 5.17 shows the average *S, s* parameters for every item, since our item is discrete, we round up these variables in to the integer values which is shown in Table 5.18.

Therefore, the expected difference between our simulation result and the current policy is IDR 1,333,601,333.-. The following is the calculation of the percentage gap between our simulation results and the current policy.

$$\left(\frac{\text{Simulation result} - \text{Current policy}}{\text{Current policy}}\right)\times 100\%$$

$$= \left(\frac{6{,}118{,}533{,}733 - 7{,}452{,}135{,}067}{6{,}452{,}135{,}067}\right)\times 100\% = -17.9\% \tag{42}$$

5.9 Sensitivity Analysis

In this part, we conduct a sensitivity analysis to our model to evaluate the differences of the cost and the solutions if some parameters are changed. The sensitivity analysis is done to the fixed PM cost, fixed CM cost, and fixed ordering cost. Table 5.19 and Table 5.20 show the result of the sensitivity analysis of fixed CM cost. In this sensitivity analysis, there are three scenarios. The first scenario is reducing the current CM cost into half, the second scenario is the current value of the CM cost, and the third scenario is increasing the CM cost into twice.

Table 5.19 Sensitivity Analysis of Fixed CM Cost

Scenario	**Coefficient**	**CC**	**Total Cost**	**Computing Time**	t_o	k
1	0.5	2,452,500.00	5,434,958,800.00	32,004.82	4	62
2	1	4,905,000.00	6,118,533,733.33	33,776.92	1	5
3	2	9,810,000.00	6,384,767,333.33	34,539.02	1	1

Table 5.20 *S*, *s* of the Sensitivity Analysis of Fixed CM Cost

Scenario	S_1	S_2	S_3	S_4	S_5	S_6	s_1	s_2	s_3	s_4	s_5	s_6
1	463	190	149	178	163	156	360	117	71	2	30	18
2	261	164	189	176	192	155	183	81	32	2	17	14
3	148	57	25	12	19	16	101	37	16	9	13	11

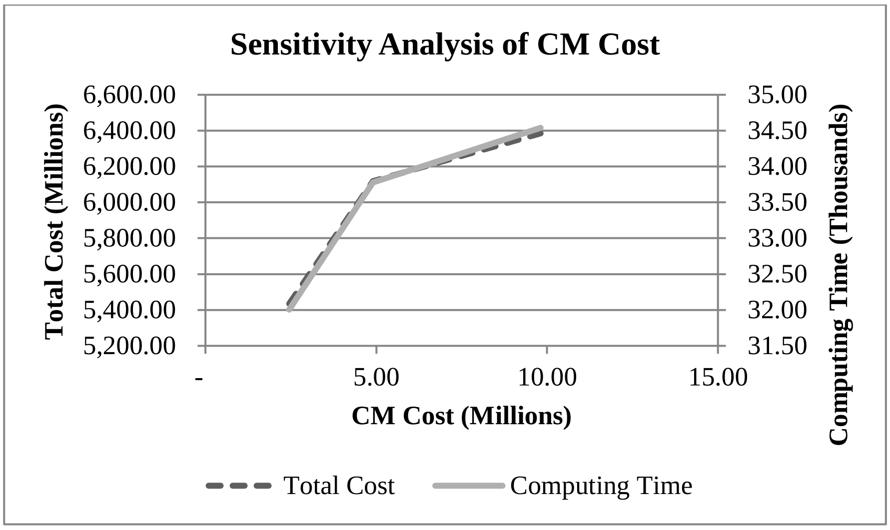

Figure 5.17 Sensitivity Analysis of CM Cost

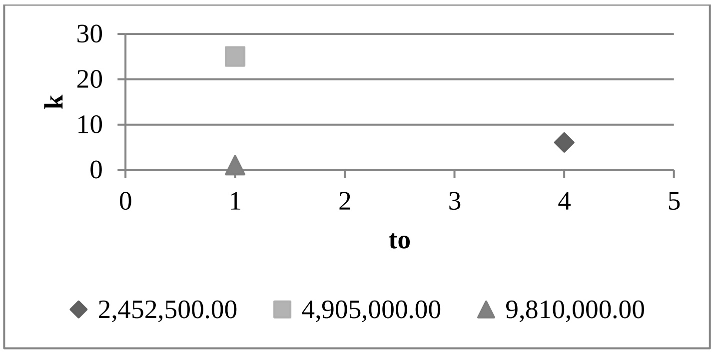

Figure 5.18 t_o and k Values of Sensitivity Analysis of the CM Cost

Based on the Table 5.19 and Table 5.20, if we decrease the CM cost into half of the current value, the PM is done in every 24 months. Compared to the current CM cost policy, there are no significant changes of the PM policy. Furthermore, the stock review is done more often compared to the current CM cost policy. The cost resulted from this scenario is also less than the original scenario. Meanwhile, if we increase the CM cost into twice of the current value, the PM is done in every month which is significantly different compared to the current PM policy. The stock review is also done in every month; this is because the spare parts requirements for the PM in every month need to be fulfilled. The cost is also increased as the fixed CM cost increases. The computing time of the scenario 1 is shorter than the original scenario, while the scenario 3 are longer compared to the original scenario.

Table 5.21 Sensitivity Analysis of Fixed PM Cost

Scenario	**Coefficient**	**PC**	**Total Cost**	**Computing Time**	t_o	k
1	0.5	2,180,000.00	6,419,244,666.67	37,857.82	10	1
2	1	4,360,000.00	6,118,533,733.33	33,776.92	1	25
3	1.5	6,540,000.00	6,135,905,666.67	39,306.04	1	24

Table 5.22 *S*, *s* of the Sensitivity Analysis of Fixed PM Cost

Scenario	S_1	S_2	S_3	S_4	S_5	S_6	s_1	s_2	s_3	s_4	s_5	s_6
1	896	384	172	72	132	105	701	248	126	52	82	74
2	261	164	189	176	192	155	183	81	32	2	17	14
3	273	207	128	179	187	157	180	75	35	2	18	16

Table 5.21 and Table 5.22 show the result of the sensitivity analysis of the fixed PM cost. We use three scenarios. The first scenario is reducing the fixed PM cost into half, the second scenario is the current PM cost, and the third scenario is increasing the fixed PM cost into 1.5 times of the current PM cost.

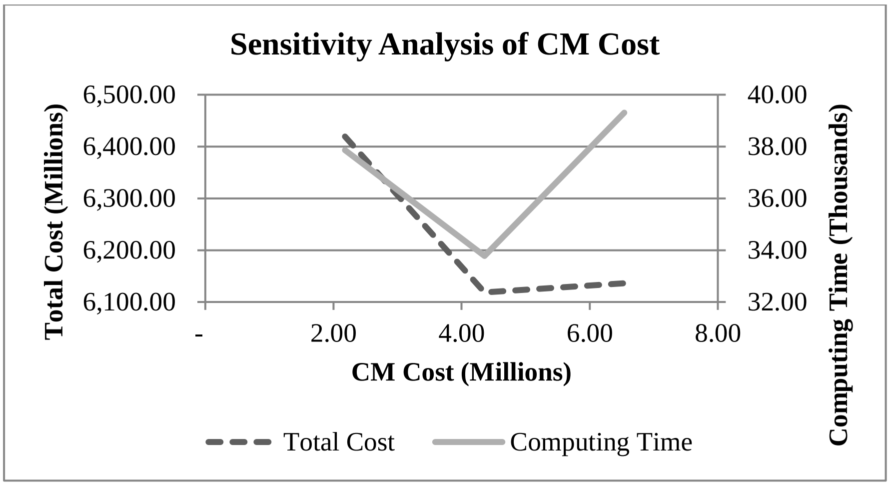

Figure 5.19 Sensitivity Analysis of PM Cost

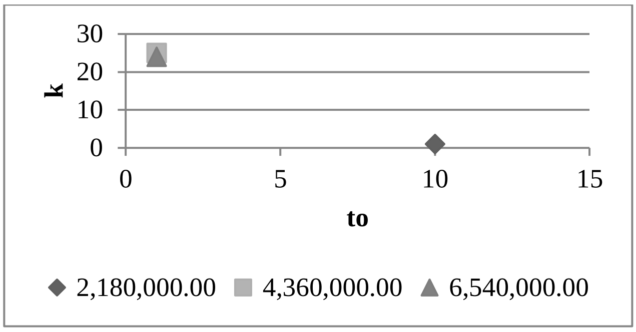

Figure 5.20 *to* and *k* Values of Sensitivity Analysis of the PM Cost

If we decrease the fixed PM cost into half, the stock review is done in every 10 months, this is significantly different compared to the original scenario. Furthermore, the PM is done in every 10 months, which is more often compared to the original scenario. The cost resulted from the first scenario is also higher compared to the second scenario. Meanwhile, if we increase the PM cost into 1.5 times, the PM is done in every 24 months and the stock review is done in very month. This means there is no significant changes if we increase the PM cost into 1.5 times. Both computing time of the scenario 1 and scenario 3 are larger compared to the original scenario.

Table 5.23 Sensitivity Analysis of Fixed PM Cost

Scenario	Coefficient	CC	Total Cost	Computing Time	t_o	k
1	5	500,000.00	6,143,032,600.00	39,918.19	1	25
2	1	100,000.00	6,118,533,733.33	33,776.92	1	25
3	2	200,000.00	6,124,316,733.33	32,522.04	2	12

Table 5.24 *S*, *s* of the Sensitivity Analysis of Fixed PM Cost

Scenario	S_1	S_2	S_3	S_4	S_5	S_6	s_1	s_2	s_3	s_4	s_5	s_6
1	304	165	174	175	191	154	194	76	36	3	16	13
2	261	164	189	176	192	155	183	81	32	2	17	14
3	24	320	185	131	186	191	152	258	97	47	2	30

Table 5.23 and Table 5.24 show the result of the sensitivity analysis of the fixed ordering cost. We use three scenarios. The first scenario is increasing the fixed ordering cost into five times, the second scenario is the current ordering cost, and the third scenario is increasing the fixed ordering cost into 2 times of the current ordering cost.

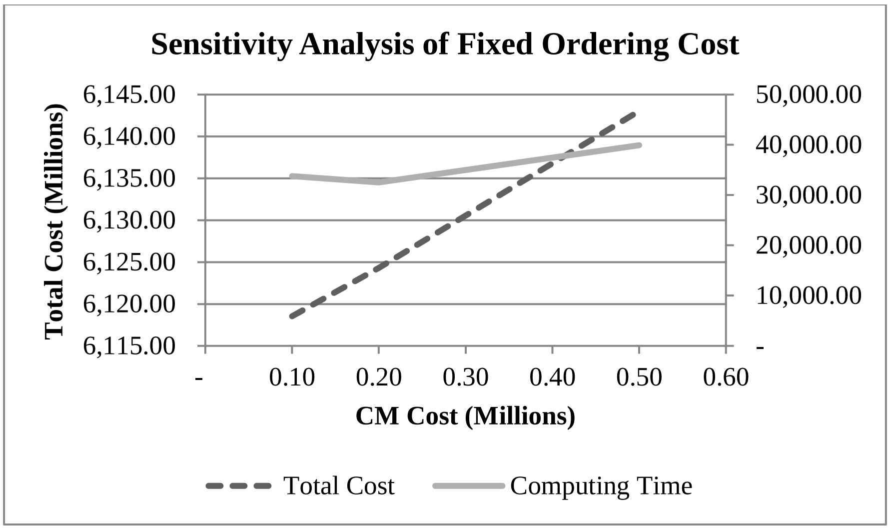

Figure 5.21 Sensitivity Analysis of Fixed Ordering Cost

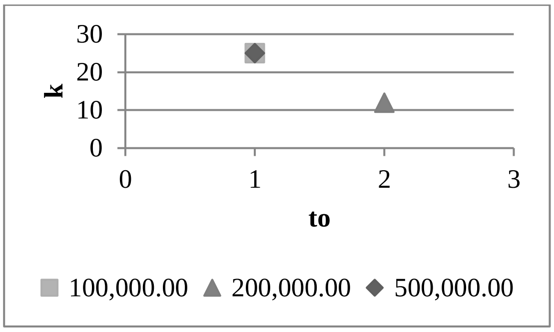

Figure 5.22 t_o and k Values of Sensitivity Analysis of the Fixed Ordering Cost

If we increase the fixed ordering cost into five times, the stock review is done in every 25 months and the PM is done in every 25 months, this means there is no difference compared to the original scenario. The cost resulted from the first scenario is also higher compared to the second scenario. Meanwhile, if we increase the ordering cost into 2 times, the PM is done in every 24 months and the stock review is done in every two months. This means there is a significant change if we increase the PM cost into 2 times. The computing time of the scenario 1 is larger than the original scenario, while the computing time of scenario 3 is longer compared to the original scenario.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

Chapter 6 contains the conclusions which are resulted from the previous analysis. This chapter also contains the recommendations for the possible future research.

6.1 Conclusions

This research has developed a mathematical model to optimize the spare parts inventory management and the planned maintenance jointly. We focus on modeling a periodic *s*, *S* inventory policy which the stock review is done in every t_o periods. Furthermore, the PM interval is done in every kt_o periods. The stochastic programming model is performed to solve the variability of the spare parts requirements under the normal distribution assumption. The mathematical model is obtained to solve a small scale problem. Otherwise, if we solve a large scale problem by the mathematical model, it would be computationally expensive. Therefore, a genetic algorithm (GA) is also developed to solve a larger scale problem. We conduct two stages of GA to solve the best t_o and *k* values under uncertain spare parts requirements.

An experimental design method is conducted to determine the best parameter setting for the proposed algorithm. Based on the algorithm testing result, the proposed GA performs good computational efficiency for the large scale problem and results a good solution in most instances. However, our proposed GA will be less efficient to be implemented in a small scale problem since the terminating condition depends on the *maxit* and *maxter* parameters.

We conduct a comparison of the different inventory policies and PM policies. From these comparisons, we found that the best inventory policy is the periodic *s*, *S* inventory policy. This is because this policy can be considered as a flexible policy, which can become *Q*, *R* policy if $s = 0$ and become continuous *s*, *S* policy if the stock review equal to 1. Based on the comparisons between the inventory policies, the gap between the (*Q*, *R*) inventory policy and the periodic *s*, *S* policy is considerably high. While sometimes if the decision is review the stock continuously, the gap between the continuous *s*, *S* inventory policy and the periodic *s*, *S* inventory policy will become 0. Based on the comparison between the PM policies, conducting PM at regular basis is much better compared to PM at every period and no PM until the last period. Conducting PM at every period is not preferable since the total cost increases because it requires more items to be replaced. Furthermore, not performing PM is also not preferable since the number of defective items could increase if we do not replace it as soon as possible.

We also implement our proposed GA to a real case study. The current policy of the real case study is reviewing the stock at every period and conducting the PM at every four years (48 months). By performing this policy, the expected total cost during four years is IDR 7,469,607,000.-. After conducting the GA simulation, the best policy is conducting the stock review at every month and the PM at every 25 months. By conducting this policy, the expected difference between our simulation result and the current policy is IDR 1,333,601,333.-, which decreases up to 17.9%.

The sensitivity analysis is also conducted to evaluate the changes of the policies due to the changes of the parameters. We conduct the sensitivity analysis to three parameters, which are the fixed ordering cost (*K*), the fixed PM cost (*PC*), and the fixed CM cost (*CM*). Based on these sensitivity analyses, the policy changes significantly by increasing the CM cost into twice of the current policy, decreasing the PM cost into half of the current policy, and increasing the fixed ordering cost into twice of the current policy.

6.2 Recommendations for Future Research

In this study, we assume that all the items are independent each other, which in reality, one item could influence the other items in a large manufacturing plant. Future studies could consider the interdependency between items and the internal failure rate of each item. Furthermore, the repairing activity could also be considered instead of only considering the replacement activity. However, the problem could become much more complex which might require other advance approaches which can model the probabilistic behavior of the system.

In this study, the solution method does not perform efficiently for the small scale problem. Although it performs better than the MINLP model for the large scale problem, it still requires long computational time. Future studies could develop other solution method which can solve the problem more effectively and efficiently.

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APPENDICES

Appendix 1. One Factor at Time Experiment Results

No	Mut	Pcross	N	Maxit1	Maxit2	Maxter	#1	#2	#3	Average	Level 1	Level 2
1	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
2	0.4	0.2	100	10000	1000	0.05	1,398,834.67	4,296,275.00	17,271,781.00	7,655,630.22		
3	0.6	0.2	100	10000	1000	0.05	1,400,556.00	4,296,025.00	17,247,381.33	7,647,987.44		
4	0.8	0.2	100	10000	1000	0.05	1,400,777.33	4,295,900.00	17,228,335.33	7,641,670.89		
5	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
6	0.2	0.4	100	10000	1000	0.05	1,434,698.67	4,296,650.00	17,362,784.33	7,698,044.33		
7	0.2	0.6	100	10000	1000	0.05	1,434,396.67	4,295,775.00	17,837,746.67	7,855,972.78		
8	0.2	0.8	100	10000	1000	0.05	1,398,673.33	4,295,900.00	17,194,816.00	7,629,796.44		
9	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
10	0.2	0.2	300	10000	1000	0.05	1,396,713.33	4,295,400.00	17,154,497.00	7,615,536.78		
11	0.2	0.2	500	10000	1000	0.05	1,397,961.33	4,295,400.00	17,833,621.67	7,842,327.67		
12	0.2	0.2	700	10000	1000	0.05	1,392,668.00	4,295,400.00	17,155,315.00	7,614,461.00		
13	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
14	0.2	0.2	100	30000	1000	0.05	1,401,108.00	4,295,650.00	17,324,455.00	7,673,737.67		
15	0.2	0.2	100	50000	1000	0.05	1,407,336.00	4,296,275.00	17,268,048.00	7,657,219.67		
16	0.2	0.2	100	70000	1000	0.05	1,400,598.67	4,295,775.00	17,277,651.33	7,658,008.33		
17	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
18	0.2	0.2	100	10000	3000	0.05	1,400,029.33	4,296,025.00	17,187,692.00	7,627,915.44		
19	0.2	0.2	100	10000	5000	0.05	1,401,624.00	4,295,900.00	17,865,456.67	7,854,326.89		
20	0.2	0.2	100	10000	7000	0.05	1,398,150.67	4,295,525.00	17,170,330.00	7,621,335.22		
21	0.2	0.2	100	10000	1000	0.05	1,412,976.00	4,297,150.00	17,251,194.00	7,653,773.33		
22	0.2	0.2	100	10000	1000	0.1	1,401,584.00	4,295,650.00	17,215,414.67	7,637,549.56		
23	0.2	0.2	100	10000	1000	0.2	1,395,461.33	4,295,400.00	17,190,518.67	7,627,126.67		
24	0.2	0.2	100	10000	1000	0.25	1,396,154.67	4,295,400.00	17,139,463.67	7,610,339.44		

Appendix 2. Distribution Parameters of Instances

8 Periods (*d*)

Item	Period								
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	0	5	15	26	44	24	15	22	10
2	0	4	23	28	50	39	26	19	32
3	0	11	14	7	11	16	31	11	48

8 Periods (*dpm*)

Period								
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
0	20	36	52	61	72	79	90	105

25 Periods (*d*)

Period 0 - 12

Item	Period												
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	11	17	26	38	53	71	92	115	138	159	175	186
2	0	23	32	42	55	70	86	103	120	136	150	161	168
3	0	20	31	47	68	95	128	166	207	248	286	315	335

Period 13 - 25

Item	Period												
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
1	190	186	175	159	138	115	92	71	53	38	26	17	11
2	170	168	161	150	136	120	103	86	70	55	42	32	23
3	342	335	315	286	248	207	166	128	95	68	47	31	20

25 Periods (*dpm*)

Period 1 - 12

Periode												
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
0	0	44	74	76	102	114	116	119	136	144	146	165

Period 13 - 25

Periode												
13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
174	183	198	204	218	260	264	284	299	318	323	482	534

Appendix 3. Distribution Parameters of Case Study

Expected *d* of period 0 – 12

Item	0	1	2	3	4	5	6	7	8	9	10	11	12
1	0	116	116	116	116	116	116	116	116	116	116	116	116
2	0	48	48	48	48	48	48	48	48	48	48	48	48
3	0	18	18	18	18	18	18	18	18	18	18	18	18
4	0	4	4	4	4	4	4	4	4	4	4	4	4
5	0	11	11	11	11	11	11	11	11	11	11	11	11
6	0	9	9	9	9	9	9	9	9	9	9	9	9

Expected *d* of period 13 – 24

Item	13	14	15	16	17	18	19	20	21	22	23	24
1	116	116	116	116	116	116	116	116	116	116	116	116
2	48	48	48	48	48	48	48	48	48	48	48	48
3	18	18	18	18	18	18	18	18	18	18	18	18
4	4	4	4	4	4	4	4	4	4	4	4	4
5	11	11	11	11	11	11	11	11	11	11	11	11
6	9	9	9	9	9	9	9	9	9	9	9	9

Expected *d* of period 25 – 36

Item	25	26	27	28	29	30	31	32	33	34	35	36
1	116	116	116	116	116	116	116	116	116	116	116	116
2	48	48	48	48	48	48	48	48	48	48	48	48
3	18	18	18	18	18	18	18	18	18	18	18	18
4	4	4	4	4	4	4	4	4	4	4	4	4
5	11	11	11	11	11	11	11	11	11	11	11	11
6	9	9	9	9	9	9	9	9	9	9	9	9

Expected *d* of period 37 – 48

Item	37	38	39	40	41	42	43	44	45	46	47	48
1	116	116	116	116	116	116	116	116	116	116	116	116
2	48	48	48	48	48	48	48	48	48	48	48	48
3	18	18	18	18	18	18	18	18	18	18	18	18
4	4	4	4	4	4	4	4	4	4	4	4	4
5	11	11	11	11	11	11	11	11	11	11	11	11
6	9	9	9	9	9	9	9	9	9	9	9	9

Expected *dpm* of period 0 – 12

0	1	2	3	4	5	6	7	8	9	10	11	12
0	6	6	10	15	17	21	30	31	34	38	40	45

Expected *dpm* of period 12 – 24

13	14	15	16	17	18	19	20	21	22	23	24
48	48	51	52	64	68	74	76	77	81	85	90

Expected *dpm* of period 25 – 36

25	26	27	28	29	30	31	32	33	34	35	36
93	97	105	108	113	116	122	130	133	139	143	148

Expected *dpm* of period 37 – 48

37	38	39	40	41	42	43	44	45	46	47	48
151	154	160	163	168	172	178	184	190	195	199	206

Appendix 4. Calculation of the Expected Total Cost of Instances

8 Periods Single Item

Period	0	1	2	3	4	5	6	7	8	Cost
PM Requirements	0	20	36	52	61	72	**36**	52	61	
CM Requirements (Item 1)	0	5	15	26	44	24	15	22	10	
Stock Review	1	0	0	0	1	0	0	0	1	
PM	0	1	0	0	0	**1**	0	0	0	8,720.00
Inventory	0	118	103	77	33	47	32	10	0	6,300.00
Backorder	0	0	0	0	0	0	0	0	0	-
Quantity	0	143	0	0	0	110	0	0	0	379,500.00
CM	0	0	1	1	1	0	1	1	1	58,860.00
Order	1	0	0	0	1	0	0	0	1	300.00
Total Cost										453,680.00

t_o	k	S	s
4	1	143	133

25 Periods Single Item

Period	0	1	2	3	4	5	6	7
PM Requirements	0	0	44	74	76	102	114	116
CM Requirements (Item 1)	0	11	17	26	38	53	71	92
Stock Review	1	0	0	0	0	0	0	0
PM	0	1	0	0	0	0	0	0
Inventory	0	1260	1243	1217	1179	1126	1055	963
Backorder	0	0	0	0	0	0	0	0
Quantity	0	1271	0	0	0	0	0	0
CM	0	0	1	1	1	1	1	1
Order	1	0	0	0	0	0	0	0

Period	8	9	10	11	12	13	14	15	16
PM Requirements	119	136	144	146	165	174	183	**44**	74
CM Requirements (Item 1)	115	138	159	175	186	190	186	175	159
Stock Review	0	0	0	0	0	1	0	0	0
PM	0	0	0	0	0	0	**1**	0	0
Inventory	848	710	551	376	190	0	902	727	568
Backorder	0	0	0	0	0	0	0	0	0
Quantity	0	0	0	0	0	0	1271	0	0
CM	1	1	1	1	1	1	0	1	1
Order	0	0	0	0	0	1	0	0	0

Period	17	18	19	20	21	22	23	24	25
PM Requirements	76	102	114	116	119	136	144	146	165

Period	17	18	19	20	21	22	23	24	25
CM Requirements (Item 1)	138	115	92	71	53	38	26	17	11
Stock Review	0	0	0	0	0	0	0	0	0
PM	0	0	0	0	0	0	0	0	0
Inventory	430	315	223	152	99	61	35	18	7
Backorder	0	0	0	0	0	0	0	0	0
Quantity	0	0	0	0	0	0	0	0	0
CM	1	1	1	1	1	1	1	1	1
Order	0	0	0	0	0	0	0	0	0

t_o	k	S	s
13	1	143	133

Ordering Cost	200.00
Purchasing Cost	3,813,000.00
Holding Cost	213,825.00
Penalty Cost	-
CM Cost	225,630.00
PM Cost	8,720.00
Total Cost	4,261,375.00

8 Periods Multi Items

Period	0	1	2	3	4	5	6	7	8
PM	0	1	0	0	0	**1**	0	0	0
PM Requirements	0	20	36	52	61	72	**36**	52	61
Re	1	0	0	0	1	0	0	0	1

CM Requirements									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	0	5	15	26	44	24	15	22	10
SP_2	0	4	23	28	50	39	26	19	32
SP_3	0	11	14	7	11	16	31	11	48

Inventory									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	0	118	103	77	33	47	32	10	0
SP_2	0	164	141	113	63	77	51	32	0
SP_3	0	147	133	126	115	90	59	48	0

Backorder									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	0	0	0	0	0	0	0	0	0
SP_2	0	0	0	0	0	0	0	0	0
SP_3	0	0	0	0	0	0	0	0	0

Quantity									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	0	143	0	0	0	110	0	0	0
SP_2	0	188	0	0	0	125	0	0	0
SP_3	0	178	0	0	0	63	0	0	0

CM									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	0	0	1	1	1	0	1	1	1
SP_2	0	0	1	1	1	0	1	1	1
SP_3	0	0	1	1	1	0	1	1	1

Order									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SP_1	1	0	0	0	1	0	0	0	1
SP_2	1	0	0	0	1	0	0	0	1
SP_3	1	0	0	0	1	0	0	0	1

Item	t_o	k	S	s
SP_1			143	84
SP_2	4	1	188	164
SP_3			178	176

Ordering Cost	900.00
Purchasing Cost	1,174,500.00
Holding Cost	27,070.00
Penalty Cost	-
CM Cost	176,580.00
PM Cost	8,720.00
Total Cost	1,387,770.00

25 Periods Multi Items

Period	0	1	2	3	4	5	6	7	8	9	10	11	12
PM	0	1	0	0	0	0	0	0	0	0	0	0	0
PM Requirements	0	0	44	74	76	102	114	116	119	136	144	146	165
Re	1	0	0	0	0	0	0	0	0	0	0	0	0

Period	13	14	15	16	17	18	19	20	21	22	23	24	25
PM	0	**1**	0	0	0	0	0	0	0	0	0	0	0
PM Requirements	174	183	**44**	74	76	102	114	116	119	136	144	146	165
Re	1	0	0	0	0	0	0	0	0	0	0	0	0

CM Requirements													
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
SP_1	0	11	17	26	38	53	71	92	115	138	159	175	186
SP_2	0	23	32	42	55	70	86	103	120	136	150	161	168
SP_3	0	20	31	47	68	95	128	166	207	248	286	315	335

CM Requirements													
Period/Item	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	190	186	175	159	138	115	92	71	53	38	26	17	11
SP_2	170	168	161	150	136	120	103	86	70	55	42	32	23
SP_3	342	335	315	286	248	207	166	128	95	68	47	31	20

Inventory													
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
SP_1	0	1260	1243	1217	1179	1126	1055	963	848	710	551	376	190
SP_2	0	1306	1274	1232	1177	1107	1021	918	798	662	512	351	183

SP_3	0	2268	2237	2190	2122	2027	1899	1733	1526	1278	992	677	342

Inventory

Period/Item	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	0	902	727	568	430	315	223	152	99	61	35	18	7
SP_2	13	978	817	667	531	411	308	222	152	97	55	23	0
SP_3	0	1770	1455	1169	921	714	548	420	325	257	210	179	159

Backorder

Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Quantity

Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	0	1271	0	0	0	0	0	0	0	0	0	0	0	0	1271	0	0	0	0	0	0	0	0	0	0	0
SP_2	0	1329	0	0	0	0	0	0	0	0	0	0	0	0	1316	0	0	0	0	0	0	0	0	0	0	0
SP_3	0	2288	0	0	0	0	0	0	0	0	0	0	0	0	2288	0	0	0	0	0	0	0	0	0	0	0

CM

Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
SP_2	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
SP_3	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1

	Order																									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
SP_1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
SP_2	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
SP_3	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0

Item	t_o	k	S	s
SP_1			1271	746
SP_2	**13**	**1**	1329	357
SP_3			2288	1295

Appendix 4. Calculation of the Expected Total Cost of Real Case Study

Period	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
PM	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PM Requirements	0	6	6	10	15	17	21	30	31	34	38	40	45	48	48	51	52	64	68	74	76	77	81	85
Re	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Period	24	25	26	27	28	29	30	31	32	33	34	35	36
PM	0	0	0	0	0	0	0	0	0	0	0	0	0
PM Requirements	90	93	97	105	108	113	116	122	130	133	139	143	148
Re	1	1	1	1	1	1	1	1	1	1	1	1	1

Period	37	38	39	40	41	42	43	44	45	46	47	48
PM	0	0	0	0	0	0	0	0	0	0	0	1
PM Requirements	151	154	160	163	168	172	178	184	190	195	199	206
Re	1	1	1	1	1	1	1	1	1	1	1	1

	CM Requirements																							
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
SP_1	0	5	5	7	9	10	14	18	19	20	22	23	24	25	25	25	25	35	38	40	42	43	45	48
SP_2	0	1	1	2	4	5	5	7	7	9	9	10	13	13	13	15	15	17	17	19	19	19	20	20
SP_3	0	0	0	1	1	1	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	7	7
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
SP_5	0	0	0	0	1	1	1	2	2	2	3	3	3	3	3	4	4	4	4	5	5	5	5	6
SP_6	0	0	0	0	0	0	0	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3	3

	CM Requirements																							
Period/Item	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
SP_1	53	55	58	60	62	64	68	73	75	78	80	83	85	86	90	92	95	98	100	105	108	110	113	116
SP_2	21	22	25	25	28	28	29	31	31	32	33	34	34	35	36	36	38	38	40	40	43	44	45	48
SP_3	8	8	9	10	10	10	10	11	12	12	13	13	14	14	14	15	15	15	16	16	16	17	17	18
SP_4	1	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4
SP_5	6	6	7	7	7	8	8	8	8	9	9	9	9	10	10	10	10	10	10	11	11	11	11	11
SP_6	4	4	4	4	4	4	5	5	5	5	5	6	6	6	7	7	7	7	8	8	8	9	9	9

	Inventory																
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
SP_1	0	313	319	312	303	293	279	261	242	304	302	279	255	230	299	299	274
SP_2	0	255	261	259	255	250	245	238	231	222	213	203	190	177	164	149	134
SP_3	0	238	244	243	242	241	240	238	236	234	231	228	225	221	217	213	208
SP_4	0	204	210	210	210	210	210	210	210	210	210	210	209	208	207	206	205
SP_5	0	211	217	217	216	215	214	212	210	208	205	202	199	196	193	189	185
SP_6	0	219	225	225	225	225	225	224	223	222	221	220	219	217	215	213	211

Inventory																
Period/Item	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
SP_1	239	286	284	242	199	279	276	225	172	269	266	264	262	260	256	251
SP_2	117	100	81	62	43	242	242	221	200	178	153	128	100	72	43	12
SP_3	203	198	192	186	180	173	166	159	151	143	134	124	114	104	94	83
SP_4	204	203	202	201	200	199	198	197	196	194	192	190	188	186	184	182
SP_5	181	177	172	167	162	157	151	145	139	133	126	119	112	104	96	88
SP_6	209	206	203	200	197	194	191	187	183	179	175	171	167	163	158	153

Inventory																
Period/Item	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
SP_1	249	246	244	241	239	238	234	232	229	226	224	219	216	214	211	2
SP_2	231	230	197	163	129	94	58	22	224	224	184	144	101	57	12	8
SP_3	232	232	219	206	192	178	164	149	134	119	103	87	71	227	227	3
SP_4	180	177	174	171	168	165	162	159	156	152	148	144	140	136	132	0
SP_5	209	208	199	190	181	171	161	151	141	131	121	110	99	88	77	0
SP_6	148	143	138	132	126	120	113	106	99	92	84	76	68	216	216	1

Backorder																									
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
SP_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Backorder																								
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Backorder																							
Period/Item	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
SP_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Quantity																								
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
SP_1	0	324	11	0	0	0	0	0	0	82	20	0	0	0	94	25	0	0	85	38	0	0	125	45	0
SP_2	0	262	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	219	20	0
SP_3	0	244	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_4	0	210	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_5	0	217	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_6	0	225	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Quantity																							
Period/Item	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**

SP_1	0	152	55	58	60	62	64	68	73	75	78	80	83	85	86	90	92	95	98	100	105	108	110	113
SP_2	0	0	0	0	0	0	0	0	250	31	0	0	0	0	0	0	240	38	0	0	0	0	0	250
SP_3	0	0	0	0	0	0	0	0	161	12	0	0	0	0	0	0	0	0	0	0	0	173	17	0
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	78
SP_5	0	0	0	0	0	0	0	0	129	8	0	0	0	0	0	0	0	0	0	0	0	0	0	140
SP_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	157	9	0

	CM																								
Period/Item	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
SP_1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_2	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_3	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_5	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_6	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

	CM																							
Period/Item	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
SP_1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SP_2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SP_3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SP_4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SP_5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
SP_6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Order

Period/Item	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SP_1	1	1	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0
SP_2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
SP_3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_5	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP_6	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Order																							
Period/Item	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
SP_1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SP_2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1
SP_3	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
SP_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
SP_5	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
SP_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0

Ordering Cost	6,400,000
Purchasing Cost	5,335,900,000
Holding Cost	853,097,000
Penalty Cost	-
CM Cost	1,265,490,000
PM Cost	8,720,000
Total Cost	7,469,607,000

Item	*S*	*s*

SP_1	324	275
SP_2	262	70
SP_3	244	102
SP_4	210	139
SP_5	217	97
SP_6	225	77

AUTHOR'S BIOGRAPHY

The author's name is Nabila Yuraisyah Salsabila or usually goes by Nabila. The author was born in Malang, July 19, 1996. The author took the formal studies in SDN Kauman 1 Malang, SMPN 5 Malang, and SMAN 3 Malang. After taking the school education level, the author took the college education at the Institut Teknologi Sepuluh Nopember, Surabaya, as an undergraduate student at the Industrial Engineering Department. After completing her undergraduate studies, the author continues to pursue a master study at the Industrial and Systems Engineering Department, Institut Teknologi Sepuluh Nopember. In 2019, the author took an opportunity to join the double degree program with the Industrial Management Department of National Taiwan University of Science and Technology in Taipei, Taiwan. By entering this program, the author earned Magister Teknik and Master of Business Administration in June 2020. During the master study, the author has published one conference paper, one abstract proceeding, and two journal papers. The first paper was published in the IOP Conference Series: Materials Science and Engineering 2019 673 012079, entitled "*A Simulation study of availability analysis on a chemical process industry considering spare part inventory*". This paper was written by the author and Nurhadi Siswanto, Ph.D. The second paper was published in Jurnal Teknik Industri Vol.21 No.2, December 2019, entitled "*Throughput Analysis on a Multi-state Manufacturing System by Considering Availability*". This paper was written by the author, Nurhadi Siswanto, Ph.D., Dr. Erwin Widodo, and Oryza Akbar Rochmadhan. The third paper was published in Teknoin Vol.26, No.1, Maret 2020, entitled "*Analisis Availabilitas Perusahaan Pythalic Anhydride Berdasarkan Persediaan Spare Part dan Penyangga*". This paper was written by Nurhadi Siswanto, Ph.D., Nabila Yuraisyah Salsabila, Oryza Akbar Rochmadhan, and Dr. Erwin Widodo. The fourth is the abstract proceeding, which was presented in Intelligent Productions and Operations 2020. This proceeding is about the author's thesis, entitled "*Joint Optimization Model of Spare Parts Inventory and Planned Maintenance under Uncertain Failures*". If there is any question about the author's thesis or publications, please e-mail at nabilayuraisyahsalsabila@gmail.com. Thank you.