OPTIMAL INVENTORY CONTROL POLICY OF A HYBRID MANUFACTURING - REMANUFACTURING SYSTEM USING A HYBRID SIMULATION OPTIMIZATION ALGORITHM

BY

PATSORN THAMMATADATRAKUL

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEMS ENGINEERING)

SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
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A Thesis Presented

By

PATSORN THAMMATADATRAKUL

Submitted to

Sirindhorn International Institute of Technology

Thammasat University

In partial fulfillment of the requirements for the degree of

MASTER OF ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEMS ENGINEERING)

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JULY 2016

Acknowledgements

I would like to take this opportinuty to reveal my gratitude for the generousness of those who have helped making this research become possible.

Firstly, I would like to express my sincere gratitude to my advisor Assoc. Prof. Dr. Navee Chiadamrong for his patience, encouragement, and valuable guidance throughout my Master study and research. It has been a wonderful experience working under his supervision. Besides, I am extremely grateful to the members of examination committee, Assoc. Prof. Dr. Jirachai Buddhakulsomsiri and Asst. Prof. Dr. Charoenchai Khompatraporn, for their useful comments and suggestions, which have widen my research perspectives. My writing skill has been improved after taking rewriting/editing course, instructed by Mr. Paul Vincent Neilson. I would like to thank him for opening this course for graduate students. In addition, I would like to reflect my appreciation to all my teachers in the curriculum of industrial engineering (Bachelor Degree), and Logistics and Supply Chain Systems Engineering (Master Degee) for their kindness and willing to provide useful knowledge to all students.

Special thanks are given to all SIIT staffs for their kind support and guidance. I thank my fellow course mates for their fruitful suggestion and encourangment in all those years. Lastly, I am grateful to my beloved parents and other family members for their extreme patience, understanding, and continuous spiritual support.

Abstract

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Remanufacturing is a process of bringing used products back to like-new products. In this study, inventory control policies in a remanufacturing with different prioritizations (remanufacturing vs manufacturing) and coordination (non-coordinating vs coordinating) are investigated. A proposed hybrid simulation optimization algorithm where outputs are exchanging between Mixed-Integer Linear Programming (MILP) and simulation models, is presented to search for the optimality. Obtained results from this Hybrid Algorithm are then compared with the results obtained from the pure analytical model and simulation-based optimization. The results show that the proposed hybrid simulation optimization algorithm outperforms other solving methods by obtaining statistically higher objective value, which is the profit of the system and using less number of iterations to find the optimal result. Regarding the inventory control policy, it is found that the level of returned ratio (proportion of returned components as compared to actual customer demand) has an effect to the inventory control policy. [At a lower level of returned ratio, there is no significant difference among policies. The priority of remanufacturing starts to show its dominant in terms of better system profit when the returned ratio is relatively high at around 50% or about half of the actual customer demand where policies with coordination have proven to bridge the effect of prioritization and help to show its effect when this proportion of returned components increases up to 75%.] The outcome of the study helps to give an alternative of finding the optimal results under the uncertain environment by using a hybrid manufacturing/remanufacturing system as a case study and recommends the best solution in each level of the returned ratios.

Keywords: Inventory control, Hybrid manufacturing/remanufacturing system, Hybrid simulation optimization

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Chapter 1
Introduction

1.1 Problem statement

According to the German Recycling and Waste Control Act, manufactures are required to produce products, which leave the smallest amount of waste at the end of their life. Concern on this issue is quickly followed by the European Nation reported by Rembert (1997). Additionally, Ilgin and Gupta (2012) claimed that the profit margin of remanufacturing is around 20%. The activity of remanufacturing has been found to be existed since early 20th century in the United States. Currently, there is a significant growth in many countries and remanufactured products are varied, ranging from laser toner cartridges to industrial machinery. In addition, some benefits are given back to the society from implementing remanufacturing: lower price products, material and energy conservation, and skilled operators. Other recovery options require components as their raw material to produce lower quality finished products, compared to remanufacturing.

Common steps in remanufacturing include cleaning, inspection, sorting, and disassembly of used products before reassembly them into new products. New components are required to support when shortage occurs. Remanufacturing can be a stand-alone process or combined with manufacturing, named as a hybrid manufacturing/remanufacturing system, which shares facilities and/or manages separated facilities in an integrated way. In the hybrid system, fluctuation in quality and quantity of arriving used product increases the difficulty in inventory management. Decision needs to be made whether how many used products should be collected or how many new components should be ordered to support the fluctuation in collecting returned products. In order to obtain answers for these questions, proper inventory management and its optimization are required to solve and recommend the best solution.

Optimization can be classified into exact and heuristic. When solving with exact optimization, i.e. analytical models, problems need to be simplified and uncertainties are compromised, giving impractical results to the real world problems. In contrast to analytical models, simulation can imitate and observe the behavior of the system, but cannot optimize and provide the best solution to the problem. Byrne and Bakir (1999) stated that a better way to solve for the real world problem might involve combining the analytical model and simulation together. A technique of combining optimization and simulation together is known as a hybrid simulation optimization algorithm. A specific combination of heuristic and simulation is named as simulation-based optimization.

In this study, performances of a proposed hybrid simulation optimization algorithm are compared with the analytical model (Mixed-Integer Linear Programming) and simulation-based optimization. For a fair comparison, all solving methods are subject to the same situation where a certain level of uncertainty is involved. In the analytical model, decision variables optimized by the MILP are input into a simulation model to obtain the results with uncertainty. OptQuest, a built-in tool in a simulation software, is selected as a representative for simulation-based optimization. Each solving method is then applied to find the optimal parameters for inventory control policies in a hybrid manufacturing/remanufacturing problem.

1.2 Objective of thesis

The objectives of this thesis are:

- To introduce the proposed hybrid simulation optimization to a hybrid manufacturing/remanufacturing inventory control problem
- To construct analytical and simulation models, which imitate the hybrid manufacturing/remanufacturing system under uncertain environment and measure the system profit for each inventory control policy
- To observe performances of a prioritization and a coordination in an inventory control policy of the hybrid manufacturing/remanufacturing system
- To recommend policy under different proportion of returned component arrival over the customer demand
- To evaluate performances of the proposed hybrid simulation optimization by comparing with analytical model and simulation-based optimization

1.3 Overview of thesis

There are totally eight chapters in this thesis, which are as follows:

Chapter 1 is the introduction part, which introduces background of problem, objectives and overview of the thesis.

Chapter 2 is the literature review part. Related researches are discussed to create more understanding about the hybrid manufacturing/remanufacturing system and the hybrid simulation optimization.

Chapter 3 is the methodology part. In this part, the solving procedure of the proposed hybrid simulation optimization, along with other comparable solving methods, is described.

Chapter 4 is the case study part. Charecteristics of the hybrid manufacturing/ remanufacturing system and details of its inventory control policies are explained.

Chapter 5 is the analytical model part, which presents significant constraints required to construct the hybrid manufacturing/remanufacturing system.

Chapter 6 is the simulation model part. Uncertainties presented in the system are introduced together with the experimental design for simulation model.

Chapter 7 is the results and discussion part. Results are divided into two sections. First section is the result from ANOVA, which involves discussion of the overall results. Second section is the result comparison in terms of the solving method performances and policy performances.

Chapter 8 is the conclusion and recommendations for future study.

Chapter 2

Literature Review

Lund (1983) defined remanufacturing as "...an industrial process in which worn-out products are restored to like-new condition. Through a series of industrial processes in a factory environment, a discarded product is completely disassembled. Usable parts are cleaned, refurbished, and put into inventory. Then, the new product is assembled from the old and, where necessary, new parts to produce a fully equivalent- and sometimes superior- in performance and expected lifetime to the original new product." Recovery options used in the industries are presented in Table 2.1 where the definition of remanufacturing, reuse, repair, reconditioning, and recycling are stated (Ijomah et al., 1999). Remanufacturing is the only option, which takes the whole products into processes, while other options take back only components or material. Reuse and repair result in functional condition of components when the best quality after processing is guaranteed by remanufacturing.

Table 2.1: Differences between recovery options

Option	Before	After
Remanufacturing	Used products	Like-new products
Reuse	Functional components	Being a part of finished products
Repair	Damaged components	Functional condition
Reconditioning	Damaged components	At satisfactory stage but not above original specification
Recycling	Component material	Same or degraded material

Remanufacturing situation in the United States was reported by Lund and Hauser (2010), who presented that an evidence of remanufacturing was found since early 20th century. Around 6,000 firmed were reported to operate as remanufacturing with 113 product areas. Major product areas are motor vehicle parts, electrical motors and generators, pumps, transformers, laser toner cartridges, industrial machinery, tires, industrial valves, and office furniture. In addition, for situation in other countries, a significant growth in Europe and a growing interest in China for remanufacturing were noticed.

Motives, identified in literatures and new finding from automotive industry, for implementing remanufacturing were reviewed and discovered by Seitz (2007) as presented in Table 2.2. Many literatures indicate that motives are ethical, legislation, and profitability. Ethical refers to the responsibility to environment since remanufacturing is claimed to be an environmental friendly process. Law enforcement regulation in some places, for instance Europe, has encouraged people to follow strictly on how to manage the end-of life state of products. An obvious evidence of remanufacturing profitability is still in doubt. Finding indicates that motives for automotive remanufacturing are spare parts supply securing, source of under-warranty engines, market share and brand protection, and customer orientation. Lund and Hauser (2010) presented that by implementing remanufacturing the following benefits are provided to the society. First, customers receive products, with the same quality, at lower prices. Remanufactured product price is between 45% and 65% of the comparable new products. Second, more material and energy are conserved throughout the processes. Third, industrial skills, e.g. product technology and process technology, of operators are developed, which can lead them to higher-paying jobs.

In most of remanufacturing facilities, common processes are cleaning, inspection, sorting, disassembly, and reassembly (Ilgin and Gupta, 2012). Li et al. (2009) broke the operation of stand-alone remanufacturing down to eight stages: product arrival, inspection, testing, disassembly, repairing, labeling, packing, and shipping. Aras et al. (2006) addressed that remanufacturing can either operate as a stand-alone process or combine with manufacturing, known as a hybrid manufacturing/remanufacturing system. The system involves sharing facilities or managing separated facilities in an integrated manner between two processes.

Previous researches on remanufacturing were classified by Guide (2000) as presented in Table 2.3. In production planning and control, the optimal setting for disassembly process draws attraction from many researchers. As for inventory control and management, attraction is placed on different inventory policies, periodic and continuous reviews. Many have interested in production planning and inventory control, which are the relevant issues as there are many complicated characteristics presented in remanufacturing. A summary of such characteristics is shown in Table 2.4. Characteristics of uncertain quality of returns and the need to balance returns with demand in inventory control will be included in this study.

Table 2.2: Motives for automotive remanufacturing

	Reasons for automotive remanufacturing	Degree of influence to induce OEM engine remanufacturing	Findings
Motives identified in the literature	Ethical/moral responsibility	Low	• No emphasis on promoting the eco-friendliness of remanufactured products • The green consumer group or 'green marketplace' could not be identified • 'Anti-remanufacturing' attitude of VMs discovered
	Legislation	Low	• History of engine remanufacturing is based on other reasons • ELV Directive does not account for remanufacturing • The research has discovered further, predominant reasons
	Direct profitability/profit maximisation	Low	• High uncertainty in core acquisition: scrap rates • Strategy 'cleaning market' from cores increases core prices (competition for cores) • Necessity to incorporate expensive new parts • High labour costs
New observations	Secure spare parts supply	High	• Decreasing dependency on suppliers with regard to prices and spare parts availability • Remanufacturing is, in some cases, the only source of spare parts • Remanufacturing of phase-out engines is technically and economically more viable than a reproduction • Balancing engine aftermarket demand through remanufacturing
	Warranty	High	• Important source of under-warranty engines
	Market share and brand protection	High	• Controlling quality of remanufactured engines • Building 'quality image' for own products by promoting employee skills and sophisticated equipment • Thorough core collection as universal key to excluding independents
	Customer orientation	High	• Availability of extensive, reasonably priced aftermarket range, 'just in case' • Vehicle manufacturer takes care of used units • Stock replenishment time reduction

Source: Seitz (2007)

Table 2.3: Overview of previous research

Forecasting	Reverse logistics	Production planning and control	Inventory control and management	General
Statistical models (Goh and Varaprasad, 1986)	Literature review and problem structure (Fleischmann et al., 1997)	Disassembly operations (Brennan et al., 1994; Guide and Srivastava, 1998)	Independent demand periodic review systems (Inderfurth, 1996, 1997; Richter, 1996a,b, 1997)	Ferrer, (1996, 1997a,b), Gungor et al. (1998), Lund (1983, 1998), Thierry et al. (1995)
Reusable container returns (Kelle and Silver, 1989)	Problem structure (Flapper, 1995a,b, 1996; Sarkis et al., 1995; Driesch et al., 1997)	Disassembly economics (Johnson and Wang, 1995; Penev and de Ron 1996; Lambert 1997; Zussman et al 1994; Veerakamilmal and Gupta, 1998)	Continuous review systems (Muckstadt and Isaac, 1981; van der Laan, 1997; van der Laan et al., 1996)	
Part recovery (Krupp, 1992)	Network design and collection strategies (Kroon and Vrijens, 1996; Krikke, 1998; Jayaraman et al., 1999)	Aggregate planning (Clegg et al., 1995)	Mixed remanufacture and new (Salomon et al., 1994; van der Laan and Salomon, 1997; van der Laan et al., 1995, 1996, 1999)	
		Scheduling and shop floor control (Guide, 1996; Guide and Srivastava 1997; Guide et al., 1997a,b)	Dependent demand (Flapper, 1994; Gupta and Taleb 1994; Guide and Srivastava, 1997; Taleb et al. 1997; Inderfurth and Jensen 1998)	
		Capacity planning (Guide and Spencer, 1997; Guide et al, 1997c)	General overview (Corbey et al., 1998)	

Source: Guide (2000)

Table 2.4: Complicating characteristics for each production planning activities

Complicating characteristic	Production planning and control activity			
	Forecasting	Logistics	Scheduling / shop floor control	Inventory control and management
(1) The uncertain timing and quality of returns	✓	✓	✓	✓
(2) The need to balance returns with demands				✓
(3) The disassembly of returned products			✓	✓
(4) The uncertainty in materials recovered from returned items			✓	✓
(5) The requirement for a reverse logistics network		✓		✓
(6) The complication of materials matching restriction			✓	
(7) The problems of stochastic routings for materials and highly variable processing times			✓	

Source: Guide (2000)

Van der Laan et al. (1999) applied simple push and pull strategies, which are practical practice, in a hybrid manufacturing/remanufacturing system to observe the influence of production lead time duration and production lead time variability on total expected system cost. Their numerical result showed that manufacturing lead time has a larger influences on system cost, compared to remanufacturing lead time. Cost reduction sometimes results from a large remanufacturing lead time or a large variability in the manufacturing lead time. Inderfurth (2004) found that the optimal inventory control policy for coordinated system between manufacturing and remanufacturing problem is order-up-to policy. The problem is constructed as a single period problem with stochastic returned of used products and customer demand to substitute remanufactured products with manufactured products when shortage occurs. Wang et al. (2011) studied on the optimal production policy for short life cycle products with fluctuation in the amount of returned products and customer demand. The optimal total cost is obtained when applying mixed strategy, which is the combination of manufacturing, remanufacturing, and disposal simultaneously. Higher total cost incurs when each strategy is applied alternatively. It is also found that significant reduction in total cost of the system can be obtained by setting optimal values of manufactured products and the ratio of remanufactured products to returned products. Li (2009) addressed production planning problems found in a dedicated remanufacturing. One of the problems is to determine an optimal receiving inventory capacity since it involves with safety inventory level and production stability. With a higher capacity, the production becomes more stable but it also results in a higher holding cost. Another problem is to determine an optimal workforce level and production capacity, which can respond well to the customer demand as well as an uncertain in returned product arrival. Cost normally increases when there is a changing in capacity of any production system.

With complicating characteristics mentioned earlier for inventory control, the optimal setting for parameters in an inventory policy is required in order to obtain the maximum profitability of the system. Optimization can be divided into two main categories, i.e. exact and heuristic. The exact optimization, i.e. analytical models, gives global optimal solutions but requires a longer processing time while the heuristic optimization provides local optimal solutions, which are good enough solutions, with a shorter processing time. A proper solving method selection deals with the tradeoff between solution quality and computation time. In addition, analytical models require simplified assumptions and give out static results. Without involvement of uncertainties, solutions found are compromised in the real world problem. Hence, simulation is brought in to pick up the amount of uncertainties and produce the results, which can reflect the real world problems. The combination of optimization and simulation can then give the practical optimal result under realistic circumstance.

Many researchers are interested in a specific combination between analytical models and simulation. Shanthikumar and Surgent (1983) classified this specific combination into 4 classes as follows:

- Class I: A model with alternation between independent simulation and analytical models. The part of simulation processes without intermediate use of the analytical part and vice versa.
- Class II: A model with parallel operation interacting between simulation and analytical models through their solution procedure.
- Class III: A model with a simulation model acting as a subordination for an analytical part of the total system.
- Class IV: A model with an analytical model acting as a portion to generate some or all of the input parameters for a simulation model.

The combination between heuristics and simulation, i.e. simulation-based optimization, is presented in many researches. A well-known simulation-based optimization is from Glover et al. (1999), named OptQuest, which combines three metaheuristics to optimize decisions based in simulation model. Fu (2002) indicated that current commercial softwares mainly employ heuristics and simulation combination in which a good-enough solution can be obtained from working with the families of solutions. The biggest problem found, when applying simulation-based optimization, is that the stochastic nature of the systems is unaware. Thus, the efficiency of computation resources are not fully utilized. Variance reduction techniques are suggested in order to improve the convergence rate.

A relatively smaller number of research papers have experimented on the hybrid simulation optimization. Franke et al. (2006) analyzes the remanufacturing processes of mobile phones. While production planning is solved using Linear Programming (LP), then, the solution is input into a discrete-even simulation model in order to create a model, which can cope well with the uncertain nature of the system. Another algorithm is found in Li et al. (2009) where a production planning in remanufacturing is optimized. The decision variables are divided into cells using Fractional Factorial Design (FFD) and the optimal solution from each cell, obtained from simulation and analyzed by FFD, is used as the candidate solutions for Genetic Algorithm (GA). Crossover and mutation process are implemented during GA operation to create the second generation, which is used back in simulation run. The whole process going back and forth until the stopping criteria is reached.

Byrne and Bakir (1999) proposed a hybrid simulation analytical approach to optimize a production planning. A quantity of product produced and inventory are first found using Linear Programming (LP) with capacity and inventory balance constraints. LP solution is then input into a simulation model for capacity checking. The solving process stops when capacity is acceptable, otherwise, capacity in LP is adjusted and the solving process is continue back to LP solving step. Kim and Kim (2001) extends Byrne and Bakir (1999) study by adding effective loading ratio and effective utilization constraints to LP. Parameters from a simulation model are input into added constraints in LP. The hybrid between Mixed Integer Linear Programming (MILP) and simulation is applied on Supply Chain Management (SCM), proposed by Nikolopoulou and Ierapetritou (2012). More realistic results with less required computational time, as compared to the initial mathematical approach, are obtained.

Chapter 3
Methodology

Three optimization solving methods are selected in order to evaluate their performance on a hybrid manufacturing/remanufacturing system in this study. They include the analytical model using Mixed-Integer Linear Programming with Simulation (MILP+Simulation), Simulation-based Optimization with OptQuest (OptQuest), and Hybrid Simulation Optimization (Hybrid algorithm). Details for each solving method can be described as follows:

3.1 Analytical Model using Mixed-Integer Linear Programming with Simulation (MILP+Simulation)

The problem is modeled and optimized using an analytical model, i.e. MILP. Since, there is no uncertainty in the analytical models, exact optimized decision variables from MILP are input into a simulation model to obtain the results under the uncertain environment. A procedure diagram is shown in Figure 3.1. Poor results can be expected from this method since the intention is to demonstrate what would happen if exact optimized decision variables are applied in the uncertain environment.

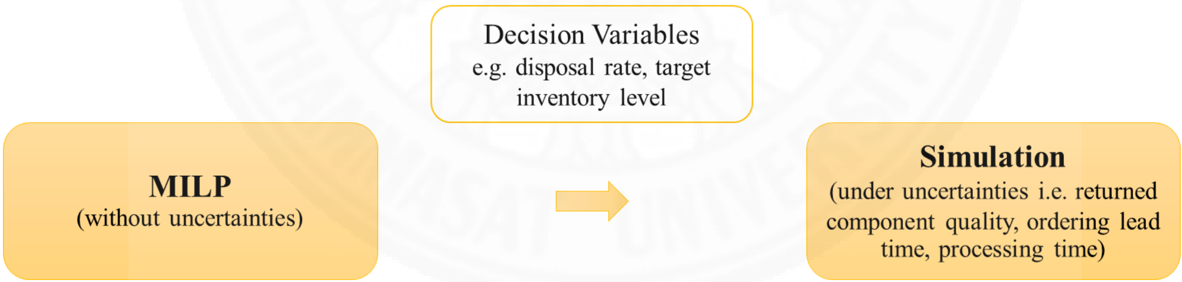

Figure 3.1: A solving procedure diagram of MILP+Simulation

3.2 Simulation-based Optimization with OptQuest (OptQuest)

An optimization software, which combines Metaheuristics with simulation, called OptQuest, is selected. It is a built-in optimization within ARENA, a simulation software. It uses the functions of Tabu Search, Neural Network, and Scatter Search together. Figure 3.2 presents the simulation-based optimization with OptQuest procedure diagram. In each iteration, interested decision variables are searched and simulated to get an objective function value. This value is used as input data for the next iteration. If the option of automatic stop option is selected, the searching stops when there is no improvement on the objective function for 100 iterations successively. Four initial input parameters are required for OptQuest: upper bound, lower bound, suggested value, and stepping size. Upper bound and lower bound define a searching space for a decision variable. In the study, this bound is guaranteed to be large enough to ensure that the optimal solution falls inside the searching space.

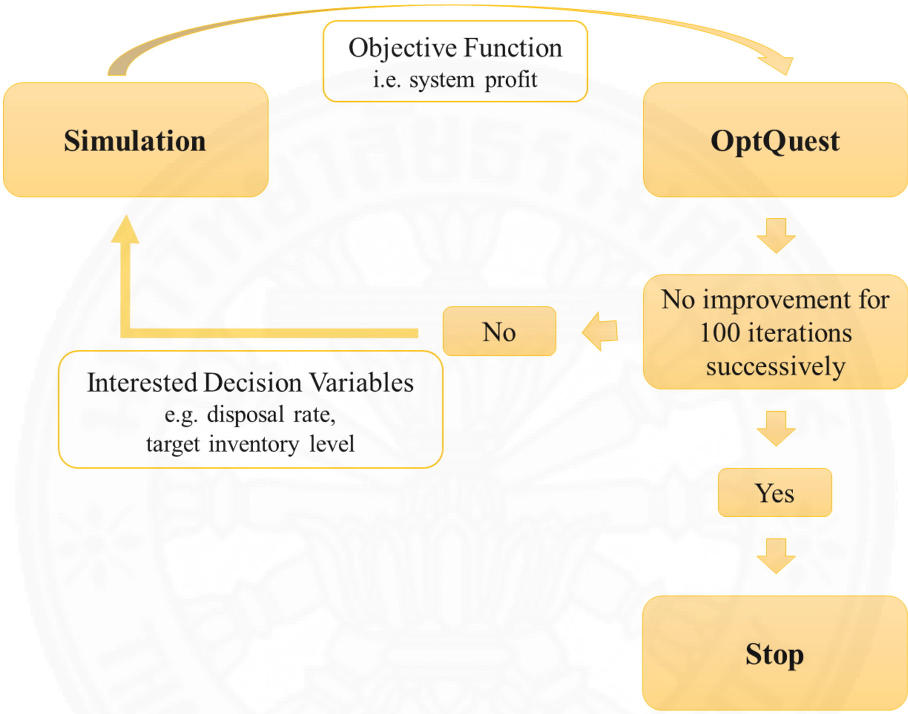

Figure 3.2: A solving procedure diagram of simulation-based optimization with OptQuest

3.3 Hybrid Simulation Optimization (Hybrid Algorithm)

As an alternation to the simulation software without a built-in optimization module, the hybrid simulation optimization can be used. This study modified Acar et al. (2009)'s solving procedure using the Hybrid Algorithm by aiming to bridge the gap between analytical and simulation models. A hybrid manufacturing/ remanufacturing is modeled with both MILP and simulation models. Then, two models have been proven to be identical as when uncertainties are not included, both models provide exactly the same result. Visual Basic for Applications (VBA) is implemented to link between MILP and simulation models. Decision variables obtained from the same iteration are grouped together in a decision variable set. An obtained decision variable set refers to a solution from a current iteration.

From Figure 3.3, where the Hybrid Algorithm's solving procedure diagram is presented, the MILP model is solved first. After that, an obtained decision variable set is transferred and simulated in the simulation model in ARENA. From the second iteration onward, if an obtained decision variable set from MILP is not similar to one of the previous sets, the obtained set is simulated again in the simulation model. An objective function value from the MILP model (Q_MILP) and an objective function value from the simulation model (Q_SIMU) in the same iteration are compared to find any difference, known as an impact of uncertainties (N). A maximum possible objective function value (Q_max) is used for a maximized problem and has an initial value of zero. Q_max is updated to be equal to Q_SIMU only when Q_SIMU is greater than existing Q_max. Values of N and Q_max are updated to the MILP model. With data from every previous iteration, the MILP model is optimized again. The solving process stops when one of these conditions is reached. First, the obtained decision variable set is similar to one of the previous sets. Second, there is no significant improvement in N for a certain number of iterations successively in which it is set at 100 iterations in this study to match with the default number of automatic stop of the OptQuest.

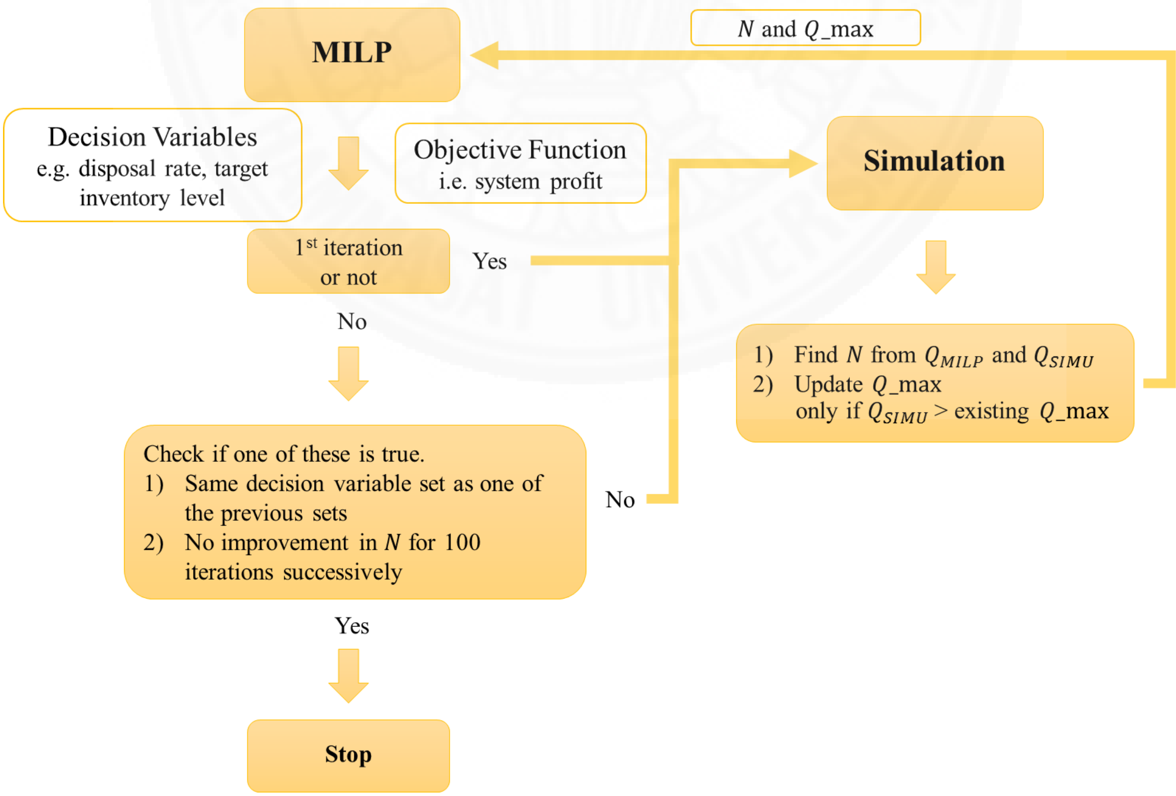

Figure 3.3: A solving procedure diagram of Hybrid algorithm

As the Hybrid Algorithm is aimed to reduce the impact of uncertainties (N), Figure 3.4 illustrates Hybrid Algorithm's solving procedure for a profit maximization problem under the uncertain environment. Figure 3.4 (I) gives an example of the results after the first iteration with an objective function value from the MILP model, Q_{MILP} (I), and an objective function value from the simulation model, Q_{SIMU} (I). The values of N_1 and Q_max are calculated and used for the next iteration. If $Q_{SIMU}(II)$ is greater than existing Q_max, Q_max is updated to be equal to $Q_{SIMU}(II)$ as shown in Figure 3.4 (II). This event occurs from the second iteration onward. On the other hand, if $Q_{SIMU}(III)$ is less than existing Q_max, Q_max remains the same as shown in Figure 3.4 (III). Figure 3.4 (IV) shows the event when an obtained decision variable set is similar to one of the previous sets, the optimal solution is then found. The obtained optimal profit, $Q_{MILP}(IV)$, is the one under the uncertain environment.

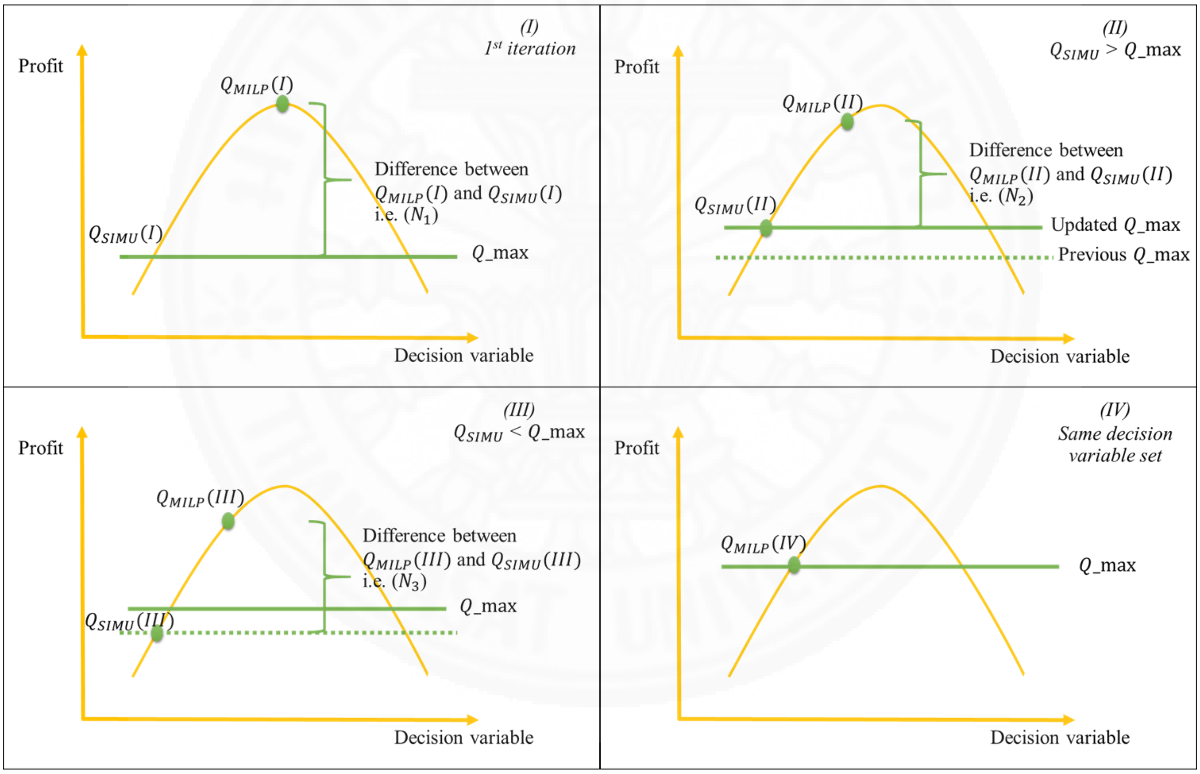

Figure 3.4: A Hybrid Algorithm's illustration for a maximized problem

Values of a decision variable set and N from every previous iteration are added as input data in the next iterations of MILP. The following notations are for Hybrid Algorithm's additional constraints.

Hybrid Algorithm's notations:

i	=	1, 2, ..., m represent iteration
j	=	1, 2, ..., p represent decision variable index
ans_j	=	A decision variable from current iteration with index j
$solSet_{ij}$	=	A decision variable from iteration i with index j
Q_max	=	A maximum possible objective function for MILP
N_i	=	An impact of uncertainties calculated from the difference between MILP and simulation objective functions from iteration i
Z_i	=	1 if a current decision variable set duplicates with one of the previous sets, 0 otherwise
$initial\,profit$	=	An example of an initial objective function of the maximized problem

In a maximization problem as our case, an initial objective function is deducted by N of the iteration where a decision variable set is similar to an obtained decision variable set as presented in equation (1). Q_{MILP} is an obtained objective function under the impact of uncertainties.

Objective function:

$$\text{Maximize} \quad Q_{MILP} = initial\,profit - \sum_{i=1}^{m}(N_i * Z_i) \tag{1}$$

Subject to:

$$ans_j = decision\,variable \quad for\,all\,j \tag{2}$$

$$Z_i = \begin{cases} 1 & if\,ans_j = solSet_{ij} \quad for\,all\,j \\ 0 & otherwise \end{cases} \tag{3}$$

$$Q_{MILP} \geq Q\_max \tag{4}$$

Values of decision variables in a current iteration are stored in ans_j as stated in equation (2). Equation (3) indicates that if every ans_j duplicates values of one of the previous decision variable sets, Z_i of the duplicated iteration becomes one, allowing the impact of uncertainties to be included in the objective function, otherwise, Z_i becomes zero. For equation (4), the obtained objective function has to be greater than Q_max.

Chapter 4
Case Study

A hybrid manufacturing/remanufacturing system is under investigation. A general flow diagram of the system is shown in Figure 4.1. The system requires two types of components for production: returned and new components. Returned components refer to parts from used products, which are returned from customers at the end of the product life's cycle. With a reorder cycle policy, at the beginning of each reviewed cycle (a week), returned components arrive in a batch. A certain percentage of returned components need to be disposed to prevent surplus. Accepted returned components are then stored in a Returned Component Inventory (RCI), waiting for remanufacturing. It is assumed that the remanufacturing time is less than the manufacturing time according to the quality of that returned components. There is also a New Component Inventory (NCI), which is reviewed to order every week. Ordering lead time for new components is one week. After arrival, these new components are kept in the NCI before they are pulled to manufacturing. One week is also required for a manufacturing period. Finished products are then stored in a Finished Product Inventory (FPI), awaiting to satisfy the customer demand.

Customer demand arrives every week. Lost sales occur when there is not enough finished products, otherwise, customers pick up finished products from the FPI. Finished products from remanufacturing and manufacturing are considered to be the same. When the inventory level in the FPI is reduced, the system triggers the production. The purpose is to restore back the inventory level of the FPI. An initial inventory quantity is equal to FPI target inventory level, which is one of the decision variables. Inventory control policies are imposed here to decide whether which process (remanufacturing vs manufacturing) has a higher priority and whether to coordinate the component inventories or not. The system is investigated for one year (or 50 weeks). With 5 days a week and 8 hours a day, there are 120,000 minutes a year (one replication).

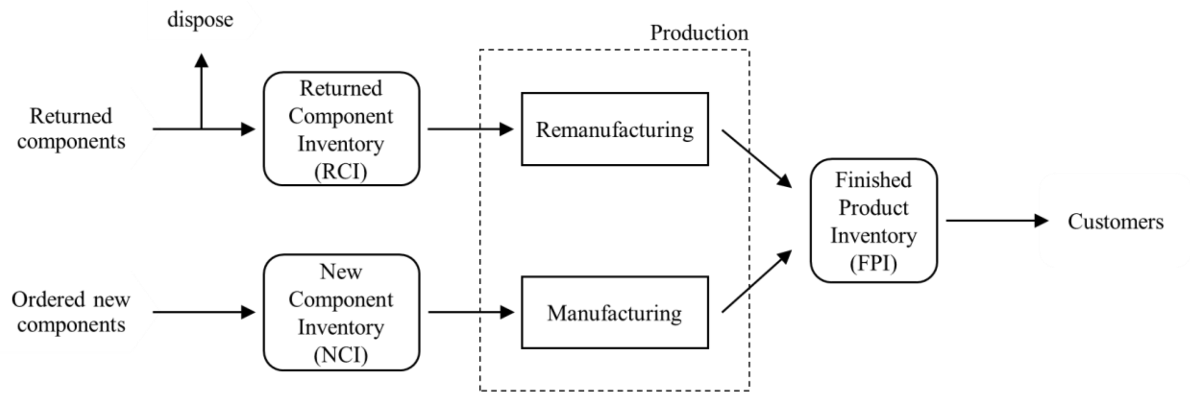

Figure 4.1: A flowchart of a hybrid manufacturing/remanufacturing system

4.1 Inventory control policy

With 4 inventory control policies under investigation, operational details of each policy can be presented as follows:

4.1.1 Priority-To-Remanufacturing (PTR)

With the priority to remanufacturing, returned components are given a higher priority than new components to be selected for production unless they are not available. Manufacturing is activated only when there is not enough returned components in RCI as seen in Figure 4.2. Controlled decision variables in this policy include Disposal Rate (disR), Target Inventory Level of NCI (TinvN), and Target Inventory Level of FPI (TinvF). A certain returned components are disposed according to disR. New components are ordered up to TinvN in every reviewed cycle (a week). The initial inventory level of NCI is equal to TinvN. When finished products are sold to customers, upstream components are pulled to replenish taken products by filling FPI up to TinvF where the initial inventory level of FPI is also equal to TinvF.

4.1.2 Priority-To-Manufacturing (PTM)

Opposite to PTR, new components have a higher priority over returned components. The process of remanufacturing, using returned components, is used to produce only when there is a shortage in new components as shown in Figure 4.2. Inventories are controlled by the decision variables similar to PTR.

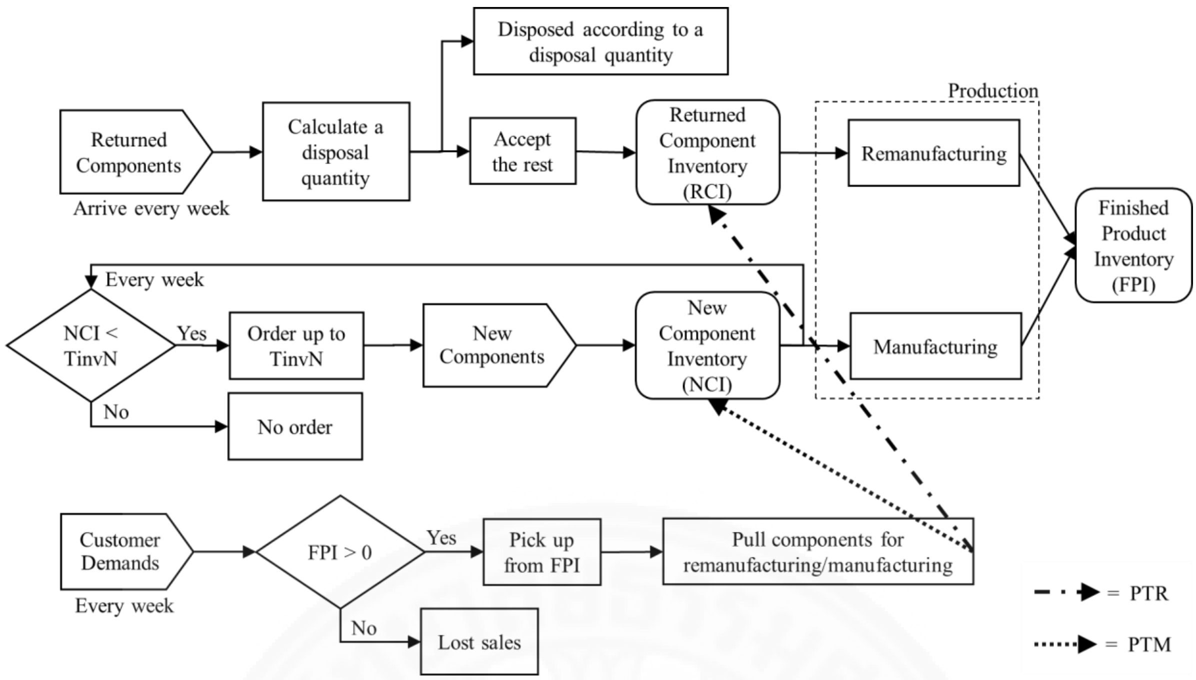

Figure 4.2: A diagram for PTR and PTM

4.1.3 Coordinated Priority-To-Remanufacturing (Co-PTR)

As presented in Figure 4.3, RCI and NCI are now coordinated and considered as one component inventory, named as Inventory Position (IP). Similar to PTR, returned components with remanufacturing in Co-PTR receives a higher priority and, hence, they are used first. Controlled decision variables in this policy are Lower Boundary for IP (lower), Upper Boundary for IP (upper), and Target Inventory Level of FPI (TinvF). IP is reviewed every week. If IP is below lower, order is placed for new components. If IP is still above upper, incoming returned components are disposed.

4.1.4 Coordinated Priority-To-Manufacturing (Co-PTM)

Component inventories, RCI and NCI, are coordinated similar to the case of Co-PTR. The priority is given to manufacturing where new components are taken to be produced first, as seen in Figure 4.3. Controlled decision variables are also similar to Co-PTR.

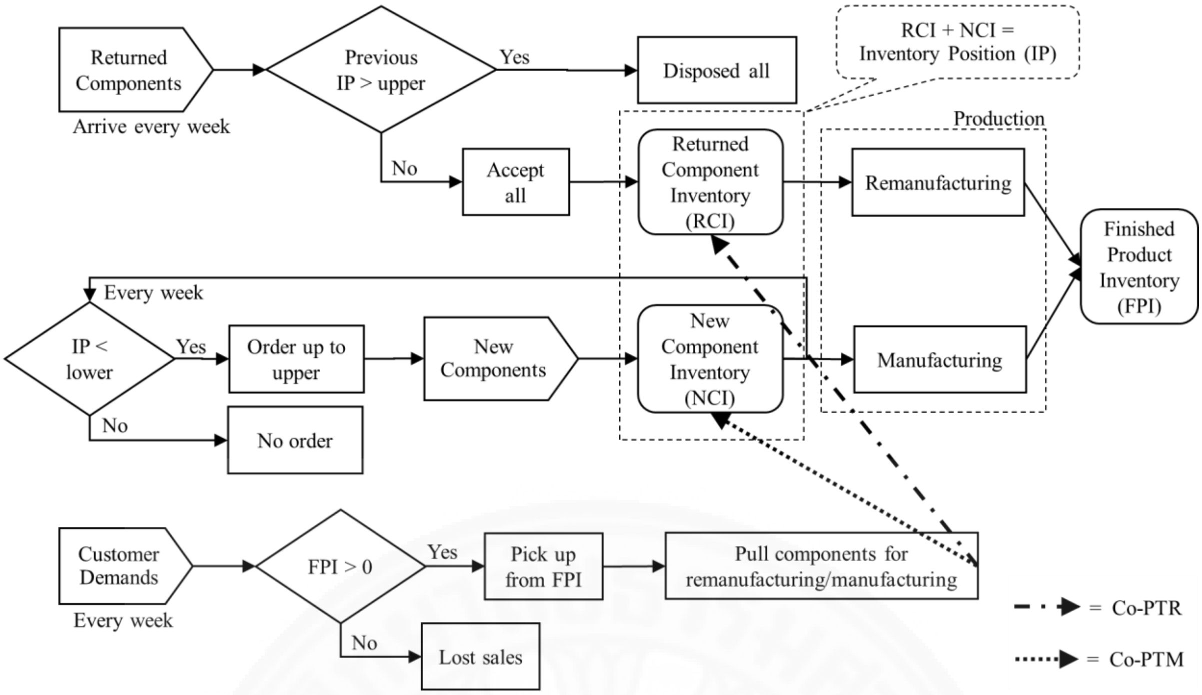

Figure 4.3: A diagram for Co-PTR and Co-PTM

4.2 Returned ratio

This is the ratio of returned component arrival per total customer demand. For example, at the returned ratio of 0.25, it represents the case that if the customer demand is 100 units a week, a quantity of returned component arrival in that week is 25 units. Table 4.1 presents three levels of the returned ratio used in the case study. The amount of returned component arrival and customer demand are also fluctuated under the normal distribution.

Table 4.1: Ratios of returned component arrival over customer demand (returned ratio)

Returned ratio	Returned component arrival (units per week)	Customer demand (units per week)
0.25	Normal (25, 5)	Normal (100, 20)
0.50	Normal (50, 10)	Normal (100, 20)
0.75	Normal (75, 15)	Normal (100, 20)

4.3 Cost structure

The study is aimed to maximize the profit of the system, which is revenue deducted by total cost. Revenue is total income from selling finished products. Each unit is sold at $45. Total cost is a summation of costs listed in Table 4.3. All costs for returned components are assumed to be lower than that of new components. Holding cost is developed using physical holding cost (h) and opportunity cost of capital tied up (α). The value of h is $10 per year per item and α is 20% of a unit cost per year.

Table 4.2: Cost structure

Parameters	Notation	Cost ($)	Formulation
Returned component disposal cost	RD_u	0 per unit	-
New component cost	NC_u	10 per unit	-
Returned component preparation cost	RP_u	5 per unit	-
Remanufacturing cost	RM_u	[0, 10] per unit	$(1 - q)(RM_{max} - RM_{min}) + RM_{min}$ Note: $RM_{max} = MM\_u,\ RM_{min} = 0$
Manufacturing cost	MM_u	10 per unit	-
Returned component holding cost	RH_y	2 per year	$h + \alpha * RP\_u$
New component holding cost	NH_y	3 per year	$h + \alpha * NC\_u$
Finished product holding cost (from returned components)	FHr_y	[3, 5] per year	$h + \alpha * (RP\_u + RM\_u)$
Finished product holding cost (from new components)	FHm_y	6 per year	$h + \alpha * (NC\_u + MM\_u)$
Lost sales cost	LS_u	45 per unit	-
Sales price	$Price\_u$	45 per unit	-

Chapter 5
Analytical Model Formulation

A MILP model is constructed using IBM ILOG CPLEX Optimization Studio software. Notations and the analytical model formulation are presented below where t refers to time period in weeks, ranging from 1 to 50.

<u>Parameters</u>

ReA_t	=	A quantity of returned component arrival in period t (units)
$dispose_t$	=	A quantity of returned component disposal in period t (units)
$R0_t$	=	A quantity of returned components accepted to an inventory in period t (units)
RCI_t	=	A quantity of ending inventory in the Returned Component Inventory (RCI) in period t (units)
$R1_t$	=	A quantity of returned components sent to remanufacturing in period t (units)
$R2_t$	=	A quantity of finished products from remanufacturing in period t (units)
$FPIr_t$	=	A quantity of ending inventory in a Finished Product Inventory (FPI) from remanufacturing in period t (units)
$R3_t$	=	A quantity of finished products from remanufacturing sent to customer in period t (units)
$order_t$	=	A quantity of new components ordered in period t (units)
NCI_t	=	A quantity of ending inventory in the New Component Inventory (NCI) in period t (units)
$M1_t$	=	A quantity of new components sent to manufacturing in period t (units)
$M2_t$	=	A quantity of finished products from manufacturing in period t (units)
$FPIm_t$	=	A quantity of ending inventory in a Finished Product Inventory (FPI) from manufacturing in period t (units)
$M3_t$	=	A quantity of finished products from manufacturing sent to customer in period t (units)

FPI_t	=	A quantity of ending inventory in the Finished Product Inventory (FPI) in period t (units)
$demand_t$	=	A quantity of customer demand in period t (units)
LS_t	=	A quantity of lost sales in period t (units)

<u>Cost parameters</u>

RD	=	Total returned component disposal cost ($)
LS	=	Total lost sales cost ($)
RMM	=	Total remanufacturing and manufacturing cost ($)
NC	=	Total new component cost ($)
RP	=	Total returned component cost ($)
CH	=	Total component holding cost ($)
FH	=	Total finished product holding cost ($)
$Total\ cost$	=	Summation of all costs ($)
$Revenue$	=	Total income received from selling finished products ($)
$Profit$	=	Net income after deducted by total cost ($)

5.1 Inventory balance constraints

Inventory balance constraints control the flow of inventory in the system. In equation (5), some of returned components are disposed and the rest is sent to a Returned Component Inventory (RCI). Remanufacturing time is negligible, as a quantity of returned components pulled to remanufacturing is even to a quantity of finished products coming out of remanufacturing within the same period, while manufacturing takes one week production time as stated in equation (6) and equation (7), respectively. There is no finished products from manufacturing in the first week. Total units of finished product combine the units of remanufacturing and manufacturing together as formulated in equation (8). In equation (9), the customer demand is satisfied by the finished products, otherwise, lost sales occurs.

$$ReA_t = dispose_t + R0_t \qquad for\ all\ t \tag{5}$$

$$R2_t = R1_t \qquad for\ all\ t \tag{6}$$

$$M2_t \;=\; \begin{cases} 0 & where\ t = 1 \\ M1_{t-1} & where\ t = 2\ to\ t = 50 \end{cases} \tag{7}$$

$$FPI_t \;=\; FPIr_t \;+\; FPIm_t \qquad for\ all\ t \tag{8}$$

$$R3_t + \; M3_t + \; LS_t \;=\; demand_t \qquad for\ all\ t \tag{9}$$

Equation (10) to equation (13) present constraints for returned component, new component, and finished product inventories. The amount of ending inventory is equal to the previous period’s ending inventory added by incoming inventory and deducted by outgoing inventory. In the first week, the previous period’s ending inventory refers to an initial inventory. Table 5.1 presents initial inventory value of NCI from different policies.

$$RCI_t \;=\; \begin{cases} R0_t - \; R1_t & where\ t = 1 \\ RCI_{t-1} \;+\; R0_t - \; R1_t & where\ t = 2\ to\ t = 50 \end{cases} \tag{10}$$

$$NCI_t \;=\; \begin{cases} initial\ NCI - \; M_t & where\ t = 1 \\ NCI_{t-1} \;+\; order_{t-1} \;-\; M1_t & where\ t = 2\ to\ t = 50 \end{cases} \tag{11}$$

$$FPIr_t \;=\; \begin{cases} R2_t - \; R3_t & where\ t = 1 \\ FPIr_{t-1} + R2_t - \; R3_t & where\ t = 2\ to\ t = 50 \end{cases} \tag{12}$$

$$FPIm_t \;=\; \begin{cases} TinvF \;-\; M3_t & where\ t = 1 \\ FPIm_{t-1} + M2_t - \; M3_t & where\ t = 2\ to\ t = 50 \end{cases} \tag{13}$$

Table 5.1: Initial inventory value of NCI

Inventory control policy	Initial inventory value of NCI
PTR and PTM	$TinvN$
Co-PTR and Co-PTM	$upper$

5.2 Priority constraints

The following constraints differentiate priorities from different policies (either remanufacturing or manufacturing).

5.2.1 PTR and Co-PTR

For the policy of the priority to remanufacturing, all returned components are sent to remanufacturing when the customer demand is greater than the amount of incoming returned components plus the amount of previous period's ending inventory. If the customer demand is less than the amount of returned components in the RCI, the returned components sent to remanufacturing is equal to the customer demand as stated in equation (14) and equation (15).

$$RCI_t = \begin{cases} 0 & if\ demand_t \geq R0_t & where\ t = 1 \\ 0 & if\ demand_t \geq R0_t + RCI_{t-1} & where\ t = 2\ to\ t = 50 \\ any\ integers & otherwise & for\ all\ t \end{cases} \quad (14)$$

$$R1_t = \begin{cases} demand_t & if\ demand_t < R0_t + RCI_{t-1} & for\ all\ t \\ any\ integers & otherwise & for\ all\ t \end{cases} \quad (15)$$

5.2.2 PTM and Co-PTM

Equation (16) and equation (17) present priority to manufacturing constraints. The amount of the ending inventory in NCI is equal to the incoming order from previous period when the customer demand is greater than the amount of previous period's ending inventory. The amount of new components sent to manufacturing is equal to the amount of customer demand if the customer demand is less than the amount of previous period's ending inventory.

$$NCI_t = \begin{cases} 0 & if\ demand_t \geq initial\ NCI & where\ t = 1 \\ order_{t-1} & if\ demand_t \geq NCI_{t-1} & where\ t = 2\ to\ t = 50 \\ any\ integers & otherwise & for\ all\ t \end{cases} \quad (16)$$

$$M1_t = \begin{cases} demand_t & if\ demand_t < NCI_{t-1} & for\ all\ t \\ any\ integers & otherwise & for\ all\ t \end{cases} \quad (17)$$

5.3 Financial constraints

Calculation of profit and costs can be presented in the following financial constraints. Total cost consists of Returned Component Disposal Cost (RD), Lost Sales Cost (LS), Remanufacturing and Manufacturing Cost (RMM), New Component Cost (NC), Returned Component Cost (RP), Component Holding Cost (CH) and Finished Product Holding Cost (FH) as presented from equation (18) to equation (24), respectively. All holding costs are calculated based on average level of inventory. Then, the profit, as stated in equation (27), is calculated by the revenue (equation (26)) deducted by total cost (equation (25)).

$$RD = \sum_{t} RD\_u * dispose_t \qquad for\ all\ t \tag{18}$$

$$LS = \sum_{t} LS\_u * LS_t \qquad for\ all\ t \tag{19}$$

$$RMM = \sum_{t} RM\_u * R1_t + \sum_{t} MM\_u * M1_t + MM\_u * TinvF \qquad forall\ t \tag{20}$$

$$NC = \sum_{t} NC\_u * (order_t + initial\ NCI + TinvF) \qquad forall\ t \tag{21}$$

$$RP = \sum_{t} RP\_u * R0_t \qquad for\ all\ t \tag{22}$$

$$\begin{aligned} CH = {} & \left(\frac{RH\_y}{50} * (R0_1 + RCI_1)\right)/2 \\ & + \sum_{t>1} \left(\frac{RH\_y}{50} * (R0_t + RCI_{t-1} + RCI_t)\right)/2 \\ & + \left(\frac{NH\_y}{50} * (initial\ NCI + NCI_1)\right)/2 \\ & + \sum_{t>1} \left(\frac{NH\_y}{50} * (order_{t-1} + NCI_{t-1} + NCI_t)\right)/2 \end{aligned} \tag{23}$$

$$\begin{aligned} FH = {} & \left(\frac{FHr\_y}{50} * (R2_1 + FPIr_1)\right)/2 \\ & + \sum_{t>1} \left(\frac{FHr\_y}{50} * (R2_t + FPIr_{t-1} + FPIr_t)\right)/2 \\ & + \left(\frac{FHm\_y}{50} * (M2_1 + TinvF + FPIm_1)\right)/2 \\ & + \sum_{t>1} \left(\frac{FHm\_y}{50} * (M2_t + FPIm_{t-1} + FPIm_t)\right)/2 \end{aligned} \tag{24}$$

$$Total\ cost = RD + LS + RMM + NC + RP + CH + FH \tag{25}$$

$$Revenue = \sum_{t} Price\_u * (R3_t + M3_t) \qquad for\ all\ t \tag{26}$$

$$Profit = Revenue - Total\ cost \tag{27}$$

5.4 Decision variables

Decision variables are classified into 2 groups. The first group is for PTR and PTM and the second group is for Co-PTR and Co-PTM.

5.4.1 PTR and PTM

Decision variables of PTR and PTM are presented below.

$disR$ = Disposal rate

$TinvN$ = A quantity of target inventory level in NCI

$Nten$ = Dummy integer variable for $TinvN$ batch

$TinvF$ = A quantity of target inventory level in FPI

$Ften$ = Dummy integer variable for $TinvF$ batch

In equation (28), new components are ordered up to TinvN. Total numbers of components sent to be produced are equal to the amount of finished products sold as shown in equation (29). Target inventories of new components and finished products are calculated in a multiple batch of ten units as shown in equation (30) and equation (31), respectively. Disposal rate is a percentage of a disposed quantity over the amount of returned components as stated in equation (32).

$$order_t = TinvN - NCI_t \quad for\ all\ t \tag{28}$$

$$R1_t + M1_t = TinvF - FPI_t \quad for\ all\ t \tag{29}$$

$$TinvN/10 = Nten \tag{30}$$

$$TinvF/10 = Ften \tag{31}$$

$$disR = 100 * (dispose_t/ReA_t) \quad for\ all\ t \tag{32}$$

5.4.2 Co-PTR and Co-PTM

Decision variables of Co-PTR and Co-PTM are presented below.

IP_t = A quantity in an inventory position in time period t

$upper$ = Upper boundary for IP

$lower$ = Lower boundary for IP

$Uten$ = Dummy integer variable for multiplication of $upper$

$Lten$ = Dummy integer variable for multiplication of $lower$

Inventory Position (IP) is a summation of remaining returned and new components as shown in equation (33). All incoming returned components are disposed if the amount of previous inventory level exceeds the upper boundary, otherwise, a whole batch is accepted into the Returned Component Inventory (RCI) as seen in equation (34). In addition, a whole batch of returned components is accepted in the first week. From equation (35), new components are ordered up to the upper boundary level when the Inventory Position (IP) is less than the lower boundary level. It is stated in equation (26) that the upper boundary is always greater than the lower boundary. In addition, the decision variable for TinvF is similar to the one of PTR and PTM as shown in equation (29) and equation (31).

$$IP_t \quad = \quad RCI_t + NCI_t \qquad for\ all\ t \tag{33}$$

$$dispose_t \quad = \quad \begin{cases} 0 & & where\ t = 1 \\ 0 & if\ IP_{t-1} < upper & where\ t = 2\ to\ t = 50 \\ 100 & if\ IP_{t-1} \geq upper & where\ t = 2\ to\ t = 50 \end{cases} \tag{34}$$

$$order_t \quad = \quad \begin{cases} upper - NCI_t & if\ IP_t < lower & for\ all\ t \\ 0 & if\ IP_t \geq lower & for\ all\ t \end{cases} \tag{35}$$

$$upper \quad \geq \quad lower \tag{36}$$

Chapter 6
Simulation Model

A simulation model is built in ARENA where the uncertainty of returned component quality, new component ordering lead time, and production time are added in the model, as shown in Table 6.1. The system is now operating under the uncertain environment. Quality of returned components can have an impact on Remanufacturing Cost (RM) and Mean Remanufacturing Production Time (RPT_{μ}) as they are varied according to the quality of returned components (q). Equation (37) shows RPT_{μ} calculation. The maximum RPT_{μ} (RPT_{max}) is equal to the Mean Manufacturing Production Time (MPT_{μ}), which is 2,400 minutes. The value for the minimum RPT_{μ} (RPT_{min}) is set at zero. For example, if the quality of returned components (q) is equal to 0.5, then $RPT_{\mu} = 1{,}200$ minutes.

Table 6.1: Controlled variables for uncertainties

Controlled Variable	With Uncertainty	Without uncertainty
Returned component quality (q)	Uniform [0, 1] Note: 1 is the best quality	1
New component ordering lead time	80% with 2,400 minutes 20% with 4,800 minutes	2,400 minutes
Remanufacturing production time (RPT)	Normal (RPT_{μ}, 300) minutes	0
Manufacturing production time (MPT)	Normal (2400, 600) minutes	2,400 minutes

$$RPT_{\mu} = (1 - q)(RPT_{max} - RPT_{min}) + RPT_{min} \quad (37)$$

For the simulation experiment, a terminating system is applied with the replication length of one year or 120,000 minutes. Less than 5% variation of the average flowtime is assured by 5 replications.

Chapter 7

Result and Discussion

As explained in Section 4 (Case Study), the hybrid manufacturing/remanufacturing system is experimented with 4 policies, 3 returned ratios, and 3 solving methods. Four policies include PTR, PTM, Co-PTR and Co-PTM while the returned ratios at 0.25, 0.50, and 0.75 are experimented. There are also 3 solving methods: MILP+Simulation, OptQuest and Hybrid Algorithm. As a result, there are 36 observation in total. Statistical techniques including Analysis of Variance (ANOVA), interaction plot and Tukey comparison test are used to investigate the significance of studied factors and differences among interested policies and solving methods on the profit of the system.

7.1 ANOVA result

ANOVA results are presented in Figure 7.1. All main factors and their interactions show to be significant under 95% confidence level. It can be concluded that the main factors of policies, returned ratios, solving methods and their interactions significantly affect the system profit, and hence, further statistical analysis is needed to investigate their impacts.

General Linear Model: System profit versus Policy, Returned ratio, Solving method

Factor	Type	Levels	Values
Policy	fixed	4	Co-PTM, Co-PTR, PTM, PTR
Returned ratio	fixed	3	0.25, 0.50, 0.75
Solving method	fixed	3	Hybrid Algorithm, MILP+Simulation, OptQuest

Analysis of Variance for System profit, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Policy	3	1337464441	1337464441	445821480	816.38	0.000
Returned ratio	2	36124185908	36124185908	18062092954	33075.10	0.000
Solving method	2	11160281919	11160281919	5580140959	10218.29	0.000
Policy*Returned ratio	6	262012083	262012083	43668681	79.97	0.000
Policy*Solving method	6	1003548098	1003548098	167258016	306.28	0.000
Returned ratio*Solving method	4	3808646595	3808646595	952161649	1743.59	0.000
Policy*Returned ratio*Solving method	12	635663855	635663855	52971988	97.00	0.000
Error	144	78637449	78637449	546093		
Total	179	54410440349				

Figure 7.1: Statistical analysis of factors using ANOVA

According to interaction plot as presented in Figure 7.2 (I) and Figure 7.2 (II), the system profits of PTR and Co-PTR are higher than the ones from PTM and Co-PTM due to the benefit of a cheaper unit cost of the returned components. Detailed analysis will be given in

Section 7.2. The system profit increases when returned ratio increases as seen in Figure 7.2 (III) and Figure 7.2 (IV). A higher quantity of returned component arrival allows the system to use cheaper cost components, and hence, it can reduce the total cost. From Figure 7.2 (V) and Figure 7.2 (VI), it can be noticed that MILP+Simulation provides the lowest profit as expected since the value of decision variables obtained from MILP are based only on the certain condition and they are not appropriate to apply in the case of having uncertainties in the model.

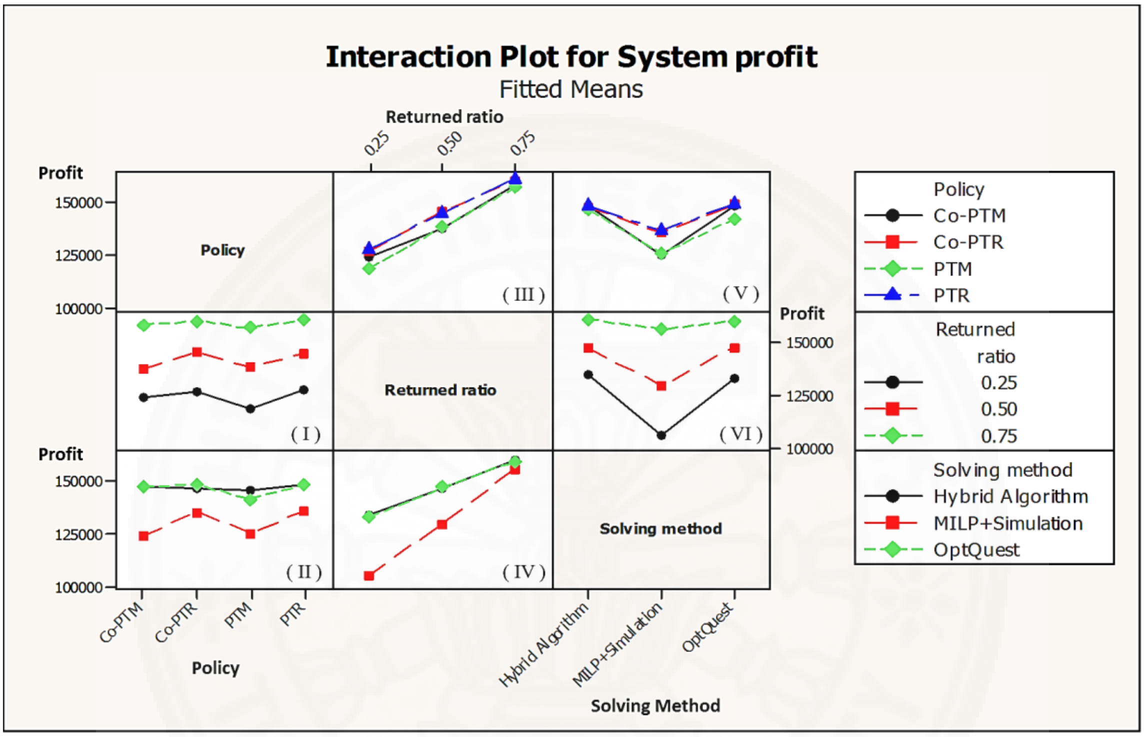

Figure 7.2: Interaction plot for profit

7.2 Comparison of the results

Results are analyzed and compared so as to present the effect among solving methods and different policies on the profit of the system.

7.2.1 Solving method performance comparison

Figure 7.3 shows the comparative result of the system profits using Tukey comparison test. It is found that the Hybrid Algorithm shows to statistically outperform the profits obtained from the OptQuest and MILP+Simulation. As expected, the result obtained from MILP+Simulation is worst as it uses the values of decision variables from MILP, which is formulated under the deterministic environment. This is why the simulation-based optimization and/or hybrid simulation optimization need to be introduced.

```
Grouping Information Using Tukey Method and 95.0% Confidence

Solving method      N      Mean  Grouping
Hybrid Algorithm   60  147475.5  A
OptQuest           60  146852.7    B
MILP+Simulation    60  130469.3      C

Means that do not share a letter are significantly different.
```

Figure 7.3: Tukey comparison test for solving methods

In addition, solving performance can be measured by the number of iterations. The smaller number of iterations to find the optimal result, the better performance of the solving method. Comparison from 12 instances between OptQuest and Hybrid Algorithm indicates that Hybrid Algorithm can reduce the number of iterations as compared to the simulation-based optimization with OptQuest up to 97.11% or 40.22% on average as presented in Table 7.1. Only two instances show a higher number of iterations from the Hybrid Algorithm. However, the computational time per iteration in Hybrid Algorithm is larger than that of the OptQuest as it requires to run with two softwares (CPLEX and ARENA) and a certain time is lost during the data transfer between these softwares. Please note that MILP+Simulation is not considered in the comparison since an optimal solution is obtained only with one iteration.

Table 7.1: Optimal solution iteration comparison between OptQuest and Hybrid Algorithm

Policy*Returned ratio	OptQuest	Hybrid Algorithm	% Reduction from OptQuest
PTR*0.25	378	321	15.08%
PTR*0.50	189	106	43.92%
PTR*0.75	381	12	96.85%
PTM*0.25	100	25	75.00%
PTM*0.50	442	20	95.48%
PTM*0.75	381	11	97.11%
Co-PTR*0.25	97	132	- 36.08%
Co-PTR*0.50	238	108	54.62%
Co-PTR*0.75	169	489	- 189.35%
Co-PTM*0.25	182	57	68.68%
Co-PTM*0.50	261	89	65.90%
Co-PTM*0.75	263	12	95.44%
Average	**257**	**115**	**40.22%**

7.2.2 Policy performance comparison using Tukey comparison test

For the overall comparison among policies, a pairwise comparison method called Tukey comparison test is selected. Only the results obtained from the Hybrid Algorithm are compared, as it shows the best performance in terms of the highest system profit among the solving methods. However, it is found that other solving methods also provide somewhat similar pattern of results to the Hybrid Algorithm in terms of the relative performances among tested policies at each returned ratio. In general, it can be noticed in Figure 7.4 that when the returned ratio increases, the profits of the systems increase (despite the solving methods) as fewer numbers of new components are used with more use of returned components, which has a cheaper cost.

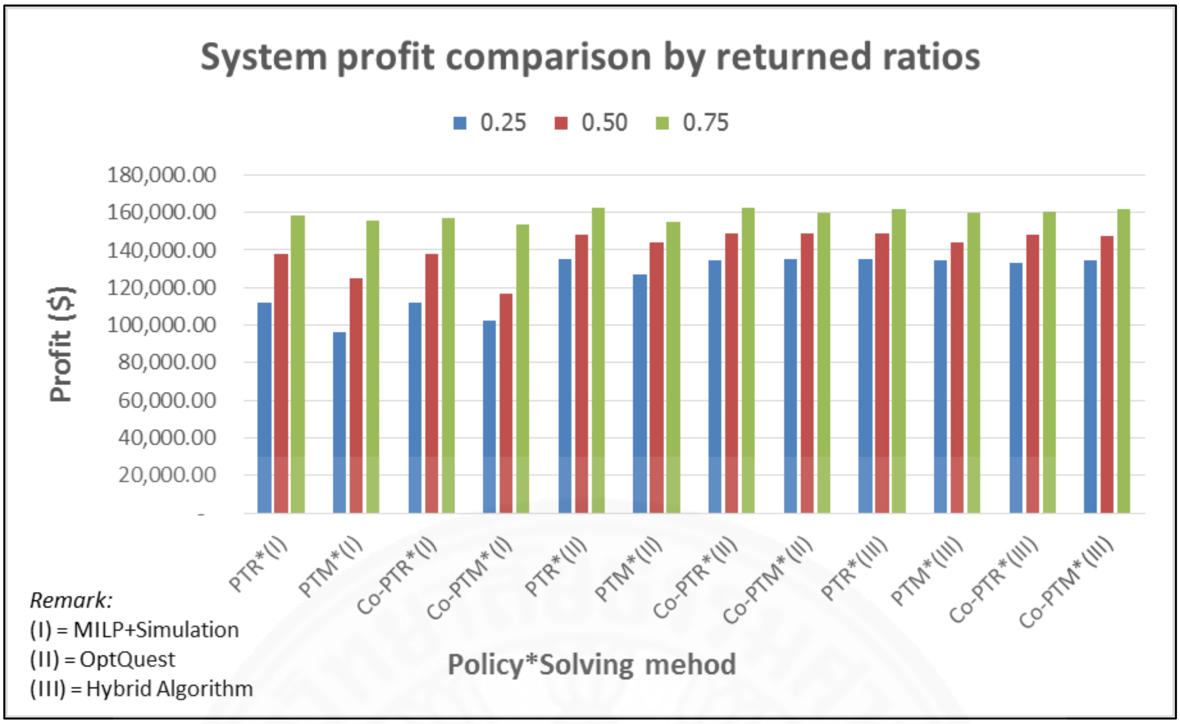

Figure 7.4: Comparison of average system profits by returned ratios

For the Hybrid Algorithm, optimal values of decision variables from each returned ratio are presented in Table 7.2. Disposal rate ($disR$) for PTR is zero for all returned ratios as expected due to the higher priority in remanufacturing. When the returned components arrive, all units are pulled to be produced first while an excess quantity of returned components (at 12% when the returned ratio is at 0.50) needs to be disposed in order to reduce the holding cost for PTM. Target inventory of new components ($TinvN$) decreases from 110 to 90 units in PTR and from 80 to 30 units in PTM, when the returned ratio increases from 0.25 to 0.75 since more returned components become available. PTR also shows to hold more new components in the inventory as compared to PTM, for instance $TinvN$ of 90 units in PTR and 60 units in PTM when the returned ratio is at 0.50. This is to cope with fluctuation in the arrival of retuned components.

A lower boundary of an inventory position ($lower$) in Co-PTR and Co-PTM operates as a buffer inventory level. With the ordering lead time around 1-2 weeks, a certain component is required to keep as a buffer inventory. Level of the buffer inventory is high when a required quantity of new components is high, which occurs when the returned ratio is low. As seen from Table 7.2, a lower boundary of Co-PTR at 0.25 returned ratio (80 units) is higher than the lower boundary at 0.75 returned ratio (50 units). Similar pattern is applied in Co-PTM. In opposite, an upper boundary of an inventory position ($upper$) determines whether to dispose or accept the whole arriving batch of returned components. When the returned ratio is high, a higher amount of returned components can be used. Then, the upper boundary increases to be able to keep more returned components. This can be noticed when the upper boundary of Co-PTM increases from 220 units to 440 units as the returned ratio increases from 0.25 to 0.75. However, an increase in component holding cost can be compensated by a decrease in raw material cost.

Target inventory of finished products ($TinvF$) is inversely proportional to the returned ratios. For example, $TinvF$ of PTR reduces instantly from 190 units to 160 units when the proportion of returned components over customer demand increases from 0.25 to 0.75. Having more returned components the production time used can be decreased, and it can reduce the inventories required in the Finished Product Inventory (FPI).

Table 7.2: Optimal values of decision variables with Hybrid Algorithm

Returned ratio at 0.25							
	$disR$	$TinvN$	$TinvF$		$lower$	$upper$	$TinvF$
PTR	0	110	190	Co-PTR	80	270	170
PTM	0	80	180	Co-PTM	70	220	200
Returned ratio at 0.50							
	$disR$	$TinvN$	$TinvF$		$lower$	$upper$	$TinvF$
PTR	0	90	180	Co-PTR	70	210	170
PTM	12	60	170	Co-PTM	60	440	200
Returned ratio at 0.75							
	$disR$	$TinvN$	$TinvF$		$lower$	$upper$	$TinvF$
PTR	0	90	160	Co-PTR	50	310	160
PTM	1	30	160	Co-PTM	30	440	170

Remark: $disR$ = Disposal rate, $TinvN$ = Target inventory level in NCI, $TinvF$ = Target inventory level in FPI, $lower$ = upper boundary for IP, $upper$ = upper boundary for IP

The analysis can be done in each returned ratio as follows:

7.2.2.1 Returned ratio at 0.25

When the returned ratio is at 0.25, Co-PTR gives statistically the lowest system profit while other policies have shown the same level of profits from the Tukey comparison test as shown in Figure 7.5. It can be also noticed from the results in Table 7.3 that Co-PTR is the only policy, which incurs lost sales. This lost sales occur from too low level of the finished product inventory. Component holding cost is higher in Co-PTR because more components need to be held in the inventory, waiting to be produced while the finished product holding cost follows the target inventory. Since all policies operate under the same level of customer demand, the number of units sold is similar. Therefore, it is a matter of reducing costs to maximize the profit of the system.

At the returned ratio of 0.25 where there is only a small number of returned components in relation to the total amount of the customer demand, all policies show no significant difference in their profits. Even though, Co-PTR shows slightly inferior profit, it is due to the cost of lost sales. If ignored, all policies can be considered to operate similarly in terms of the profit. As a result, at the returned ratio of 0.25 the differences among policies and their coordination cannot be clearly noticed.

```
Grouping Information Using Tukey Method and 95.0% Confidence for Returned ratio at 0.25

Policy  N      Mean  Grouping
PTR     5  135095.2  A
Co-PTM  5  134649.6  A
PTM     5  134465.5  A
Co-PTR  5  132907.0    B

Means that do not share a letter are significantly different.
```

Figure 7.5: Tukey comparison test for the returned ratio at 0.25

Table 7.3: Results from the returned ratio at 0.25 with Hybrid Algorithm ($)

	PTR	PTM	Co-PTR	Co-PTM
$Profit$	135,095.20	134,465.46	132,906.97	134,649.56
$Revenue$	230,760.00	230,760.00	229,086.00	230,760.00
$Total\ cost$	95,664.80	96,294.54	96,179.03	96,110.44
RD	-	-	-	-
LS	-	-	1,674.00	-
RMM	46,886.06	47,173.94	46,301.37	47,349.12
NC	41,770.00	42,140.00	41,058.00	41,580.00
RP	6,330.00	6,330.00	6,330.00	6,330.00
CH	238.15	242.22	440.03	358.74
FH	440.58	408.39	375.63	492.58

7.2.2.2 Returned ratio at 0.50

When the proportion of returned component increases to 50% in relation to total amount of the customer demand, we can notice the differences among policies form the Tukey comparison test as shown in Figure 7.6 where PTR and Co-PTR outperform PTM and Co-PTM. From Table 7.4, with the policy of the priority to remanufacturing, the total production cost can be reduced since the unit cost is lower for producing the returned components (less cost of materials and less production time required). New component cost is also reduced as fewer quantity of new components is ordered for this type of priority. However, the differences between PTR and Co-PTR cannot be seen at this level of the returned ratio, while Co-PTM is shown to give a higher profit than PTM. When there is a coordination, it seems that more returned components can be pulled for production and hence, a lower cost can be achieved as explained before.

```
Grouping Information Using Tukey Method and 95.0% Confidence for Returned ratio at 0.50

Policy  N      Mean  Grouping
PTR     5  148568.1  A
Co-PTR  5  148447.5  A
Co-PTM  5  147580.1    B
PTM     5  144389.2      C

Means that do not share a letter are significantly different.
```

Figure 7.6: Tukey comparison test for the returned ratio at 0.50

Table 7.4: Results from the returned ratio at 0.50 with Hybrid Algorithm ($)

	PTR	PTM	Co-PTR	Co-PTM
$Profit$	148,568.05	144,389.22	148,447.49	147,580.09
$Revenue$	230,760.00	230,733.00	230,553.00	230,760.00
$Total\ cost$	82,191.95	86,343.78	82,105.51	83,179.91
RD	-	-	-	-
LS	-	27.00	207.00	-
RMM	40,291.06	42,287.39	40,110.52	40,862.94
NC	28,474.00	32,300.00	28,214.00	28,400.00
RP	12,780.00	11,120.00	12,780.00	12,780.00
CH	243.32	236.57	421.10	635.20
FH	403.57	372.83	372.89	501.77

7.2.2.3 Returned ratio at 0.75

The highest system profit can be obtained from PTR and Co-PTM when the returned component arrival is set at 75% of the total amount of the customer demand. PTM gives the lowest system profit as classified by Tukey comparison test as shown in Figure 7.7. A cheaper cost of returned components causes PTR to outperform PTM as mentioned earlier. According to Table 7.5, Co-PTR has a higher total cost of new components than PTR, which indicates that more inventory is held at the component level of Co-PTR despite the same level of variation in returned component arrival and the same inventory policy, which is the priority-to-remanufacturing. Similar to the case of 0.50 returned ratio, total cost of new components is less in Co-PTM as compared to PTM, which can be referred that higher amount of returned components is used in the production. At this level of returned ratio, it appears that a coordination has an ability to compromise the effect of prioritization. It can force the priority-to-manufacturing to use more returned components and force the priority-to-remanufacturing to use more new components. As a result, it helps to improve the profit of Co-PTM to be quite close to PTR (in the same group) while deteriorate the profit of Co-PTR to be lower than PTR and Co-PTM as more new components are forced to be used for the production. Still, PTM always shows to have the lowest profit as its cost is the lowest.

```
Grouping Information Using Tukey Method and 95.0% Confidence for Returned ratio at 0.75

Policy  N      Mean  Grouping
PTR     5  161704.1  A
Co-PTM  5  161544.4  A
Co-PTR  5  160749.2    B
PTM     5  159606.0      C

Means that do not share a letter are significantly different.
```

Figure 7.7: Tukey comparison test for the returned ratio at 0.75

Table 7.5: Results from the returned ratio at 0.75 with Hybrid Algorithm ($)

	PTR	PTM	Co-PTR	Co-PTM
Profit	161,704.15	159,605.98	160,749.18	161,544.41
Revenue	230,661.00	230,760.00	230,661.00	230,670.00
Total cost	68,956.85	71,154.02	69,911.82	69,125.59
RD	-	-	-	-
LS	99.00	-	99.00	90.00
RMM	33,677.97	34,657.37	33,606.64	33,887.25
NC	15,288.00	16,900.00	16,000.00	14,900.00
RP	19,235.00	18,965.00	19,235.00	19,235.00
CH	314.41	289.72	628.60	620.66
FH	342.47	341.93	342.58	392.69

7.2.3 Policy performance comparison using Dunnett comparison test

Priority-to-Remanufacturing is considered to give the highest system profit, i.e. the lowest total cost due to a cheaper cost of returned components. The policy, which has a comparable performance to the priority to remanufacturing such as PTR, is to be searched since the priority to remanufacturing policy contains a certain amount of risk in the operation and it could cause some difficulties in the planning of the production process as mentioned in some of the reviewed literature. Hence, PTR is used as a benchmark or a control policy in order to find a policy with an equivalent performance. Dunnett comparison test is applied to compare results between other policies and the control policy (PTR in this case), which can set the controlled group as a benchmark for comparison.

7.2.3.1 Returned ratio at 0.25

When returned component arrival is at 25% of the whole customer demand, the system profit obtained from Co-PTM and PTM are statistically similar to PTR as presented in Figure 7.8. This is similar to the result obtained from the Tukey comparison test with the case of the returned ratio at 0.25. However, the lower profit of Co-PTR is the result of the lost sales cost, as mentioned earlier. Without lost sales cost, all three policies (PTM, Co-PTR, and Co-PTM) are relatively similar to PTR.

Grouping Information Using Dunnett Method and 95.0% Confidence

Policy	Returned ratio	Method	N	Mean	Grouping
PTR	0.25	Hybrid Algorithm (control)	5	135095.2	A
Co-PTM	0.25	Hybrid Algorithm	5	134649.6	A
PTM	0.25	Hybrid Algorithm	5	134465.5	A
Co-PTR	0.25	Hybrid Algorithm	5	132907.0	

Means not labeled with letter A are significantly different from control level mean.

Figure 7.8: Dunnett comparison test for the returned ratio at 0.25

7.2.3.2 Returned ratio at 0.50

At the returned ratio of 0.50, where returned component arrival is about half of the whole customer demand, Co-PTR and Co-PTM are considered to be in the same group of PTR in terms of the profit of the system as shown in Figure 7.9. This shows that the policy of coordination can start to help improve the performance of the priority to manufacturing to be equivalent to the policy of priority to remanufacturing despite the fact that more new components are used as well as less amount of returned components is used. Hence, the risk of using too high amount of returned components can be reduced.

Grouping Information Using Dunnett Method and 95.0% Confidence

Policy	Returned ratio	Method	N	Mean	Grouping
PTR	0.5	Hybrid Algorithm (control)	5	148568.1	A
Co-PTR	0.5	Hybrid Algorithm	5	148447.5	A
Co-PTM	0.5	Hybrid Algorithm	5	147580.1	A
PTM	0.5	Hybrid Algorithm	5	144389.2	

Means not labeled with letter A are significantly different from control level mean.

Figure 7.9: Dunnett comparison test for the returned ratio at 0.50

7.2.3.3 Returned ratio at 0.75

Similar to the case of the returned ratio at 0.50, both coordination policies show to have an equivalent performance to PTR when the proportion of returned components over the customer demand is at 0.75 as seen in Figure 7.10. As a result, it may be concluded that when the returned ratio exceeds about half of the total amount of customer demand, the policies with coordination scheme performs equivalently to the priority to remanufacturing policy (PTR). With an intention to control and reduce the risk of acquiring the returned components, which are subject to many uncertainties, the coordinated PTM would be a better choice as it tries to use more new components than the returned components while produce equivalent amount of the profit.

Grouping Information Using Dunnett Method and 95.0% Confidence

Policy	Returned ratio	Method	N	Mean	Grouping
PTR	0.75	Hybrid Algorithm (control)	5	161704.1	A
Co-PTM	0.75	Hybrid Algorithm	5	161544.4	A
Co-PTR	0.75	Hybrid Algorithm	5	160749.2	A
PTM	0.75	Hybrid Algorithm	5	159606.0	

Means not labeled with letter A are significantly different from control level mean.

Figure 7.10: Dunnett comparison test for the returned ratio at 0.75

Chapter 8

Conclusion and Recommendations

8.1 Conclusion

In this study, three solving methods were implemented in order to test their performances on a hybrid manufacturing/remanufacturing system. Solving methods include the analytical model using Mixed-Integer Linear Programming with Simulation (MILP+ Simulation), Simulation-based Optimization with OptQuest (OptQuest), and Hybrid Simulation Optimization (Hybrid algorithm). Results on the system profit was used as an indicator to interpret their performances. The highest system profit is obtained when solving with the Hybrid Algorithm. Not only giving the highest profit of the system, but the Hybrid Algorithm could also reach the optimal result with less number of iterations as compared to the simulation-based optimization with OptQuest.

Referring the inventory control policy, PTR, PTM, Co-PTR, and Co-PTM were tested under three different returned ratios (0.25, 0.50, and 0.75). This ratio has proven to have an effect on the policy performance. The significant difference among policies cannot be seen under a low level of returned ratio (at 0.25). Any policies can be selected to implement in the system. When there is a higher amount of returned component arrival, at about half of the customer demand, policies with the priority-to-remanufacturing show to overcome other policies with a higher profit of the system and the coordination scheme starts to show its effect at this level of returned ratio. With the highest level of returned ratio (0.75), the effect of prioritization is observed to be compromised by policies with coordination. Hence, Co-PTM is recommended due to its equivalent performance to PTR and risk reduction in returned component uncertainties from priority-to-manufacturing. With the study's cost structure where the returned components pose a cheaper cost per unit, the priority to manufacturing performs pooly but the coordination scheme has proven to help improve its performance, especially when there is sufficient amount of returned components (about half of the customer demand).

8.2 Recommendations for further study

For further study, as for the solving method, the proposed hybrid simulation optimization algorithm can be implemented in other case studies to investigate its performance in different situations and it can also be improved by adding more algorithms to speed up the solving process. In the part of the case study, more factors (such as uncertain timing of returned component arrival) and costs (such as disposal cost) of remanufacturing can be added in the model to make it more realistic. In addition, the sensitivity analysis of importance costs can be done to see the effect of cost variation to the conclusion made.

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Appendices

Appendix A
CD Directories

Model

- Analytical models
  - PTR
  - PTM
  - Co-PTR
  - Co-PTM
- Simulation models
  - PTR
  - PTM
  - Co-PTR
  - Co-PTM

Report

- Final report.docx

Appendix B
Raw Data

The following contain raw data from each policy, which is classified by solving method applied. The page numbers of the datas are given as follows:

MILP+Simulation: PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	110,008.56	213,885.00	103,876.44	-	16,875.00	42,567.54	37,540.00	6,330.00	280.29	283.61	0	120	140	1
	111,869.29	215,100.00	103,230.71	-	15,660.00	42,855.69	37,820.00	6,330.00	279.42	285.60				
	114,182.46	216,675.00	102,492.54	-	14,085.00	43,300.79	38,210.00	6,330.00	278.13	288.62				
	111,969.96	215,145.00	103,175.04	-	15,615.00	42,756.04	37,910.00	6,330.00	278.91	285.09				
	111,723.51	215,055.00	103,331.49	-	15,705.00	42,872.72	37,860.00	6,330.00	279.15	284.63				
0.50	138,950.63	224,055.00	85,104.37	-	6,705.00	38,362.51	26,700.00	12,780.00	278.01	278.85	0	100	140	1
	138,205.45	223,560.00	85,354.55	-	7,200.00	38,246.84	26,570.00	12,780.00	278.46	279.25				
	137,856.89	223,470.00	85,613.11	-	7,290.00	38,424.77	26,560.00	12,780.00	278.46	279.88				
	137,433.27	223,200.00	85,766.73	-	7,560.00	38,378.68	26,490.00	12,780.00	278.70	279.36				
	138,499.44	223,740.00	85,240.56	-	7,020.00	38,277.91	26,600.00	12,780.00	278.40	284.26				
0.75	158,621.56	228,285.00	69,663.44	-	2,475.00	32,926.34	14,460.00	19,235.00	286.98	280.13	0	80	140	1
	157,671.26	227,610.00	69,938.74	-	3,150.00	32,678.77	14,310.00	19,235.00	286.41	278.56				
	158,857.30	228,510.00	69,652.70	-	2,250.00	33,093.18	14,510.00	19,235.00	285.21	279.31				
	158,145.53	227,925.00	69,779.47	-	2,835.00	32,763.84	14,380.00	19,235.00	286.32	279.31				
	159,169.10	228,600.00	69,430.90	-	2,160.00	32,939.42	14,530.00	19,235.00	285.15	281.34				

MILP+Simulation: PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	94,142.71	208,980.00	114,837.29	-	21,780.00	44,354.53	41,720.00	6,060.00	633.62	289.14	3	80	140	1
	93,761.01	208,845.00	115,083.99	-	21,915.00	44,314.98	41,860.00	6,060.00	642.39	291.62				
	98,414.79	211,320.00	112,905.21	-	19,440.00	44,613.93	41,870.00	6,060.00	629.57	291.70				
	97,401.90	210,825.00	113,423.10	-	19,935.00	44,590.65	41,910.00	6,060.00	633.18	294.26				
	96,197.21	210,150.00	113,952.79	-	20,610.00	44,456.38	41,880.00	6,060.00	655.24	291.17				
0.50	124,852.50	219,960.00	95,107.50	-	10,800.00	40,754.22	32,000.00	10,865.00	406.12	282.16	14	60	140	1
	125,842.43	220,500.00	94,657.57	-	10,260.00	40,859.18	32,000.00	10,865.00	390.25	283.14				
	123,041.92	219,060.00	96,018.08	-	11,700.00	40,737.61	32,000.00	10,865.00	433.80	281.66				
	124,779.56	219,915.00	95,135.44	-	10,845.00	40,731.05	32,000.00	10,865.00	411.58	282.81				
	126,618.25	220,860.00	94,241.75	-	9,900.00	40,775.68	32,000.00	10,865.00	414.66	286.41				
0.75	156,332.86	228,735.00	72,402.14	-	2,025.00	34,384.01	16,700.00	18,730.00	283.69	279.44	2	30	140	1
	155,235.78	228,060.00	72,824.22	-	2,700.00	34,118.34	16,700.00	18,730.00	297.33	278.55				
	156,713.58	228,870.00	72,156.42	-	1,890.00	34,274.44	16,700.00	18,730.00	279.31	282.67				
	153,701.14	227,430.00	73,728.86	-	3,330.00	34,379.26	16,700.00	18,730.00	312.20	277.40				
	156,407.39	228,735.00	72,327.61	-	2,025.00	34,308.09	16,700.00	18,730.00	283.60	280.92				

MILP+Simulation: Co-PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	110,008.56	213,885.00	103,876.44	-	16,875.00	42,567.54	37,540.00	6,330.00	280.29	283.61	80	120	140	1
	111,869.29	215,100.00	103,230.71	-	15,660.00	42,855.69	37,820.00	6,330.00	279.42	285.60				
	114,182.46	216,675.00	102,492.54	-	14,085.00	43,300.79	38,210.00	6,330.00	278.13	288.62				
	111,605.52	214,965.00	103,359.48	-	15,795.00	42,773.09	37,900.00	6,330.00	276.57	284.82				
	111,605.73	215,010.00	103,404.27	-	15,750.00	42,912.69	37,850.00	6,330.00	277.02	284.56				
0.50	139,000.56	224,100.00	85,099.44	-	6,660.00	38,402.72	26,700.00	12,780.00	276.78	279.94	80	100	140	1
	138,204.37	223,560.00	85,355.63	-	7,200.00	38,249.71	26,570.00	12,780.00	277.14	278.78				
	137,925.00	223,515.00	85,590.00	-	7,245.00	38,438.14	26,570.00	12,780.00	276.63	280.23				
	137,481.31	223,200.00	85,718.69	-	7,560.00	38,332.98	26,490.00	12,780.00	276.72	278.98				
	138,620.70	223,785.00	85,164.30	-	6,975.00	38,280.30	26,570.00	12,780.00	274.65	284.35				
0.75	156,165.96	227,835.00	71,669.04	-	2,925.00	33,071.51	15,000.00	19,235.00	1,156.28	281.25	10	680	140	1
	157,031.08	228,060.00	71,028.92	-	2,700.00	32,675.51	14,960.00	19,235.00	1,176.33	282.07				
	157,012.03	228,285.00	71,272.97	-	2,475.00	33,142.48	14,970.00	19,235.00	1,168.62	281.87				
	157,295.87	228,375.00	71,079.13	-	2,385.00	33,090.71	14,920.00	19,235.00	1,168.86	279.56				
	156,992.58	228,195.00	71,202.42	-	2,565.00	33,020.63	14,930.00	19,235.00	1,173.00	278.80				

MILP+Simulation: Co-PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	100,006.39	208,260.00	108,253.61	-	22,500.00	42,177.27	36,600.00	6,330.00	353.82	292.52	70	220	140	1
	102,222.49	210,195.00	107,972.51	-	20,565.00	42,092.00	38,330.00	6,330.00	359.65	295.86				
	103,426.81	209,745.00	106,318.19	-	21,015.00	42,216.85	36,100.00	6,330.00	356.82	299.52				
	104,218.95	211,275.00	107,056.05	-	19,485.00	42,203.10	38,380.00	6,330.00	361.44	296.51				
	103,716.82	210,015.00	106,298.18	-	20,745.00	42,149.27	36,420.00	6,330.00	360.48	293.43				
0.50	115,262.21	213,075.00	97,812.79	-	17,685.00	38,239.86	27,500.00	12,780.00	1,311.56	296.36	30	870	140	1
	117,358.81	214,065.00	96,706.19	-	16,695.00	38,135.65	27,500.00	12,780.00	1,300.88	294.66				
	118,147.87	214,605.00	96,457.13	-	16,155.00	38,436.51	27,500.00	12,780.00	1,285.56	300.05				
	115,774.82	213,390.00	97,615.18	-	17,370.00	38,374.23	27,500.00	12,780.00	1,294.06	296.89				
	118,217.06	214,515.00	96,297.94	-	16,245.00	38,173.38	27,500.00	12,780.00	1,303.54	296.02				
0.75	152,866.42	225,540.00	72,673.58	-	5,220.00	33,071.43	14,600.00	18,830.00	662.02	290.13	30	440	140	1
	154,648.67	226,440.00	71,791.33	-	4,320.00	33,103.47	14,600.00	18,830.00	647.76	290.10				
	153,149.41	225,765.00	72,615.59	-	4,995.00	33,229.38	14,600.00	18,830.00	668.64	292.57				
	153,829.08	226,035.00	72,205.92	-	4,725.00	33,098.33	14,600.00	18,830.00	660.96	291.63				
	153,704.21	225,945.00	72,240.79	-	4,815.00	33,053.10	14,600.00	18,830.00	655.36	287.33				

OptQuest: PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	134,966.61	230,490.00	95,523.39	-	270.00	46,801.37	41,510.00	6,330.00	206.60	405.42	0	100	180	378
	135,189.58	230,580.00	95,390.42	-	180.00	46,729.59	41,540.00	6,330.00	206.08	404.74				
	135,341.96	230,760.00	95,418.04	-	-	46,921.33	41,550.00	6,330.00	206.62	410.09				
	135,315.00	230,580.00	95,265.00	-	180.00	46,651.21	41,490.00	6,330.00	206.56	407.23				
	135,320.20	230,670.00	95,349.80	-	90.00	46,756.31	41,560.00	6,330.00	206.38	407.11				
0.50	148,123.45	230,760.00	82,636.55	-	-	40,449.77	28,700.00	12,780.00	303.48	403.29	0	110	180	189
	148,498.62	230,760.00	82,261.38	-	-	40,097.05	28,680.00	12,780.00	303.60	400.73				
	148,305.62	230,760.00	82,454.38	-	-	40,291.36	28,670.00	12,780.00	303.66	409.36				
	148,367.94	230,760.00	82,392.06	-	-	40,245.66	28,660.00	12,780.00	303.72	402.69				
	148,242.64	230,760.00	82,517.36	-	-	40,372.75	28,660.00	12,780.00	303.72	400.88				
0.75	162,808.13	230,760.00	67,951.87	-	-	33,557.51	14,710.00	19,235.00	108.27	341.08	0	30	160	381
	162,672.82	230,760.00	68,087.18	-	-	33,694.20	14,710.00	19,235.00	107.53	340.45				
	162,686.97	230,760.00	68,073.03	-	-	33,675.06	14,710.00	19,235.00	109.05	343.92				
	162,677.17	230,760.00	68,082.83	-	-	33,693.23	14,710.00	19,235.00	107.29	337.31				
	162,663.82	230,760.00	68,096.18	-	-	33,702.87	14,710.00	19,235.00	109.33	338.99				

OptQuest: PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	126,344.31	230,760.00	104,415.69	-	-	50,799.31	49,690.00	3,115.00	354.33	457.05	50	100	190	100
	126,708.51	230,760.00	104,051.49	-	-	50,725.10	49,450.00	3,115.00	300.19	461.21				
	126,519.93	230,760.00	104,240.07	-	-	50,760.31	49,580.00	3,115.00	318.36	466.40				
	127,093.78	230,760.00	103,666.22	-	-	50,620.43	49,200.00	3,115.00	271.69	459.10				
	126,693.86	230,760.00	104,066.14	-	-	50,711.57	49,460.00	3,115.00	314.83	464.74				
0.50	144,109.09	230,625.00	86,515.91	-	135.00	42,349.43	32,300.00	11,120.00	240.01	371.47	12	60	170	442
	144,437.88	230,760.00	86,322.12	-	-	42,295.64	32,300.00	11,120.00	235.52	370.96				
	144,620.07	230,760.00	86,139.93	-	-	42,108.83	32,300.00	11,120.00	236.17	374.93				
	144,361.12	230,760.00	86,398.88	-	-	42,368.94	32,300.00	11,120.00	236.14	373.79				
	144,417.92	230,760.00	86,342.08	-	-	42,314.11	32,300.00	11,120.00	234.99	372.98				
0.75	154,676.37	230,715.00	76,038.63	-	45.00	37,156.51	22,000.00	16,245.00	251.45	340.67	15	40	160	381
	154,832.87	230,760.00	75,927.13	-	-	37,091.30	22,000.00	16,245.00	250.77	340.06				
	154,780.55	230,760.00	75,979.45	-	-	37,140.29	22,000.00	16,245.00	251.33	342.83				
	154,611.11	230,760.00	76,148.89	-	-	37,313.45	22,000.00	16,245.00	251.42	339.02				
	154,768.05	230,760.00	75,991.95	-	-	37,156.02	22,000.00	16,245.00	251.24	339.69				

OptQuest: Co-PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	134,658.58	230,760.00	96,101.42	-	-	47,012.36	42,020.00	6,330.00	298.26	440.80	110	130	190	97
	134,938.45	230,715.00	95,776.55	-	45.00	46,704.26	41,960.00	6,330.00	298.59	438.71				
	134,975.61	230,760.00	95,784.39	-	-	46,785.69	41,930.00	6,330.00	298.80	439.90				
	134,791.12	230,760.00	95,968.88	-	-	46,917.99	41,980.00	6,330.00	298.50	442.39				
	134,753.75	230,760.00	96,006.25	-	-	46,986.84	41,950.00	6,330.00	298.68	440.73				
0.50	149,064.51	230,760.00	81,695.49	-	-	40,220.52	27,860.00	12,780.00	431.88	403.09	10	290	180	238
	149,114.30	230,760.00	81,645.70	-	-	40,171.69	27,860.00	12,780.00	431.52	402.50				
	148,956.57	230,760.00	81,803.43	-	-	40,325.29	27,860.00	12,780.00	429.54	408.59				
	149,244.61	230,760.00	81,515.39	-	-	40,040.54	27,860.00	12,780.00	431.28	403.57				
	149,012.59	230,760.00	81,747.41	-	-	40,274.81	27,860.00	12,780.00	431.04	401.56				
0.75	162,358.31	230,535.00	68,176.69	-	225.00	33,341.62	14,620.00	19,235.00	413.12	341.95	20	220	160	169
	162,489.40	230,760.00	68,270.60	-	-	33,667.14	14,620.00	19,235.00	408.05	340.42				
	162,187.13	230,760.00	68,572.87	-	-	33,965.70	14,620.00	19,235.00	408.71	343.45				
	162,696.03	230,760.00	68,063.97	-	-	33,459.04	14,620.00	19,235.00	408.17	341.76				
	162,224.76	230,580.00	68,355.24	-	180.00	33,566.90	14,620.00	19,235.00	410.99	342.34				

OptQuest: Co-PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	135,284.13	230,760.00	95,475.87	-	-	47,248.98	41,100.00	6,330.00	284.92	511.97	10	260	210	182
	135,578.36	230,760.00	95,181.64	-	-	46,955.63	41,100.00	6,330.00	284.56	511.45				
	135,338.88	230,760.00	95,421.12	-	-	47,187.91	41,100.00	6,330.00	284.32	518.89				
	135,263.46	230,760.00	95,496.54	-	-	47,271.48	41,100.00	6,330.00	284.56	510.50				
	135,243.74	230,760.00	95,516.26	-	-	47,289.47	41,100.00	6,330.00	284.14	512.65				
0.50	148,244.72	230,760.00	82,515.28	-	-	40,365.94	28,800.00	12,780.00	161.98	407.37	20	90	180	261
	148,559.47	230,535.00	81,975.53	-	225.00	40,505.07	27,900.00	12,780.00	157.27	408.19				
	149,064.44	230,760.00	81,695.56	-	-	40,445.04	27,900.00	12,780.00	160.02	410.50				
	149,007.13	230,670.00	81,662.87	-	90.00	40,326.47	27,900.00	12,780.00	159.29	407.12				
	148,212.14	230,760.00	82,547.86	-	-	40,400.06	28,800.00	12,780.00	157.83	409.97				
0.75	159,841.50	230,760.00	70,918.50	-	-	34,766.22	16,200.00	18,830.00	699.70	422.58	60	480	180	263
	160,115.06	230,760.00	70,644.94	-	-	34,488.64	16,200.00	18,830.00	698.98	427.31				
	160,048.75	230,760.00	70,711.25	-	-	34,549.61	16,200.00	18,830.00	699.10	432.55				
	160,001.98	230,760.00	70,758.02	-	-	34,603.82	16,200.00	18,830.00	698.14	426.06				
	159,737.64	230,535.00	70,797.36	-	225.00	34,423.86	16,200.00	18,830.00	689.08	429.41				

Hybrid Algorithm: PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	134,884.22	230,760.00	95,875.78	-	-	47,047.59	41,820.00	6,330.00	237.74	440.45	0	110	190	321
	135,196.81	230,760.00	95,563.19	-	-	46,785.82	41,770.00	6,330.00	238.16	439.22				
	135,235.53	230,760.00	95,524.47	-	-	46,785.87	41,730.00	6,330.00	238.46	440.15				
	135,074.21	230,760.00	95,685.79	-	-	46,895.33	41,780.00	6,330.00	238.04	442.42				
	135,085.25	230,760.00	95,674.75	-	-	46,915.70	41,750.00	6,330.00	238.36	440.69				
0.50	148,361.96	230,760.00	82,398.04	-	-	40,470.82	28,500.00	12,780.00	243.08	404.14	0	90	180	106
	148,742.85	230,760.00	82,017.15	-	-	40,113.19	28,480.00	12,780.00	243.38	400.58				
	148,609.02	230,760.00	82,150.98	-	-	40,248.56	28,470.00	12,780.00	243.36	409.05				
	148,641.46	230,760.00	82,118.54	-	-	40,231.88	28,460.00	12,780.00	243.38	403.28				
	148,484.98	230,760.00	82,275.02	-	-	40,390.87	28,460.00	12,780.00	243.38	400.77				
0.75	161,635.02	230,625.00	68,989.98	-	135.00	33,684.15	15,280.00	19,235.00	314.52	341.32	0	90	160	12
	161,550.90	230,445.00	68,894.10	-	315.00	33,448.87	15,240.00	19,235.00	314.16	341.07				
	161,845.60	230,760.00	68,914.40	-	-	33,709.71	15,310.00	19,235.00	314.85	344.84				
	161,655.92	230,715.00	69,059.08	-	45.00	33,822.32	15,300.00	19,235.00	314.40	342.37				
	161,833.29	230,760.00	68,926.71	-	-	33,724.80	15,310.00	19,235.00	314.13	342.78				

Hybrid Algorithm: PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	disR	TstkM	TstkS	
0.25	134,070.28	230,760.00	96,689.72	-	-	47,399.74	42,290.00	6,330.00	262.45	407.54	0	80	180	25
	134,483.55	230,760.00	96,276.45	-	-	47,137.02	42,160.00	6,330.00	241.52	407.91				
	134,564.10	230,760.00	96,195.90	-	-	47,120.80	42,100.00	6,330.00	233.17	411.93				
	134,475.37	230,760.00	96,284.63	-	-	47,204.39	42,110.00	6,330.00	231.43	408.81				
	134,733.99	230,760.00	96,026.01	-	-	47,007.74	42,040.00	6,330.00	242.52	405.75				
0.50	144,109.09	230,625.00	86,515.91	-	135.00	42,349.43	32,300.00	11,120.00	240.01	371.47	12	60	170	20
	144,437.88	230,760.00	86,322.12	-	-	42,295.64	32,300.00	11,120.00	235.52	370.96				
	144,620.07	230,760.00	86,139.93	-	-	42,108.83	32,300.00	11,120.00	236.17	374.93				
	144,361.12	230,760.00	86,398.88	-	-	42,368.94	32,300.00	11,120.00	236.14	373.79				
	144,417.92	230,760.00	86,342.08	-	-	42,314.11	32,300.00	11,120.00	234.99	372.98				
0.75	159,502.04	230,760.00	71,257.96	-	-	34,763.79	16,900.00	18,965.00	288.44	340.73	1	30	160	11
	159,725.84	230,760.00	71,034.16	-	-	34,537.99	16,900.00	18,965.00	290.23	340.94				
	159,483.28	230,760.00	71,276.72	-	-	34,777.40	16,900.00	18,965.00	290.45	343.87				
	159,628.29	230,760.00	71,131.71	-	-	34,635.39	16,900.00	18,965.00	289.83	341.49				
	159,690.47	230,760.00	71,069.53	-	-	34,572.29	16,900.00	18,965.00	289.63	342.61				

Hybrid Algorithm: Co-PTR policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	132,040.55	228,600.00	96,559.45	-	2,160.00	46,302.81	40,950.00	6,330.00	441.30	375.34	80	270	170	132
	133,927.32	229,680.00	95,752.68	-	1,080.00	46,339.18	41,190.00	6,330.00	436.92	376.59				
	133,242.20	229,275.00	96,032.80	-	1,485.00	46,302.35	41,100.00	6,330.00	440.55	374.91				
	132,775.38	229,005.00	96,229.62	-	1,755.00	46,289.20	41,040.00	6,330.00	441.15	374.27				
	132,549.40	228,870.00	96,320.60	-	1,890.00	46,273.32	41,010.00	6,330.00	440.22	377.06				
0.50	147,932.77	230,265.00	82,332.23	-	495.00	40,115.38	28,150.00	12,780.00	420.57	371.27	70	210	170	108
	148,523.54	230,580.00	82,056.46	-	180.00	40,082.05	28,220.00	12,780.00	420.36	374.05				
	148,586.37	230,715.00	82,128.63	-	45.00	40,257.22	28,250.00	12,780.00	420.87	375.54				
	148,833.60	230,760.00	81,926.40	-	-	40,092.65	28,260.00	12,780.00	420.66	373.09				
	148,361.19	230,445.00	82,083.81	-	315.00	40,005.30	28,190.00	12,780.00	423.03	370.48				
0.75	160,363.26	230,445.00	70,081.74	-	315.00	33,610.87	15,950.00	19,235.00	628.62	342.25	50	310	160	489
	160,924.83	230,760.00	69,835.17	-	-	33,609.66	16,020.00	19,235.00	628.23	342.29				
	160,597.00	230,715.00	70,118.00	-	45.00	33,846.15	16,020.00	19,235.00	629.52	342.33				
	160,916.28	230,715.00	69,798.72	-	45.00	33,538.54	16,010.00	19,235.00	627.72	342.46				
	160,944.55	230,670.00	69,725.45	-	90.00	33,427.97	16,000.00	19,235.00	628.89	343.59				

Hybrid Algorithm: Co-PTM policy

Returned ratio	Profit	Revenue	Total cost	Costs							Decision variables			Optimal solution iteration
				RD	LS	RMM	NC	RP	CH	FH	lower	upper	TstkS	
0.25	134,731.06	230,760.00	96,028.94	-	-	47,269.30	41,580.00	6,330.00	357.56	492.08	70	220	200	57
	134,628.84	230,760.00	96,131.16	-	-	47,372.54	41,580.00	6,330.00	359.48	489.14				
	134,539.54	230,760.00	96,220.46	-	-	47,455.94	41,580.00	6,330.00	359.30	495.22				
	134,634.85	230,760.00	96,125.15	-	-	47,363.15	41,580.00	6,330.00	359.06	492.94				
	134,713.51	230,760.00	96,046.49	-	-	47,284.68	41,580.00	6,330.00	358.28	493.53				
0.50	147,427.95	230,760.00	83,332.05	-	-	41,015.68	28,400.00	12,780.00	635.60	500.77	60	440	200	89
	147,642.38	230,760.00	83,117.62	-	-	40,801.33	28,400.00	12,780.00	634.88	501.40				
	147,507.32	230,760.00	83,252.68	-	-	40,931.73	28,400.00	12,780.00	635.06	505.89				
	147,801.40	230,760.00	82,958.60	-	-	40,643.09	28,400.00	12,780.00	635.24	500.27				
	147,521.38	230,760.00	83,238.62	-	-	40,922.86	28,400.00	12,780.00	635.24	500.52				
0.75	161,553.85	230,760.00	69,206.15	-	-	34,057.53	14,900.00	19,235.00	623.48	390.13	30	440	170	12
	161,744.40	230,760.00	69,015.60	-	-	33,864.88	14,900.00	19,235.00	622.82	392.90				
	161,054.08	230,445.00	69,390.92	-	315.00	33,922.95	14,900.00	19,235.00	620.80	397.17				
	161,679.56	230,625.00	68,945.44	-	135.00	33,671.33	14,900.00	19,235.00	613.24	390.87				
	161,690.14	230,760.00	69,069.86	-	-	33,919.53	14,900.00	19,235.00	622.94	392.39				