Data driven decision-making methodology : a study of repair decision in remanufacturing

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**DATA DRIVEN DECISION-MAKING METHODOLOGY:
A STUDY OF REPAIR DECISION IN REMANUFACTURING**

PASSAPORN KANCHANASRI

A THESIS SUBMITTED TO NANYANG TECHNOLOGICAL
UNIVERSITY IN PARTIAL FULFILLMENT OF
THE REQUIREMENT FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

20/04/2019

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Date

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Authorship Attribution Statement

This thesis contains material from papers published in book which I am listed as an author.

Chapter 3 is published as Kachanasri, P., Moon, S.K., and Ng, G.K.L., "Decision making criteria for sustainable remanufacturing," Toward Sustainable Operations of Supply Chain and Logistics Systems, Springer International Publishing Switzerland, pp. 153-160, 2015.

The contributions of the co-authors are as follows:

- I prepared the manuscript draft. The manuscript was revised by Professor Moon and Dr. Gary Ng Ka Lai.
- I co-designed the study with Professor Moon and performed research work at the Advanced Remanufacturing and Technology Centre (ARTC) Singapore. I also summarized the data.

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Abstract

Decisions on recovering a low volume product such as a High Pressure Compressor Stage 3 Stator Vane (HPC Stg 3) could make a significant difference in cost saving. By a traditional assessment method considering only physical conditions of End-Of-Life parts, the cost of repairing the end-of-life parts is costly when comparing to replacement with spare parts due to dynamic resource constraints, human and machine limitations. This research is focused on investigating and developing an approach to solving the difficulty of repair decisions under various constraints. The main objective of this work is to provide quantitative decision rules for justification of the repairing of the returned parts. The proposed method consists of a data driven decision-making model that, given a set of parameters, determines the optimal damage point. The application of the system to possible scenarios is demonstrated through numerical studies. By comparing execution time, the proposed model solving by the linear programming provides a better optimal solution than the evolutionary approach. Taking more execution time, the evolution approach can also provide the optimal solution as good as by the linear programming. The numerical study demonstrates how to apply the proposed decision-making model to assess the acceptability of End-Of-Life parts and enable identification of the optimal solution. The optimal solution shows the significant cost saving when comparing repair and replacement options. In this research, there are three major accomplishments which are (1) an investigation of non-trivial decision-making factors, (2) a simulation model of End-Of-Life part repair decision constructed by using ARENA® to examine the concept of part sentencing in remanufacturing and (3) the development of a decision-making model to minimize repair and inventory costs by integrating the concept of data driven decision-making and optimization techniques i.e. the linear programming and the evolutionary approach. This work addresses the repair decision of returned parts. The research concept can be deployed to various industrial applications which include (1) multinational original equipment manufacturers in areas such as aerospace, automotive and marine regarding restoration of components to serviceable condition and remanufacturing of products, (2) small and medium enterprises about improvements of

remanufacturing operational process and (3) optimization of remanufacturing for implementation in various industries.

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Chapter 1 Introduction

This chapter introduces the background to the study of repair decision in remanufacturing. The contents include motivation, objectives of the research, research scope. At the end of this chapter, the organization of the thesis is presented.

1.1 Background

Sustainability and product recovery operations have been gotten attention [1, 2]. The increasing cost of disposal treatment causes manufacturers to focus on improving product recovery management [3-6]. To develop a sustainable society, the effective recovery of mechanical parts is important [7]. The importance of life cycle scenario has been recognized [8]. Researchers proposed methods to select appropriate life cycle options for a product by evaluating various values throughout its life cycle [9]. Life cycle assessment was used to support strategic decision making [10]. Evaluation of life cycle options could be made by many approaches. One is using a life-cycle simulation [11]. When an individual part is focused, an agent-based approach is another option to be employed [12]. Using a multi-agent simulation, a method for assembly of reused parts was developed [13]. Also, a framework for a part agent to promote recovery of parts was developed [14]. To achieve an efficient and effective decision in life cycle engineering and assessment, decision support was also researched and developed [15].

An awareness of environmental issues leads to sustainable practice. A closed loop supply chain is one way to achieve a sustainability goal. Moving forward to sustainable development requires a cautious decision making. Product recovery is one way to contribute to sustainability. It leads to the salvaging of material and energy of a product at its End-Of-Life. People have taken care of reducing waste [16, 17]. Instead of disposing of End-Of-Life products, researchers have developed approaches to reduce waste and also manufactured product volume by considering other recovery alternatives such as reuse, remanufacturing and so on. Generally, a product is

manufactured and then used until its End-Of-Life phase; when holders discard the product. The product components or parts have values which can be recovered [18]. The product recovery can yield benefits to many parties. It could be more cost-effective [19, 20]. Obviously, for example, a reuse option, a product can be utilized several times while resources and money are spent in manufacturing just a time. Original Equipment Manufacturers can reduce costs. A recovered component cost could be lower than a manufactured one [21]. When the cost decreases, the product price could be reduced. As a result, end users can buy a product at a lower price. Additionally, recovering a product could help reduce natural resource consumptions. Pollutant emissions or negative environmental impacts can be reduced also. Benefits to human, society, and environment cause the product recovery to be gotten attention by stakeholders and researchers [20, 22, 23]. The maximum utilization of resources in the End-Of-Life stage helps enterprises save money and time [24].

Remanufacturing is one of the adopted End-Of-Life strategies in a closed-loop system. It is an industrial process in which worn-out products are restored to like-new products [25]. At their End-Of-Life phase, they are recovered to meet manufacturing standards and specifications [26]. In other words, it is a process of bringing products back to sound working status or like-new or having a better quality by surpassing specifications through upgrading the function to the latest technology [27] through the process of disassembly, cleaning, sorting, inspection, repair, verification and reassembly [28]. Studies in the remanufacturing area are various such as research on additive manufacturing for remanufacturing, operation management in remanufacturing, business models for remanufacturing and design for remanufacturing [29]. Remanufacturing is one key to sustainable development. It can lead to economic, environmental and societal sustainability [11]. It can save costs and resources while reducing waste [12].

A growing number of original equipment manufacturers such as Caterpillar, Kodak, Xerox, Delphi have exhibited an increased interest in remanufacturing due to the potential for

competitive gains while improving their environmental performance [30] and many original equipment suppliers expand their remanufacturing operations overseas [31].

Remanufacturing acts on End-Of-Life products to recover manufacturing standards and specifications [32]. A used product is disassembled into parts. A unit fully equivalent in product quality, durability, performance and an expected lifetime to the original new product is produced by reassembling from a reusable part [25].

Remanufacturing provides several benefits. It could save energy resources, material, pollutant emissions, value retention, cost reduction and provide low-cost products to customers. That is a reason why it becomes an important research topic, given the increasing sustainability concern in production processes nowadays. Remanufacturing is about 25 percent less expensive than new production [33]. Nortel saved about US \$75 million by the remanufacturing. The publication reveals that the financial and economic viability of remanufacturing can be assured [34]. The remanufacturing is complicated by a range of decision-making issues that affect the effectiveness of operational practices [35]. In the case of decision-making, issues could relate to uncertainty, quality of returned parts, and part assessment criteria.

Figure 1 shows a general product life cycle. The cycle starts with designing the desired product. Materials are used to produce a product or a component. Then a finished product is

delivered to customers. It is used until its end of life. It can be disposed of or considered to recover by other alternatives such as recycling or remanufacturing.

Figure 1: Product life cycle

There are several procedures in a remanufacturing process. A discarded product is disassembled into parts. The product is reassembled from reusable parts to produce a unit fully equivalent in product quality, durability, performance and expected lifetime to the original new product [36]. The product part is inspected if it can be remanufactured. Accepted parts are reassembled to be a remanufactured product. It then is tested to ensure to meet manufacturing standards and specifications. A remanufacturing process in the product life cycle diagram is demonstrated in Figure 2.

Figure 2: Product life cycle in remanufacturing

The used product is returned to be disassembled into parts. After that, each part is inspected to check if it can be used to be reassembled. The part which passes an inspection process is reassembled and tested consecutively. One of the important steps of the product remanufacturing process is an inspection procedure. At the present time, many manufacturers have a manual inspection decided by skilled inspectors. The part is processed through many steps, generally are a visual inspection, a physical inspection, an identification inspection and a performance inspection [37] as shown in Figure 3 (adapted from Errington and Childe [38]). The first step is a visual inspection. It gets rid of a part that has excessive damage. The second step is a physical inspection. It classifies the part by usability. A usable part is sent to an identification inspection. A business criterion such as demand is considered. Finally, a part that passes a performance inspection is accepted and sent to a recovery process. Inspecting an End-Of-Life product, and selecting a recovery option are crucial. There are various product End-Of-Life options [23, 39-42]. A product can be determined to be reused if it can be used further with no or minimal treatments such as cleaning. If the product can be used after getting treatment such as damage fixing, it can be determined to be repaired. If the product is determined that it cannot be

used, it will be disposed of. Other options are refurbishing, remanufacturing, cannibalization, recycling with disassembly, recycling without disassembly, reconditioning, etc.

Original equipment manufacturers(OEMs) have to take care of products when they are returned at their End-Of-Life phase [43]. OEMs require a proper decision to manage their products effectively under economic and non-economic constraints and uncertain return product volumes.

Figure 3: Component assessment

For a product recovery decision problem with complexities in an operational process, it is difficult for operators to handle. Additionally, differences in the operators' skill and expertise could affect their decisions. The operators select recovery options based on their experiences.

A product recovery decision could have an impact on the manufacturing industry and society. Without taking care of a product recovery decision, it could lead to negative impacts such as lack of natural resources and harming human life, etc.

In various sectors like aerospace, shipping, and defense, manufacturers and customers are focused on sustaining their products for prolonged periods due to the high costs and a long time horizons associated with new product development [44]. The lifecycle of products in these

sectors could span over 20, 30, or even more than 40 years [45]. Once reaching the End-Of-Life phase, a recovery solution such as repairing becomes an option to sustain the product.

Repair in Remanufacturing

A repair of worn out or obsolete components is an important process in remanufacturing. Figure 4 represents a remanufacturing flow. Basically, a returned product is disassembled into parts. Each part is cleaned. After that, it is inspected and sentenced if it is reusable, recoverable or unrecoverable, following a guide and standard defined for each particular product. A recoverable part is then sent to repair.

Figure 4: Remanufacturing flow

Geometric inspection has a high possibility to enhance to be an automation operation due to advanced methods such as a Geometric Optical Measuring (GOM), Coordinate Measurement Machines (CMM), etc. The GOM and CMM yet have not been able to determine a condition on components and a positioning in space of the damage (wear, erosion, nicks, cracks, pitting, etc.). In the aerospace industry, a repair decision-making process has been done by operators. A difficulty to assess acceptability for repair has existed.

Problems could be encountered when managing expensive and important products or components. For example, Air Force was experiencing engine shortages [46]. One of the reasons was that a methodology for computing product requirements lacks considering an operational environment. When repairing products, there is often a requirement to replace defective components or parts. These replacement parts are commonly called service parts. The service parts play a critical role in the effective operation of commercial and military systems, as well as in the personal lives of individuals. The list of such commercial environments requiring the

service parts is seemingly unlimited. In some cases, products cannot be repaired if their service parts are not readily available. Thus, it is critically dependent on the abundant availability of the service parts within short periods of time.

Not only parts could differ in terms of cost and demand rates but the parts also differ in terms of criticality. Therefore, repair or replacement process can be delayed for certain parts but not for others. Thus, decisions concerning part and stock are important to the providers of the parts. If too few parts are available in the system, a customer will be not satisfied. If too many parts exist in the system, the cost to operate the system - inventory, facilities, transportation, and other operating costs - will be high.

Determining the components where repair or replacement is also necessary for aircraft maintenance. Case-based reasoning was applied to aid electronic ballast fault diagnosis of Boeing 747-400 airplanes [47].

Focusing on the operational aspect of the repair decision of jet engine parts, there are two questions as follows:

- how to provide a quantitative method to justify repairing the End-Of-Life parts?
- is repairing all repairable parts always the best solution to manage End-Of-Life parts?

1.2 Motivation

Decisions on recovering high value products such as a High Pressure Compressor Stage 3 Stator Vane (Appendix A: A High Pressure Compressor Stage 3 Stator Vane) could make a significant difference in cost saving because of high replacement costs of aircraft vanes [48]. Recovered values and costs of parts could be also different depending on End-Of-Life options [49].

By a traditional assessment method considering only physical conditions of End-Of-Life parts, the cost of repairing the End-Of-Life parts is sometimes costly comparing to replacement with spare parts due to dynamic resource constraints, human and machine limitations.

Commonly used rule of thumb to allow quick decisions is 'not to repair when damage exceeds 50%'. It makes more sense to consider a new service part if the repairing cost is higher than the cost of the new one [50].

The finding from using system dynamics to understand the profitability of reverse logistics for replacement parts to suppliers and refurbished parts to manufacturers for the computer industry, part replacements from suppliers are more profitable than refurbished computer parts [51]. Behfard, et al. [52] revealed their finding that repair was an excellent option as alternative sourcing, even if it was more expensive than buying a new part, because of the option to postpone the repair until the parts were needed. The cost of operating and supporting an industrial machine tool probably exceeds the purchase price of the tool [53].

Even with state-of-the-art part sentencing, an assessment of the acceptability of End-Of-Life parts together with controlling costs can still be difficult to perform because of dynamic input, resource constraints and human limitations. The parts are mostly assessed using results of physical condition checking, which have been carefully performed over the years. Operators probably accept a repairing option although the cost of repairing parts is high due to lacking resources i.e. materials or machines, and no spare parts.

The author is aware of the importance of part sentencing and benefits to those involved. The author brought the topic up for discussion. It gets attention from senior-level leaders also. Once the author found out that a decision support framework could help improve a decision-making approach from the traditional way to a more sustainable, inclusive and dynamic decision-making process [54], the author aims to investigate and develop an approach to assist solving a difficulty of making repair decisions.

1.3 Objectives

The main objective of this study is to investigate the part sentencing process and to develop a decision-making method for repair decisions that could assist in part sentencing by assessing the acceptability of End-Of-Life parts in remanufacturing favoring those of high-value items such as jet engine parts. To achieve the goal, three key tasks are to be conducted as follows.

(1) To investigate non-trivial decision-making factors regarding product recovery option selection.

(2) To examine the concept of part sentencing in remanufacturing and to develop a simulation model of End-Of-Life parts repair decision.

(3) To develop a decision-making model to minimize repair and inventory costs by integrating the concept of data driven decision-making and optimization techniques i.e. the linear programming and the evolutionary approach.

1.4 Research Scope

Operators form an important role in a remanufacturing strategy. Each End-Of -Life part should be assessed and assigned to its next processing stage. The decision regarding the recovery options after inspection of mechanical parts is labor-intensive and time-consuming. Also, it subjects to human errors and limitations.

With a traditional repair and restoration decision in remanufacturing that considers a physical condition, the decision-making process is a critical stage which can result in unnecessary costs being incurred.

A methodology that can aid the decision-making process will ultimately reduce errors in costly mistakes. This leads to the research to develop a methodology to assist in making a repair decision for remanufacturing.

This work covers repair decisions (either repair or replacement) for remanufacturing of high value parts in the aerospace industry with the concern of a service part inventory cost. So, the part or component level is only focused on.

1.5 Organization of the Thesis

An overview of the structure of the thesis is depicted in Figure 5. Having introduced a background of research, motivation, objectives, scope and organization of the thesis in this chapter, in the following chapter decision-making approaches, and accessible resources of research regarding decision-making of End-Of-Life products or components are described and discussed. An investigation of non-trivial the decision-making criteria for product recovery option selection is described in Chapters 3. Chapter 4 describes an examination of the concept of part sentencing in remanufacturing and the development of a simulation model of End-Of-Life part repair decision. The development of a decision-making model to support repair decisions is described in Chapters 5. The numerical studies are conducted and the results are shown in Chapter 6. Chapter 7 is the last chapter including research summary, contributions, limitations of the research and directions for future work.

Figure 5: Overview of a structure of the thesis

Chapter 2 Related Literature and Theoretical Framework

Literature reviews of relevant studies are presented in this chapter. They include studies of repair decision making, decision-making methods in remanufacturing, and decision-making methods in product recovery. Decision-making approaches are also described. Furthermore, decision-making criteria for product recovery option selection are reviewed. At the end of this chapter, there is a discussion section about decision-making methods and the research gap.

2.1 Repair Decision Making

An assessment of an acceptable part is a labor-intensive and time-consuming task [55]. There are a number of automation inspection systems proposed such as an automated solder joint visual inspection method in the printed circuit board (PCB) assembly process [56] and an automated system to inspect O-ring sealing surfaces by utilizing a laser digitizing system presented by Keith [57]. The other is an automated inspection system for a manufactured part using a cloud of three-dimensional measured points and CAD models proposed by Prieto, et al. [58]. Also, there is a method to detect form deviations of standard geometrical features (line, circle, plane, cylinder, cone, and sphere) of a manufactured part using a genetic algorithm (GA) proposed by Killmaier and Babu [59]. The other is an automated approach for an inspection process utilizing robot programming which was introduced by Kuhlenkötter and Sdahl [60]. An automated inspection system of aircraft sheet metal parts was presented by Shao, et al. [61]. A real-time surface inspection system of plastic parts was presented by Jaramillo, et al. [62]. There are various automated inspections presented and showed their accuracy and effectiveness [63-73]. Automated laser scanning system for reverse engineering and inspection presented by Zhou and Xi [74] can save processing time, increase quality improvement while minimizing errors caused by human operators.

The types of decisions that must be made relating to service parts could be divided into three planning categories.

1. Strategic planning - to determine what customer requirements are and will be over the next several years and then determine how to allocate resources to meet the requirements.

2. Tactical planning - to establish what inventories will be required to meet operational objectives at some future time, given the design and operation characteristics of an existent resupply system infrastructure. It is associated with budget, procurement and repair decisions. That is for some planning horizon to determine how much budget should be allocated for investment in which service parts.

3. Operational planning – for the given the stocks having on hand in repairable condition, what to repair or not repair.

The available literature and theory on operational decision-making for repair in remanufacturing is limited. Studies regarding repair decision making could be found in the area of maintenance, for example, a simulation study of an approach to maintenance and repair decision-making for infrastructure facilities [75]. A few papers that work on product recovery decision-making for End-Of-Life management that consider a repair option found are described below.

Ahmed, et al. worked on the development of a comprehensive decision-making model for an automobile sector [76]. They utilized AHP and Fuzzy AHP as approaches. Decision-making criteria included economic, environmental, social and technology. Tan, et al. focused on life extension and repair decision making for an offshore sector. They utilized Delphi, AHP, Grey Theory, and Fuzzy Evaluation. Physical conditions and environment are considered as decision-making criteria [77].

In the paper presented by Ahmed, et al., the repair option was considered. The integrated analytic approach based on the DEMATEL, AHP and Fuzzy AHP methodologies was proposed to evaluate an End-Of-Life option. The proposed methodology requires experts' opinions to assist in making strategic decisions. While in the paper presented by Tan, et al., a DHGF method - a combination of Delphi, AHP, Grey relational analysis, and fuzzy assessment method was presented. Although multiple factors including an item condition and a repair cost, were considered in decision making but experts' opinions were required as well. A comparison of the advantage and disadvantage of different evaluation models are summarized in the following table.

Table 1: A comparison of the advantage and disadvantage of different evaluation models

Method	Advantage	Disadvantage
AHP	It is one of the most commonly used methods for solving multi-criteria decision-making problems and excellent in identifying criteria and sub-criteria in a decision hierarchy and assigning a ranking to the alternative options through pairwise comparison matrices.	Decision-making is based on personal perspectives. The subjectivity is strong.
Fuzzy AHP	It offers a quantitative description method for a vague situation.	Decision-making is based on personal perspectives. The subjectivity is strong.
DHGF	The subjectivity is reduced.	A great deal of calculation is needed.

2.2 Decision-Making Methods in Remanufacturing

Decision-making techniques have been effectively applied in remanufacturing. Jiang, Zhang, and Sutherland introduced a multi-criteria decision-making model for remanufacturing technology portfolio selection with employing the analytic hierarchy process [98]. Subramoniam, Huisinigh, Chinnam, and Subramoniam proposed a transparent decision-making tool to make an effective remanufacturing decision in the conceptual stage of product development [99]. Ondemir and Gupta proposed an advanced product recovery system utilizing valuable life-cycle data to make informed recovery decisions [100]. Venkata Rao and Patel developed an integrated method by utilizing AHP, the fuzzy logic and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) for a manufacturing environment [101]. Cho, Jun, and Kiritsis proposed an algorithm for maximizing the profit of End-Of-Life computer remanufacturing [49]. Alghamdi, Prickett, and Setchi proposed a conceptual decision-making framework to support the process planning of remanufacturing engineering processes (REP) [102]. Other significant studies encompass uncertainty management by using mathematical analysis [103]. Jiang, Zhang, and Sutherland developed a multi-criteria decision making model for remanufacturing technology portfolio selection by employing the pair-wise comparison approach of Analytic Hierarchy Process (AHP) [104]. Zhang, Ong, and Nee proposed a simulation-based genetic algorithm approach for remanufacturing process planning and scheduling [105].

Existing decision making in remanufacturing includes an end-of-use product disassembly decision for subsequent recycling, remanufacturing and repair. for example, Pochampally, Vadde, Kamarthi, and Gupta, by considering a remaining lifetime, employed Bayesian updating and fuzzy set theory to aid in making a disassembly decision for a sensor embedded product (SEP) [106]. Trappey, Wu, Trappey, and Hsu proposed a fuzzy cognitive map integrated decision support model and network design [107]. It deployed a differential evolution (evolutionary computation method) and illustrated a case study of the compressed air and generator industry. Bhattacharjee and Cruz presented a system dynamics model of a high-value consumer electronic product with

a short lifecycle i.e. a mobile smartphone, for a closed-loop supply chain policy including refurbishing and recycling [108]. Lieckens, Colen, and Lambrecht developed a profit-maximizing model to determine an optimal remanufacturing numerical study, aiming to develop decision models that could be used for maintenance planning and predicting product residual life [110, 111].

2.3 Decision-Making Methods in Product Recovery

There are some studies related to the decision on product recovery or dispositioning, called in some literature [112, 113]. Agrawal, Singh, and Murtaza worked on disposition decisions in reverse logistics by using graph theory and matrix approach [114]. A simulation model was constructed to determine an end-of-life option based on item quality but the repair was out of consideration [115]. To make a quick and effective decision, Ng, Lu, and Song proposed a concept of deciding the End-Of-Life product recovery option [116]. The concept demonstrated in the Crankshaft case study essentially delivers cost benefits to the company and ensures sustainability by lowering costs and environmental impact. Kuik, Kaihara, and Fujii presented an integrated model to determine an optimal recovery plan by using the genetic algorithm [117]. Its objective was to maximize its recovery value when producing a remanufactured product by considering practical constraints of the manufacturing lead-time, waste, and quality as a whole. The results showed that the selection of different product recovery configurations has a direct impact on the achievable recovery value of a remanufactured product. Iakovou, et al. (2009) proposed a multi-criteria matrix evaluation framework considering the significant aspects of remanufactured product residual value, environmental burden, the quantity for electronic industries [118]. The importance of trade-off decision makings in order to achieve significant cost savings when implementing product recovery operations was also even discussed [119]. Nagalingam, et al. proposed a decision model for evaluating various product recovery configuration options for manufactured products in manufacturing industries [120]. However, the issue of lacking the trade-off assessment for recovery operations and the aspects are not clearly defined [121, 122].

Thierry, et al. presented an approach to recovery durable products called Product Recovery Management (PRM) [39]. Its objective is to minimize the quantities of waste by recovering the commercial and ecological value of products, components, and materials. Krikke, et al. introduced a two-phase algorithm using stochastic dynamic programming for optimal product recovery and disposal strategy of televisions [40]. It considered technical state, processing properties of materials, the presence, and removability of hazardous contents in assemblies, technological status, lost sales in primary markets, quality requirements for secondary products and materials including functionality, reliability, remaining lifetime and perception of customers. Its objective was to maximize an estimated net profit. Kiritsis, et al. proposed a multi-criteria decision-making handling several conflicting criteria that were not necessarily quantitatively defined for electro-mechanical and electronic products [123]. The objectives were to maximize the number of employees to perform the scenario, minimize carbon dioxide emissions and minimize the disassembly cost by considering environmental, economic, social indicators and user preference. In addition, due to the success of the evolutionary algorithm, an interest in how various constraints and objectives can be handled has rapidly increased [124]. A variety of multi-objective evolutionary algorithms were presented. Jun, et al. proposed a multi-objective evolutionary algorithm for maximizing a recovery value [23]. It considered conflicting criteria which were cost and before and after recovery quality to solve the product recovery option selection problem of a turbocharger. A mixed integer nonlinear programming model and heuristic search algorithms were proposed to minimize the total recovery cost of end-of-life turbocharger [125]. Ondemir and Gupta proposed an optimal recovery decision approach using linear physical programming to determine the optimum number of End-Of-Life products to be disassembled for sensor-embedded products (SEPs) [100]. The decision criteria included a demand for components and materials, a remaining useful life of a component and a recycled material demand. However, Ilgin and Gupta suggested more research efforts for End-Of-Life decision making that was still needed for improvement [126].

There are many practitioners and researchers, who examined the aspects based on the

entire product lifecycle by minimizing total associated costs along a supply chain [127, 128]. The End-Of-Life dispositions can vary significantly in practice because of the complexity in managing recovery operations [129, 130]. Product recovery decision making approaches, their objectives, criteria/constraints and applied area are summarized in Table 2.

Table 2: Product recovery decision making approaches, objectives, criteria and applied area

Approach	Objective	Criteria/Constraints	Applied area
An integrated model to determine an optimal recovery plan by using the genetic algorithm	Maximize recovery value	Lead-time, Waste, Quality	Remanufactured product
A multi-criteria matrix evaluation	Save cost	Remanufactured product residual value, Environmental burden, The quantity for electronic industries	Electronic industries
A decision model for evaluating various product recovery configuration options	Estimate utilization value of a manufactured product	Total recovery cost, Manufacturing lead-time, Minimization for landfill waste, Quality characteristic	Manufacturing industries
An approach to recovery durable products	Minimize the quantities of waste	Commercial and ecological value of products, components, and materials	Not indicated

Approach	Objective	Criteria/Constraints	Applied area
Stochastic dynamic programming	Maximize net profit	<p>Technical state,</p> <p>Processing properties of materials,</p> <p>The presence and removability of hazardous contents in assemblies,</p> <p>Technological status,</p> <p>Perception of consumers,</p> <p>Lost sales in primary markets,</p> <p>Quality requirements for secondary products and materials</p>	TV
Multi-Criteria Decision-making	<p>Maximize the number of employees to perform the scenario,</p> <p>Minimize CO₂ emissions,</p> <p>Minimize disassembly cost</p>	<p>Environmental indicator,</p> <p>Economic indicator,</p> <p>Social indicator,</p> <p>User preference</p>	<p>Electro mechanical, electronic products: telephone</p>

Approach	Objective	Criteria/Constraints	Applied area
Multi-objective evolutionary algorithm	Maximize recovery value	Quality- before and after recovery, Cost	Turbocharger
Linear physical programming	Determine the optimum number of End-Of-Life products to disassemble	Demand for components and materials, Remaining useful life of the components, Recycled material demand	Sensor-embedded products (SEPs)
A fuzzy logic model solved by genetic algorithm	Maximize net profit	Recovery value, Disassembly cost	An electric drill
A genetic algorithm and a multi-attribute utility function	Maximize utility across different segments and across different lifecycles within each segment	Price, Environmental impact, Reliability	Computer

2.4 Decision-Making Approaches

Decision making is a critical activity in the sequence of the remanufacturing process. Rational decisions are defined by logic or statistical models in contrast to a heuristic decision. For some decisions, the assumptions of rational models are not met [78]. In such a case, the heuristic approach would be a good choice. For logical or statistic models, numeric techniques are applied. Multi-criteria decision-making methods (MCDM) uses numeric techniques to aid decision makers to select among a discrete set of alternative decisions [79]. It could involve both quantitative and qualitative factors [80]. MCDM could be considered as a complex and dynamic process including one managerial level and one engineering level [81]. Results from the study show that the multi-criteria methods are effective tools that can be used as a structured decision to assist evaluation and selection [82]. The decision-making technique to be applied to solve a problem should be carefully selected. In this section, three commonly used decision-making techniques which are the analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and fuzzy logic concepts are summarized to show how the techniques work.

2.4.1 Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) was developed by Saaty [83]. It decomposes a complex MCDM problem into a system of hierarchies [84, 85]. The AHP provides a methodology to calibrate the numeric scale for both qualitative and quantitative measurements [86]. A decision objective or a goal is defined together with decision criteria in a hierarchy. A hierarchy could help a decision maker select an alternative that is fit the criteria.

The goal or objective has a value '1' totally. For n criterions, each of them has its value weight by its impact or significance. A summation of every criterion value is one, as same as the value of the goal. For m alternatives, each alternative has its value calculated by the product of the matching criterion value. The alternative value is considered for making a decision. The alternative that has the highest value is selected since it can satisfy the decision criteria the most.

The matrix is constructed by using the relative importance of the alternatives in terms of each criterion. The result of reviewing a total of 393 articles published from 2000 to 2014 in more than 120 peer-reviewed journals (extracted from Web of Science) indicated that the analytic hierarchy process (AHP) method was ranked as the most popular method in use [80].

2.4.2 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS developed by Ching-Lai Hwang [87], is a multi-criteria decision analysis method. It has been developed further by Yoon [90] and Hwang, et al. [89]. The multiple criteria decision-making method are based on an aggregating function representing “closeness to the ideal”, which originated in the compromise programming method [90]. This method concept is to select the alternative that has the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution [87-89]. The relative closeness of the alternative represents the basic principle in the TOPSIS method [91].

2.4.3 Fuzzy logic

Zadeh proposed a fuzzy set theory as the means for quantifying the inherent fuzziness that is presented in ill-posed problems (which by many accounts are the majority of the real-life problems in decision making) [92]. Examples of fuzzy sets are classes of objects (entities) characterized by adjectives [92]. A comprehensive description of the importance of fuzzy set theory in engineering and scientific problems is illustrated in many references [93, 94]. This is particularly critical to people who build decision support systems, for the knowledge they are dealing with is almost always riddled with vague concepts and judgmental rules [95].

While a traditional binary set provides exact reasoning, which is either true/positive ideal solution (1) or false/negative ideal solution (0), the fuzzy logic deals with approximate reasoning to manage an imprecision. Zadeh proposed a fuzzy concept [92, 96]. The range between completely true (1) and completely false (0) could be a truth value [97]. The reasoning can be formed by a supervised or unsupervised training depending on data available. It can be defined

in a form of a conditional statement as IF <condition> THEN <consequence>. Fuzzy multi-criteria decision-making methods are well explained in the available source [79].

2.5 Decision-Making Factors

A product recovery option selection is challenging. Various criteria can be involved in decision-making. There are also numerous influential factors when implementing sustainable manufacturing and product recovery operations [116, 139, 140].

A product recovery option selection can be varied by types of users [123]. Recycling companies, remanufacturers, and original equipment manufacturers have their own objectives and priorities [123]. The solution for each user could be different depending on the decision-making factors. In addition, it is possible to have many factors in selecting a product recovery option. A decision-making factor is one of the essential information for decision-making. There is a study to identify critical factors and investigates the causal relationship among the factors that influence the operations [141].

There are various factors or criteria to decide how to manage an end-of-life product. Law clearly assigns an explicit responsibility to producers or original equipment manufacturers for their products. For example, car manufacturers were obliged to take their products back and recycle them at 85% by 2005 and at 95% by 2015 respectively. Electronic product producers had to do so as well [142]. Apart from the law, other factors were stated in studies as follows. O'Shea et al. considered reliability, flexibility and environmental aspects, adding destructive operations, costs specification, integration in the disassembly planning system [143]. Goggin and Browne focused on material cost, inventory material cost, fixed-cost associated with process allocated to products or options undergoing the process according to their volume and a standard absorption rate, variable cost associated with the processing of a certain volume of products or options, and inventory carrying cost [144]. Lee et al. determined the optimal end-of-life options by considering cost and environmental impact [145]. Santochi et al., in order to decide the appropriate strategy,

considered influences factors which were the age of the product, general conditions, service status, innovations, market demands, wear damage, reusability, material, toxicity, and value [146]. List of criteria presented in Bufardi's work includes logistics costs (collection and transport), disassembly costs, a product value (what is gained from incineration recycling, landfilling etc.), product costs, the number of employee necessary to perform relevant operations, an exposure to hazardous materials, CO₂/SO₂ emissions and an energy consumption [147]. Staikos and Rahimifard considered three main factors in their decision- making model for waste management in the footwear industry [148]. The first factor includes economic factors which are cost and benefit. The second factor includes environmental factors (global warming potential, ozone depletion, acidification, eco-toxicity, human toxicity, hazardous waste). The third factor includes technical factors (technical feasibility, compliance with legislation, market pressures, public opinion). Gomes et al. considered investments, operating costs, disposal and treatment costs, CO₂ emissions, corporate image, and benefits to select an optimal alternative for plastic waste [149]. According to Xanthopoulos and Iakovou study, financial, environmental, legislative and technological criteria were considered for an optimal recovery operation [150]. Wadhwa et al. considered time, material costs, labor, overheads, etc. [151]. Environmental impacts which include resource consumption, resource conservation, waste release, and waste impact were also taken into consideration. Moreover, they considered market factors (demand, supply), quality factors both technical-related and operational-related and a legislative impact. Dhouib selected a market factor, profits, jobs created, an environmental impact to be criteria for a reverse manufacturing alternative selection [152]. Ghazilla et al. considered a return product volume, a demand, a maintenance plan, an engineering design, ease of disassembly and an ability to be disassembled a product [153].

2.6 Research Gap and Preview

Each method used in studies on a product recovery option selection has its advantage with specific constraints. A multi-criteria decision making can handle multiple conflicting criteria. A multi-objective evolutionary algorithm can generate multiple possible good alternative solutions in a single run. Even though some studies are related to product recovery option selection, they focus on a managerial strategy. It determines in advance how to manage returned products. In a case that little data are available for decision making since the products had not yet been returned, decision factors or parameters are estimated or forecasted. In an operational part sentencing process, products have already been returned and data are available. Yet there is no approach clearly identified to assist in selecting a product recovery option. Various criteria can be involved in decision making. Basically, decision criteria are selected relying on a specific business objective in each industry case. Economic factors are commonly found in many studies. To gain the highest revenue or minimizing cost, a product recovery option is selected based on a cost factor. Apart from the cost, there are other factors involving in product recovery. There are also concerns about sustainability and social impacts [131].

The decision-making methods: AHP, TOPSIS, and the fuzzy logic have their characteristics. The AHP could analyze a complex decision by handling multiple criteria. Criteria weighting seriously affects the selected solution. It could involve a bias mathematically unmeasurably. The TOPSIS can handle multiple criteria including positive and negative criteria. This could be fit for problems that have completely ideal solutions. On the other hand, in the case of no completely ideal solution, the fuzzy logic concept could be used to make a decision. Approximate reasoning could be used for modeling expert experiences. To develop fuzzy rules requires field expert experience and, historical results [132]. However, fuzzy reasoning sacrifices some explanation for accuracy, reliability, and lack of concept of justification for a fact [133].

The approaches in existing studies that are related to decision making that consider a repair option require expert opinions. They are not suitable for some circumstances, for example, when requiring prompt decisions, when lacking experts, etc. The decision to End-Of-Life product recovery is complicated [121]. Many factors could be involved. Not only the number of factors could be large but also some factors could be dependent on each other.

In summary, from the literature above, there is room for a study to solve mistakes for repair decisions in remanufacturing with spare part inventory concern. Even though the studies regarding repair decisions were found, the key factor to be considered was cost. They do not cover an issue of repair decisions with the inventory concern. Although some studies regarding inventory could be found they are not related to repair decision that this work focuses on. For example, Caggiano, et al. investigated two critical decisions on allocating available repair capacity and allocating available inventories to field stocking locations in the two-echelon supply system [134]. Yuan and Gao proposed inventory decision-making models for a closed-loop supply chain system to determine an optimal policy [135]. Andrew-Munot and Ibrahim presented the decision-making tool to address inventory lot-sizing problems in a hybrid remanufacturing-manufacturing system and address a production and inventory planning problem in a remanufacturing system [136].

In this chapter, previous research on repair decision making and relevant studies including studies of decision making in remanufacturing and product recovery, decision-making approaches and decision-making criteria are reviewed.

Decision-making factors are critical when making an important decision. An investigation of decision-making factors is presented in the next chapter.

Chapter 3 Investigation of Decision-Making Factors for Product Recovery Option Selection

This chapter presents two main studies regarding decision-making criteria for product recovery option selection. One is an investigation of decision-making criteria available in academic resources including journals and conference papers. Another is an investigation of decision-making criteria by questionnaire survey.

3.1 Investigation of Decision-Making Criteria by Reviewing of Literature

According to literature, various decision criteria can be involved in product recovery. Observably they are related to the product, process, and people. Cost minimizing, and engineering quality are the criteria that are commonly focused on in many pieces of research.

This section presents decision criteria for product recovery option selection including economic and non-economic factors. They cover business aspects, work safety, impacts on a product, a process and people, environment, etc. Highlighted environmental factors, the criteria are useful for who carefully makes a product recovery decision and look for long term benefits to the environment and society. Decision makers can consider economic and environmental decision-making criteria. Furthermore, the decision criteria include product, process, and people-related factors. The decision factors for product recovery option selection are presented in Table 3. In this study, each criterion is classified by two dimensions which are:

- Category Dimension I indicates that a criterion is environment-oriented or economy-oriented
- Category Dimension II indicates that a criterion is related to product, process or people

Economic factors are basically focused. One is a return product volume. Decision makers should concern about handling the uncertainty of return product volume. A product that has regularly high return product volume can be inspected and considered to be reused or

remanufactured. A selected recovery option and volume can depend on market demand as well. For example, if the markets or customers accept and require the remanufactured product, remanufacturing will be added as a recovery option. On the other hand, a decision maker might consider other options instead. The other is product reliability. Failure frequency of recovering products can help determine if a product should be recovered or not. Additionally, a condition or quality of the product is a common factor in product recovery. If the product has huge damage or is not good enough to recover, it will be disposed of. Furthermore, ease of product disassembling can be taken into consideration. Disassembly is a process in which a product is separated into its components and/or subassemblies [154]. Easy-to-disassembling designed product takes a shorter time in processing. It is attractive for remanufacturing. According to disassembly experiments, disassembly processing time could greatly affect cost also [153]. The other factor is a cost such as inventory cost, material cost, landfill cost, logistic cost, machine cost, disassembly cost, recycling cost, etc.

Even a disposal cost is one of the influences. The effect of disposal costs on a disassembly-for-recycling process is shown by Dini et al. [155]. High disposal costs can cause recycling to be more attractive. Commonly, a product recovery option is selected based on cost optimization or profit maximizing. The other factors which are related to the process can be processing time, machine capability, the number of equipment, the number of machines, machine failure, dependent machines failure, and process bottleneck. Decision makers can consider human factors also. Human capabilities such as working memory, eyes sight and different skill can affect product recovery effectiveness. The number of required manpower and effective labor working hours can be additionally considered if further needed in product recovery. Moving to non-economic focused factors, many factors highlight environmental and societal benefits. Obviously, legislation pays an attention to save the earth. Law in different countries probably assigns different responsibilities in product recovery. Gas, heat and pollutant emission can be limited in order to not harm an environment and human. These can affect the number of the product to be recovered. The following factors are focused on both economic and environmental. Product

useful lifetime is one factor that the decision makers can consider. A product that has short and long useful lifetime can have different strategies in managing its end of life. Additionally, according to Ondemir and Gupta, a useful lifetime can be considered as a measure of quality [156]. Furthermore, natural resource consumption including energy, electricity, and material can be considered. In a case of limited resources, options such as reuse and remanufacture should be included. Natural resource consumption is related to the economic aspect as well. The less natural resource is consumed, the less money is spent. Also, less harm occurs in the environment. Last but not least, user preferences can be taken into consideration. Product recovery option selection can be varied by user type [123]. OEMs may prefer to remanufacture the product while recycling companies may prefer to recycle the product. The decision makers should know user preferences (if any) and select the product recovery options to finally satisfy the real user.

A repair cost limit policy has been discussed in many papers. The repair cost limit policy is that a repairing decision depends on a repair cost. The repair cost is estimated when a failure occurs. If the cost exceeds a certain threshold, a replacement will be performed. Otherwise repairing will be performed. The repair cost limit policy was first studied by Drinkwater and Hastings [157]. Extensions of repair cost policy have been proposed and investigated by Nakagawa and Osaki [158], Clroux, et al. [159], Nguyen and Murthy [160], Beichelt [161], Park [162], Bai and Yun [163], Berg, et al. [164], Kapur, et al. [165], Chung and Lin [166], Dohi, et al. [167]. The deficiency of traditional repair cost limit policies is that the repair decision is based solely on repair cost [168].

Table 3: Decision-making factors for product recovery option selection

Decision Criteria/Factors	Category Dimension I (environment-oriented or economy-oriented)	Category Dimension II (Product-related, process-related or people-related)
Return product volume	Economy-oriented	Product
Demand/ market need	Economy-oriented	Product
Product reliability	Economy-oriented	Product
Product/part before recovery quality	Economy-oriented	Product
Product/part after recovery quality	Economy-oriented	Product
Product design (ease of disassembly)	Economy-oriented	Product
Inventory cost	Economy-oriented	Product
Material cost	Economy-oriented	Product
Landfill cost	Economy-oriented	Process
Logistic cost - location, transportation, collecting	Economy-oriented	Process
Machine cost including maintenance	Economy-oriented	Process
Processing cost by machine – disassembly, repair/restoration, remanufacture, disposal etc.	Economy-oriented	Process
Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc.	Economy-oriented	Process
Machine capability/ failure	Economy-oriented	Process
Labor – human factors, skill	Economy-oriented	People
Labor cost/Processing cost by people – disassembly, repair/restoration, remanufacture, disposal etc.	Economy-oriented	People
Processing time by people - disassembly, repair/restoration, remanufacture, disposal etc.	Economy-oriented	People
Legislation	Environment-oriented	Process
Gas emission – CO ₂ , SO ₂ etc.	Environment-oriented	Process
Pollutant or toxic emission	Environment-oriented	Process
Heat emission	Environment-oriented	Process
Product useful life time	Economy-oriented/Environment-oriented	Product
Natural resource consumption – material, fuel, energy etc.	Economy-oriented/Environment-oriented	Product
User preference	Economy-oriented/Environment-oriented	Product, Process, People

3.2 Investigation of Decision-Making Criteria by Survey

In addition to the literature, the questionnaire survey was conducted in order to investigate the importance of decision-making criteria. The questionnaire form is attached in Appendix C. The subjects and the survey results are as follows.

Subjects/participants: domain experts including a technical lead (automation), a senior research engineer, development engineers, a senior group manager, a general manager, a development engineer from the company representative.

The result regarding the importance of each criterion from the literature is shown in Table 4. A ranking of the importance of each criterion from the literature is shown in Table 5.

There are written comments about decision-making criteria mentioned additionally as follows.

- automation capability
- durability and cost to repair compared to purchase new.
 - cost of original product
 - cost of recovery (repair, disassembly, assembly, machine, people, etc.)
- cost of new material to make new and availability of new material
 - volume to recover
 - quality when new
 - reliability when recovered
 - customer demand for a new and recovered product

According to participants' responses, decision rules should consider:

- repair product life after repair/recovery.
- if the product cannot be repaired economically and performance cannot be guaranteed.

- cost of new versus recovered.
- condition of used part
- automated recovery process
- return volume
- damage should not be more than 50% of the total area
- repair time should not be more than 40% of a new manufactured part
- reliability of recovered product compared to new
- cost (new and cost for recovery) (including the availability of new material for new product creation)
- customer acceptance of the recovered product
- ability(technology) to remanufacture the product
- repair cost, disassembly cost, labor cost not prohibitive versus new product (L50% of the cost of manufacturing new product)
- profit by repairing the machine/equipment is greater than that of selling a new product

Interestingly, the OEM representative also suggests that the OEM prefers customers to purchase new products rather than repair or restoration.

3.3 Summary and Preview

Decision-making criteria were investigated by both reviewing literature and conducting a survey. Cost is a factor that was found in many research studies and gets the first order in ranking from the survey conducted. As a result, cost calculation and optimization were included

in this study. Part sentencing in remanufacturing is further examined and modeled using ARENA modeling and simulation software in the next chapter.

Table 4: An importance of decision-making criteria from literature

Criteria	Not important	Low	Medium	High	Very important
Return product volume	0.00%	0.00%	37.50%	50.00%	12.50%
Demand/ market need/customer need	0.00%	0.00%	0.00%	50.00%	50.00%
Product reliability	0.00%	12.50%	25.00%	0.00%	62.50%
Before-recovery product quality	0.00%	0.00%	50.00%	37.50%	12.50%
Product design (ease of disassembly)	0.00%	0.00%	37.50%	37.50%	25.00%
Total recovery cost	0.00%	0.00%	12.50%	25.00%	62.50%
Inventory cost	12.50%	25.00%	37.50%	25.00%	0.00%
Material cost	0.00%	0.00%	25.00%	62.50%	12.50%
Landfill cost	12.50%	37.50%	25.00%	25.00%	0.00%
Logistic cost - location, transportation, collecting	0.00%	25.00%	25.00%	37.50%	12.50%
Machine cost including maintenance	0.00%	0.00%	12.50%	87.50%	0.00%
Processing cost by machine – disassembly, repair/restoration, remanufacture, disposal, etc.	0.00%	0.00%	25.00%	12.50%	62.50%
Processing time by machine - disassembly, repair/restoration, remanufacture, disposal, etc.	0.00%	12.50%	25.00%	12.50%	50.00%
Machine capability/ failure	0.00%	12.50%	37.50%	37.50%	12.50%
Labor - number of operators/manpower	0.00%	25.00%	12.50%	37.50%	25.00%
Labor – skilled operators/decision makers	0.00%	12.50%	37.50%	25.00%	25.00%
Labor cost/Processing cost by people – disassembly, repair/restoration, remanufacture, disposal, etc.	0.00%	0.00%	50.00%	25.00%	25.00%
Processing time by people - disassembly, repair/restoration, remanufacture, disposal, etc.	0.00%	12.50%	37.50%	12.50%	37.50%
Legislation	0.00%	25.00%	37.50%	12.50%	25.00%
Carbon/gas emission - CO ₂ ,SO ₂ , etc.	12.50%	37.50%	25.00%	12.50%	12.50%
Heat emission	37.50%	50.00%	0.00%	12.50%	0.00%
Product useful lifetime	0.00%	0.00%	50.00%	12.50%	37.50%
Natural resource consumption – material, fuel, energy electricity, etc.	0.00%	50.00%	25.00%	12.50%	12.50%

Table 5: A ranking of the importance of decision-making criteria from the literature

Criterion	Rank
Total recovery cost	1
Material cost	2
Return product volume	3
Logistic cost - location, transportation, collecting	4
Processing cost by machine – disassembly, repair/restoration, remanufacture, disposal, etc.	5
Processing time by machine - disassembly, repair/restoration, remanufacture, disposal, etc.	6
Product reliability	7
Labor – number of operators/manpower	8
Demand/ market need/customer need	9
Machine cost including maintenance	10
Labor cost/Processing cost by people – disassembly, repair/restoration, remanufacture, disposal, etc.	11
Legislation	12
Before-recovery product quality	13
Natural resource consumption – material, fuel, energy, electricity, etc.	14
Inventory cost	15
Labor – skilled operators/decision makers	16
Processing time by people - disassembly, repair/restoration, remanufacture, disposal, etc.	17
Product useful lifetime	18
Landfill cost	19
Machine capability/ failure	20
Carbon/gas emission – CO ₂ , SO ₂ , etc.	21
Heat emission	22
Product design (ease of disassembly)	23

Chapter 4 Examination of Part Sentencing in Remanufacturing and Development of a Simulation Model

Recovering the right product at the right time could lead to several benefits such as cost saving, resource saving, etc. One remanufacturing process that requires critical decision making is 'part sentencing' (Figure 6). It is a procedure that determines whether a product or component will be recovered (repaired) or not. Up until 2016, it is commonly found executed manually by skilled operators. In an operational environment, many factors such as a financial constraint, product complexity, and resource limitation can be considered in an assessment of the acceptability of repairable components, in order to support sustainability. The sustainability in this context considers a balance of economic vitality, natural environment, and human life quality. Repairing every repairable product or component may not be always a good decision. This thought leads to the research study of a data driven decision-making modeling and simulation to support product recovery option selection to assist in making repair decisions. The research study proposes a systematical decision-making method that could help reduce the workload of decision makers (operators) and assist in selecting a product recovery option by assessing the acceptability of the End-Of-Life parts.

Figure 6: Part sentencing in a cell process flow

4.1 Part Sentencing in Remanufacturing

Two items data including an assessment manual and part sentencing sheets are collected to examine the current state-of-art part sentencing in remanufacturing.

Data from a Component Assessment Manual

According to a component assessment manual, the High Pressure Compressor Stage 3 Vanes is examined physically indicated in TASK 72-41-42-210-003 below. Decision-making is subjective and unqualified.

“TASK 72-41-42-210-003

Initially, examine the HP compressor stage 3 vanes

A. Damage that is seen to be too much to continue the inspection **Reject”**

There are a number of repair decision steps, 13 tasks totally for one single component. All 13 tasks are in a conditional statement.

First, according to TASK 72-41-42-220-027-B-1, a part will be accepted if Zone1_Nick which reduce the chord width up to 0.13 mm. A part will be sent to repair if Zone1_Nick which reduce the chord width more than 0.13 mm but less than 0.25 mm in depth.

Second, according to TASK 72-41-42-220-027-B-2, a part will be accepted if zone1_dents which reduce the chord width up to 0.13 mm. A part will be sent to repair if zone1_dents which reduce the chord width more than 0.13 mm but less than 0.25 in depth.

Third, according to TASK 72-41-42-220-027-F, a part will be accepted if mean surface finish of 0.35 micrometers or less. A part will be sent to repair if mean surface finish more than 0.35 micrometers

Forth, according to TASK 72-41-42-220-031-B, a part will be accepted if galled up to 0.25 mm in depth on not more than 25 percent of each face. A part will be sent to repair if galled more than 0.25 mm.

Fifth, according to TASK 72-41-42-220-031-C, a part will be accepted if worn location 15 – thickness is between 1.80 mm and 2.00 mm. A part will be sent to repair if worn location 15 – thickness is less than 1.80 mm.

Sixth, according to TASK 72-41-42-220-031-D, a part will be accepted if worn location 16 – thickness is between 2.30 mm and 2.50 mm. A part will be sent to repair if worn location 16 – thickness is less than 2.30 mm.

Seventh, according to TASK 72-41-42-220-032-B, a part will be accepted if galled up to 0.25 mm in depth or (more than 0.25 mm and up to 0.50 mm in depth on not more than 50 percent of each face). A part will be sent to repair if more than 0.50 mm in depth on not more than 50 percent of each face.

Eighth, according to TASK 72-41-42-220-034-B, a part will be accepted if hard coating (location AF): worn with an effect on up to 5 percent of face area. A part will be sent to repair if hard coating (location AF): worn with an effect on more than 5 percent of face area.

Ninth, according to TASK 72-41-42-220-035-B, a part will be accepted if galled up to 0.25 mm in depth or (more than 0.25 mm in depth and up to 0.5 mm in depth on not more than 30 percent of each cheek). A part will be sent to repair if more than 0.25 mm in depth and more than 0.5 mm in depth on not more than 30 percent of each cheek

Tenth, according to TASK 72-41-42-220-10 036-C, a part will be sent to repair if galled up to 0.20 mm in depth. A part will be sent to reject if more than 0.20 mm.

Eleventh, according to TASK 72-41-42-220-037-B, a part will be sent to Repair if galled up to 0.20 mm in depth. A part will be sent to reject if more than 0.20 mm.

Twelfth, according to TASK 72-41-42-220-404-C, a part will be sent to repair if cracked in the vane braze. A part will be sent to reject if cracked in any other areas.

Thirteenth, according to TASK 72-41-42-220-794-B, a part will be sent to repair if galled or scored not more than 0.41 mm in depth. A part will be sent to reject if more than 0.41 mm.

Items from Part Sentencing Sheets

There are 30 raw data records totally: 14 records in Sheet A, 12 records in Sheet B, two records in Sheet C and two records in Sheet D. On each assessment sheet, the following attributes including component name, part number, part ID number, task number, task description, inspection location, inspection result and inspector disposition are used for repair decision. Attributes and sample values are shown in Table 6.

Table 6: Attributes for repair decisions

No	Name	Type	Value
1	Component name	String	T800 HPC Stg 3 Stator Vane
2	Part number	String	FW50340
3	Part ID number	Numeric	1,2,3...,14
4	Task	String	72-41-42-220-027
5	Task description	String	FPI
6	Inspection location	String	Surface Finish
7	Inspection result - dimension	Double	1.92
8	Inspector disposition	String	Repair/Not repair

Table 7 shows the statistical summary of the data records of part sentencing tasks and corresponding assessment results. The part properties and part sentencing results were also transformed into the simulation model for visualization purposes to assist in designing how to make a better repair decision. The simulation model is constructed by using Arena simulation software (ARENA®) which is a commercial tool for simulation. The term 'model' is used throughout various fields especially in businesses. A model is defined here as a representation of a product recovery option selection system that is constructed to study the decision-making aspect of the repair in the remanufacturing. The model could be used for applied purposes [137]. The model for manufacturing line or inventory attempts to solve practical needs. Description, exploration, and simulation are three major functions of modeling. Each of these functions is appropriate for applied research. The simulation model could be used to clarify the relations of the system. In order to understand the flow of the remanufacturing process, a remanufacturing line of end-of-life jet engine components was explored. The research methodology involved is adapted from Sterman modeling process which consists of the following steps [138]. The first step is defining the problem to be solved and its scope. The second step is identifying the variables involved and their relationship. The third step is drawing the causal diagram. The next step is selecting software suitable to model the system. One more step to do is constructing the flow diagram and then simulating the model. Finally, the model is tested for verification purposes.

Table 7: A summary of part sentencing tasks and corresponding assessment results

Task	Result		
	Accept	Reject	Repair
72-41-42-220-003-B-a	30	0	0
72-41-42-220-003-B-b	30	0	0
72-41-42-220-003-B-c	30	0	0
72-41-42-220-027-B-1	30	0	0
72-41-42-220-027-B-2	30	0	0
72-41-42-220-027-B-3	30	0	0
72-41-42-220-027-C-1	30	0	0
72-41-42-220-027-C-2	30	0	0
72-41-42-220-027-D-1	30	0	0
72-41-42-220-027-F	9	0	21
72-41-42-220-029-B	30	0	0
72-41-42-220-029-D	30	0	0
72-41-42-220-031-B	30	0	0
72-41-42-220-031-C	30	0	0
72-41-42-220-031-D	30	0	0
72-41-42-220-032-B	30	0	0
72-41-42-220-033-B	30	0	0
72-41-42-220-034-B	30	0	0
72-41-42-220-034-C	30	0	0
72-41-42-220-034-D	30	0	0
72-41-42-220-034-E	30	0	0
72-41-42-220-035-B	30	0	0
72-41-42-220-036-B	30	0	0
72-41-42-220-036-C	30	0	0
72-41-42-220-404-B-2	30	0	0
72-41-42-220-794-B	30	0	0

4.2 Developing Environment

Operating System: Window 10 Home 64-bit

Processor: Intel(R) Core(TM) i7 CPU@2.20 GHz.

Software: ARENA® Version 14.7 (Student)

ARENA Configuration Setting

Number of Replications	1
Time horizon:	one day
Hours per day	24
Base Time Unit	Hour

4.3 Simulation Model

The simulation model was constructed using ARENA software. The summary of the module is presented in Table 8.

Table 8: Simulation model summary

Data Module	Type	Operands
Entity 1	Entity	Report Statistics : Yes
Damage	Attribute	Data Type: Real
Part Arrival	Create	<p>Entities per Arrival: 1</p> <p>Entity Type: Entity 1</p> <p>Expression: POIS(1)</p> <p>First Creation: 0.0</p> <p>Max Arrivals: Infinite</p> <p>Name: Part Arrival</p> <p>Schedule Name: Schedule 1</p> <p>Type: Expression</p> <p>Units: Hours</p> <p>Value: 1</p>
Part Exit	Dispose	Record Entity Statistics Yes
Pre inspection process	Process	<p>Delay Type: Triangular</p> <p>Expression: 1</p> <p>Maximum: 1.5</p> <p>Minimum: .5</p> <p>Name: Pre inspection process</p> <p>Priority: 2</p> <p>Report Statistics Yes</p> <p>Std Dev: .2</p> <p>Type: Standard</p> <p>Units: Hours</p> <p>Value 1</p>
Queue	Batch	Batch Size: 1

		Name: Queue Representative Entity Type: Rule: Any Entity Save Criterion: Last Type: Permanent
Repair rail	Dispose	Name: Repair rail Record Entity Statistics Yes
Submodel "inspection"		
Physical inspection	Decide	Column: 1 If: Entity Type Is: >= Row: 1 Type: With Value: 1
Submodel "DSS"		
Record NOT REPAIR	Record	Counter Name: Record NOT REPAIR Counter Set Name: Counter Set 1 Name: Record NOT REPAIR Record into Set No Set Index: 1 Tally Name: Record NOT REPAIR Tally Set Name: Tally Set 1 Type: Count Value: 1
Record repair	Record	Counter Name: Record repair Counter Set Name: Counter Set 1

		Name: Record repair Record into Set No Set Index: 1 Tally Name: Record repair Tally Set Name: Tally Set 1 Type: Count Value: 1
Repair class	Decide	Column: 1 If: Attribute Is: == Name: Repair class Named: S value Named: Entity 1 Named: Variable 1 Percent True 50 Row: 1 Type: If Value: 1

In this study, the author demonstrates the repair decision making in remanufacturing through a case study of a High Pressure Compressor Stage 3 Vane. The snapshot of the simulation model by using ARENA® are shown in Figure 7. The model was tested with two sets of data which contained (I) 100 part instances and (II) 10000 part instances. Figures 8 and 9 represent the comparison between part sentencing results obtained from the model simulation and part sentencing results obtained from domain experts. The testing result of two sets of data achieves a 100% similarity between simulation part sentencing results and part sentencing results obtained from domain experts.

Figure 7: A simulation model

Figure 8: Part sentencing results of data set (I) comparing between expected results and simulation results

Figure 9: Part sentencing results of data set (II) comparing between expected results and simulation results

4.4 Summary and Preview

This chapter describes the details of the simulation model development. Before developing a model, understanding a flow of part sentencing is essential. In order to get a better understanding of part sentencing, a component assessment manual and check sheets for part sentencing were examined. The model was developed using ARENA software simulation based on the collected data. The model was tested with two sets of data and achieving 100% similarity between simulation part sentencing results and part sentencing results obtained from domain experts. The model was presented to engineers and directors who worked in remanufacturing. In part sentencing, the output(decision) could be varied by different decision-making rules. In the next chapter, details of the development of a proposed decision-making model are described.

Chapter 5 Development of a Decision-Making Model

A decision support system (DSS) has been well known as a tool for supporting decision making [169]. The DSS combining linear programming and information systems was developed for sustainable forest management [170]. The DSS was developed for planning remanufacturing for Nortel Networks [33] and for choosing the best alternative [171]. The DSS could assist in making a decision by providing accurate and timely information [172]. The DSS can benefit enterprise decision makers by providing an objective second opinion [173]. The DSS has a potential that could help solve the decision-making problem. In order to help make a decision, a data-driven DSS could extract data to select an optimal solution and give a suggestion.

As mentioned in an introduction section, an assessment of the acceptability of parts is labor-intensive and requires skilled operators to make a decision. A DSS could be a potential tool to assist in making a repair decision systematically. According to Pepin (2015), there is no success demonstration use of the DSS for repair decision in remanufacturing.

There are various product End-of-Life options: reuse, repair, refurbishing, remanufacturing, cannibalization, recycling with disassembly, recycling without disassembly, reconditioning, disposal [23, 39-42]. In this study, focusing on repair for remanufacturing, two options at a part level are considered as follows:

- Repair: a part has some damage on its function or quality. It is determined that it could be used after getting treatment such as damage fixing. During repairing processing, the repair cost will occur. This is concerning with repairing and returning back to customers [174].
- Replacement: a part is determined that it cannot be repaired. The spare part will be replaced instead.

Defining criteria is one important step in decision making [175]. The author investigated the decision criteria previously. In this research, factors which are the repair cost and inventory cost are considered.

When each used component is returned to an original equipment manufacturer, the returned component then is inspected and managed depending on its physical condition. There are many end-of-life options available such as repair and replacement. Selecting the different options for an end-of-life component could result in different costs incurred. The repair cost is not always less than the cost of an equivalent new manufactured component or spare component. Interestingly, having a repair cost greater than the cost of new manufacture can be acceptable. Furthermore, a difficulty to assess the acceptability for the repair has existed. In this regard, the author develops a mathematical decision-making model to help make a repair decision. The problem under consideration in this study is to identify the acceptability of the repair by determining damage level that yields the optimum repair cost and inventory cost.

5.1 Optimization Techniques

An optimization using mathematical programming is a widely used approach in supply chain management [176-178]. For a single objective, cost optimization could be considered as the objective function and other decision-making criteria taken into consideration as constraints [179-183]. A cost minimization problem can be solved by a linear programming model [184]. An evolutionary approach can be employed to solve multi-objective optimization problems [185].

Under the assumption that the repair cost has a linearly positive correlation with a damage level, a linear optimization model is developed. The main steps of the decision-making method are described here.

```

CONSTRUCT a linear model;
READ parameter;
IF (N != 0)
THEN
    IF (solution (minimize repair and inventory
cost).EXISTS ())
    THEN
        RETURN (solution);
    ELSE
        RETURN ("No global optimum is found.
Constraints and optimality
conditions are not satisfied");
ELSE
    EXIT (0);

```

A linear programming model is a technique that is widely used in optimization even in modern management. An objective to minimize the cost with limited resources is focused. The repair decision can be characterized and expressed as the linear programming problem. Before the model is explained in the following section, a concept of linear programming is briefly described below.

A linear programming model or a linear optimization is a method for the optimization of the linear objective function, subject to linear constraints to achieve the optimal solution (such as the lowest cost). A linear programming algorithm finds a point where the function has the smallest (minimize objective function) or largest (maximize objective function) value. This method is quite efficient and can be guaranteed to find the global optimum if the point exists [186]. A linear programming model can be applied to various fields of study. It is widely used in business and economics and is also utilized for some engineering problems. Industries that use a linear programming model include manufacturing. It has proved useful in modelling diverse types of problems in planning.

5.2 Decision Support Architecture

Figure 10 shows the architecture of the proposed decision-making model. The modules comprised in the decision-making approach are presented. Inputs for making a decision i.e. part properties including a damage level of a returned part are considered and sent to the decision-making module. Also, cost data from data controllers (of repair and inventory), and resource availability are considered to make a proper decision. The decision-making model returns the result of a damage level that yields the optimum cost. The summary of decision-making modules is shown in Table 9.

Figure 10: Decision making architecture

Table 9: Summary of decision-making modules

Module	Role	Key Data
Decision-Making Module	Read inputs (Part damage, repair cost, inventory cost and resource availability) and determine optimal damage level	Part damage Optimal damage level
Repair Controller Module	Calculate repair cost Control resources for repair	Part damage Repair cost Machine availability
Inventory Controller Module	Calculate inventory cost Control spare parts in inventory	Part damage Inventory cost

5.3 End-Of-Life Part Assessment Structure

A returned product will be checked accordingly as shown in the flowchart in Figure 11. The damage of the item is firstly determined, if a damage level is over 50 percent, the part is sorted out as a non-repairable part. Otherwise, the part will be checked for repair and inventory cost. The determination of the damage level of the part is necessary for cost analysis. This allows

the decision maker to decide on other recovery options if the cost of repair is high.

Figure 11: Part assessment structure flowchart

5.4 Data Input

Table 10 shows properties and descriptions of individual parts and related information that are considered as inputs which include a damage level, a repair cost, an inventory cost and an availability of resources i.e. machines.

The decision support is based on two main components: a database and a mathematical decision-making model.

Table 10: Part properties

Part Property	Description
Damage Level	The proportion of crack to the total face area of the High Pressure Compressor Stage 3 Stator Vane (percent)
Repair Cost	Cost of repair a part in dollar
Inventory Cost	Cost of spare part that is kept in inventory in dollar
Resource Availability	The number of machines available to be able to use

5.5 Data Management

The repair decision in the proposed decision-making model is relying on the data related to the part or component. In order to process the data and manage the data efficiently, the data are kept in the database. The data management was created using Microsoft SQL Server 2016 Express Edition as shown in Figure 12. Table 11 shows four key tables and their descriptions.

5.6 Developing Environment

OS Microsoft Window 10 Home

System Type x64

Processor Intel(R) Core(TM) i7-3632QM CPU @ 2.20GHz, 2201 Mhz, 4 Core(s), 8 Logical Processor(s)

Table 11: Data management

Table Name	Description
Item (product/component)	This table contains data of an individual product/component i.e.an identification number, material, size, color and damage.
Machine (Resource)	This table contains data of an individual machine i.e. an identification number, name and status.
Repair	This table contains data regarding the repair type and the machine that will be used for repair.
Material	This table contains material details of item components.

Figure 12: Data tables

5.7 Mathematical Model

The aim is to identify and select an optimal repair decision and avoiding unnecessary costs by minimizing the repair cost and the inventory cost while complying with resource constraints.

A proposed mathematical model is developed to determine a damage level for the repair based on a linear programming technique under the following circumstance. The decisions to be made each period are whether a part should have its repair commenced in the first period of the rolling horizon. The proposed model employs a rolling horizon basis so that a decision is made

every period based on the current state of the system. That is, given updated information about the system at the beginning of a period, the model recommendation would be followed for the current period only, recognizing that the solution considers the consequences of the current period decisions on future period decisions.

Problem Statement

After some time, each used product unit is returned to an original equipment manufacturer. The returned unit then is assessed and managed depending on its condition. There are many end-of-life options available. Selecting the different options for an end-of-life part could result in different costs. The decision-making model determines the end-of-life option at the end-of-life stage. The objective is to minimize the cost incurred by the selected recovery option.

Assumptions

- Demand volume is equal to the number of returned parts
- Repair cost has a linearly positive correlation with damage levels.
- To repair a returned component, it requires a resource (machine).
- Resources used for repairing is varied by the damage levels.

Notation

d_j :Damage level of component j (decision variable)

N :Number of returned components

N_r :Number of components recommended to be repaired

N_i :Number of components recommended to be replaced

C_r :Cost of repair (\$)

T_j :Repair time of component j (minutes)

C_i : Cost of the spare item (\$)

$R_{available}$: Number of resource (machine) available (units)

U_j : Resource usage for repairing component j per damage level (units)

D_{max} : Maximum acceptable damage for repairing (percent)

Cost Functions

Repair Cost

The cost of repairing the returned part can be evaluated as the summation of the cost of the machine used for repair ($C_{machine}$), the cost of labor (C_{Labor}) and the cost of material used ($C_{Material}$) as follows:

$$C_r(C_{machine}, C_{Labor}, C_{Material}) = \sum_{j=1}^{N_r} (C_{Machine,j} + C_{Labor,j} + C_{Material,j}) \times d_j \times T_j \quad (1)$$

Inventory Cost

The inventory cost can be evaluated as the summation of the cost of ordering parts ($C_{Ordering}$) and holding parts ($C_{Holding}$) in the warehouse as follows:

$$C_i(C_{Ordering}, C_{Holding}) = \sum_{j=1}^{N_i} (C_{Ordering,j} + C_{Holding,j}) \quad (2)$$

Objective Function

$$\text{Minimize } C_r(C_{machine}, C_{Labor}, C_{Material}) + C_i(C_{Ordering}, C_{Holding}) \quad (3)$$

Constraints

$$N = N_r + N_i \quad (4)$$

$$R_{available} \geq U_j \quad (5)$$

$$0 \leq d_j \leq D_{max} \quad (6)$$

$$N, N_r, N_i, C_r, C_i, U_j, R_{available} \geq 0 \quad (7)$$

The objective of the proposed model (3) is to minimize cost incurring in repair and inventory. Constraint (4) ensures that every arrival part has a repair option suggestion (either repair or not). Constraint (5) ensures that there are enough resources available for repair. Constraint (6) ensures that the damage of a component is not greater than the maximum acceptable damage for repair (following a guideline or standard for repair in remanufacturing). Finally, Constraint (7) imposes non-negative restrictions on the cost variables and the number of resources.

5.8 Summary and Preview

This chapter describes the proposed mathematical model formulation in terms of a cost optimization problem for repair decision-making in remanufacturing. A numerical study is conducted to demonstrate the proposed model. The results of various cases including a single repair machine and multiple repair machines are explained in the next chapter.

Chapter 6 Numerical Study

In order to illustrate the proposed approach in the previous chapter and to gain insight into the impact of the problem parameters on the optimal decision, the author has solved a numerical example by the numerical analysis, the linear programming, and the evolutionary solver. The numerical analysis method is a mathematical calculation using algebra and statistics knowledge. For the numerical study to verify the proposed decision-making model, 100 data are demonstrated to prove the concept. This amount of data is able to be handled by a mathematical calculation. The numerical analysis would take time for execution. However, for verification purposes, it was executed in order to carefully cross-check the results with the linear programming. Moreover, the evolutionary approach, one of the popular methods applied by researchers [23, 124] was executed for verification purposes. The evolutionary solver that was implemented is based on a genetic algorithm and search methods [187]. Figure 13 shows a chromosome representation that consists of parameters of the number of components recommended to be repaired type 1, type 2, type 3, type 4 and replaced. Chromosomes are evaluated by the objective function. The evaluation step is repeated until a termination condition is reached. The termination condition is determined by a convergence criterion. Additionally, the evolutionary solver stops the search process when the objective function value of the solution has not improved for a certain amount of time. The procedure of the evolutionary solver is shown in Figure 14.

X1: The number of components recommended to be repaired type 1
X2: The number of components recommended to be repaired type 2
X3: The number of components recommended to be repaired type 3
X4: The number of components recommended to be repaired type 4
X5: The number of components recommended to be replaced

Figure 13: Chromosome representation

Figure 14: Evolutionary solver procedure

The 100 data used for the numerical studies are shown in Appendix B. The data contains component identification number (i.e. part ID), damage level and damage type. Each record (with a part identification number) represents each arrival part that needs to decide if it should be repaired or not. In this section, the author reports results obtained from the linear programming (LP), the evolutionary approach (EA) and the numerical analysis four times repeatedly (Trial#1-4) in order to compare both obtained solutions and execution times. Details are as follows.

6.1 Case I Single Machine

In case I (a single machine required for repairing), 100 data are uniformly distributed into 10 bins that are [0%, 10%], [10%, 20%], [20%, 30%], [30%, 40%], [40%, 50%], [50%, 60%], [60%, 70%], [70%, 80%], [80%, 90%], [90%, 100%]. The histogram is shown in Figure 15. The data used to demonstrate the proposed model contains 100 entries of arrival parts (N) with damage data. From damage level [0%,10%] is assigned to damage type 1 that requires machine#1. For damage level [10%,20%] is assigned to damage type 2 that require machine#2. For damage level [20%,30%] is assigned to damage type 3 that require machine#3. From damage level [30%,40%] is assigned to damage type 4 that require machine#4. For damage level [40%,50%] is assigned to damage type 5 that require machine#5.

Figure 15: Histogram of Part Damage Case I

Table 12 presents the use case data including parameter and its value for the numerical study. For inventory cost calculation, an ordering cost ($C_{Ordering}$) is assigned to be \$10 per part and a holding cost ($C_{Holding}$) is assigned to be \$15 per part. There are 5 machines available ($R_{available}$) to be used depending on a damage type (damage type 1 to 5 corresponding to machine 1 to 5). Repair time is assigned to 1 minute. The cost of repair including the machine, labor and, material for damage types 1, 2, 3, 4 and 5 are assigned to be \$10, \$10, \$10, \$10 and \$10 respectively. The maximum acceptable damage for repairing is assigned to be 50%.

Table 12: Use case data including parameter and its value for numerical study Case I

Parameter	Value
N	100
$C_{Ordering}$ (\$)	10
$C_{Holding}$ (\$)	15
$R_{available}$	5
The cost of the machine, labor, and material for damage type 1 (\$)	10
The cost of the machine, labor, and material for damage type 2 (\$)	10
The cost of the machine, labor, and material for damage type 3 (\$)	10
The cost of the machine, labor, and material for damage type 4 (\$)	10
The cost of the machine, labor, and material for damage type 5 (\$)	10
$D_{max}(\%)$	50

Table 13 shows resource constraints regarding the machine used for each damage type. For damage type 1, machine number one is required. For damage type 2, machine number two is required. For damage type 3, the machine number three is required. For damage type 4, machine number four is required. For damage type 5, the machine number five is required.

Table 13: Resource Constraint for Case I

<i>Resource</i>	<i>Resource Usage for Each Damage Type</i>				
Machine#	damage types 1	damage types 2	damage types 3	damage types 4	damage types 5
<i>1</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>0</i>
<i>2</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>0</i>	<i>0</i>
<i>3</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>0</i>	<i>0</i>
<i>4</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>0</i>
<i>5</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>

Figure 16 shows the result of the numerical analysis. 50 out of 100 part damage levels are not greater than 50%. The cost of repair and inventory of the 50 parts were calculated. The result is that the optimal damage level is 20% costing \$1,050 totally. \$200 will be saved if not replacing all 50 parts (which will cost \$1,250 totally). \$450 will be saved if not repairing all 50 parts (which will cost \$1,500 totally). A screenshot of a display interface of the optimal solution is shown in Figure 17.

Figure 16: Result of Case I (Numerical Analysis)

The 'Display - I' window shows the following data:

Damage Type:	2
Damage Level (%):	20
Amount:	1
Total Repairable Parts:	20
Repair Flag:	1
Repair Time(min):	20
Repair Cost \$:	20
Total Repair Cost (\$):	300
Spare Required:	30
Inventory Cost (\$):	25
Total Inventory Cost (\$):	750
Total Repair and Inventory Cost (\$):	1050

Right sidebar buttons: New, Delete, Restore, Find Prev, Find Next, Criteria, Close. Status: 21 of 51.

Figure 17: A screenshot of a display interface of the optimal solution(Case I)

Case I – LP Trial#1-4

The setting for the LP is as follows.

Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by using the LP algorithm (Table 14 and Table 15), the total repair cost is \$1,050. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 10. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 30.

Table 14: Optimal Cost (Case I – LP Trial#1-4)

Name	Original Value	Final Value
Total Cost(\$)	0	1050

Table 15: Optimal Solution (Case I – LP Trial#1-4)

Name	Cell Value
Amount T1	10
Amount T2	10
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	30

Case I – EA Trial#1

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by using the EA algorithm (Table 16 and Table 17), the total repair cost is \$1,125. The number of parts for repair type one (T1) is 8. The number of parts for repair type two (T2) is 8. The number of parts for repair type three (T3) is 4. The number of parts for repair type four (T4) is 1. The number of parts for repair type five (T5) is 0. The number of inventory parts is 29.

Table 16: Optimal Cost (Case I - EA Trial#1)

Name	Original Value	Final Value
Total Cost(\$)	0	1125

Table 17: Optimal Solution (Case I - EA Trial#1)

Name	Cell Value
Amount T1	8
Amount T2	8
Amount T3	4
Amount T4	1
Amount T5	0
Amount Inventory	29

Case I – EA Trial#2

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by using the EA algorithm (Table 18 and Table 19), the total repair cost is \$1,130. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 7. The number of parts for repair type three (T3) is 3. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 2. The number of inventory parts is 28.

Table 18: Optimal Cost (Case I - EA Trial#2)

Name	Original Value	Final Value
Total Cost(\$)	0	1130

Table 19: Optimal Solution (Case I - EA Trial#2)

Name	Cell Value
Amount T1	10
Amount T2	7
Amount T3	3
Amount T4	0
Amount T5	2
Amount Inventory	28

Case I - EA Trial#3

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by using the EA algorithm (Table 20 and Table 21), the total repair cost is \$1,200. The number of parts for repair type one (T1) is 5. The number of parts for repair type two (T2) is 4. The number of parts for repair type three (T3) is 3. The number of parts for repair type four (T4) is 2. The number of parts for repair type five (T5) is 0. The number of inventory parts is 36.

Table 20: Optimal Cost (Case I - EA Trial#3)

Name	Original Value	Final Value
Total Cost(\$)	0	1200

Table 21: Optimal Solution (Case I - EA Trial#3)

Name	Cell Value
Amount T1	5
Amount T2	4
Amount T3	3
Amount T4	2
Amount T5	0
Amount Inventory	36

Case I – EA Trial#4

In this trial, the time setting (Maximum Time without improvement) is changed from 30 to 43200(12x60x60) in order to check if the result obtained could be improved. The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	43200
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by using the EA algorithm (Table 22 and Table 23), the total repair cost is \$1,050. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 10. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 30.

Table 22: Optimal Cost (Case I - EA Trial#4)

Name	Original Value	Final Value
Total Cost(\$)	0	1050

Table 23: Optimal Solution (Case I - EA Trial#4)

Name	Cell Value
Amount T1	10
Amount T2	10
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	30

The optimal cost solutions and their execution times obtained by the numerical analysis, the LP and the EA algorithm are compared in Table 24. By the LP algorithm, the optimal cost solution is 1,050 with a 20% optimal damage level. The execution times in four trials are less than one minute. By the numerical analysis, the optimal cost solution is 1,050 with a 20% optimal damage level. This result is as same as the result obtained by the LP algorithm. The execution times in four trials are less than one hour. By the EA algorithm, the results from four trials are not all the same. In trial one, the execution time is less than 1 minute 33 seconds and 3 milliseconds. The optimal cost solution is 1,125. In trial two, the execution time is less than 1 minute 38 seconds and 8 milliseconds. The optimal cost solution is 1,130. In trial three, the execution time is less than 1 minute 32 seconds and 2 milliseconds. The optimal cost solution is 1,200. In trial four, the execution time is less than 13 hours 9 minutes 33 seconds and 457 milliseconds. The optimal cost solution is 1,050 with a 20% optimal damage level, as same as the results obtained from the numerical analysis and the LP algorithm.

Table 24: Method/Result Comparison of Case I

Method	Trial#	Optimal Cost Solution (Corresponding Damage Level)	Execution Time (HH:MM:SS.mmm)
Numerical Analysis	1	1050 (20)	Less than 01:00:00:000
	2	1050 (20)	Less than 01:00:00:000
	3	1050 (20)	Less than 01:00:00:000
	4	1050 (20)	Less than 01:00:00:000
LP	1	1050 (20)	Less than 00:01:00.000
	2	1050 (20)	Less than 00:01:00.000
	3	1050 (20)	Less than 00:01:00.000
	4	1050 (20)	Less than 00:01:00.000
EA	1	1125 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:33.003
	2	1130 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:38.008
	3	1200 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:32.002
	4	1050 (20)	Less than 13:09:33.457

6.2 Case II Multiple Machines (Identical Machine Cost)

In case II (a single machine and multiple machines required for repairing), 100 data are uniformly distributed into 10 bins that are [0%, 10%], [10%, 20%], [20%, 30%], [30%, 40%], [40%, 50%], [50%, 60%], [60%, 70%], [70%, 80%], [80%, 90%], [90%, 100%]. The histogram is shown in Figure 18. The dataset used to test the proposed model contains 100 entries of arrival parts (N) with damage data. For damage level [0%,10%] is assigned to damage type 1 that require machine#1. For damage level [10%,20%] is assigned to damage type 2 that require machine#1 and machine#2. For damage level [20%,30%] is assigned to damage type 3 that require machine#1, machine#2 and machine#3. For damage level [30%,40%] is assigned to damage type 4 that require machine#1, machine#2, machine#3 and machine#4. For damage level [40%,50%] is assigned to damage type 5 that require machine#1, machine#2, machine#3, machine#4 and machine#5.

Figure 18: Histogram of Part Damage Case II

Table 25 presents the use case data including parameter and its value for the numerical study. For inventory cost calculation, an ordering cost ($C_{Ordering}$) is assigned to be \$10 per part and a holding cost ($C_{Holding}$) is assigned to be \$15 per part. There are 5 machines available ($R_{available}$) to be used depending on a damage type. Repair time is assigned to 1 minute. The cost of the machine, labor and, material for damage types 1, 2, 3, 4 and 5 are assigned to be \$10, \$10, \$10, \$10 and \$10 respectively. The maximum acceptable damage for repairing is assigned to be 50%.

Table 25: Use case data including parameter and its value for numerical study Case II

Parameter	Value
N	100
$C_{Ordering}$ (\$)	10
$C_{Holding}$ (\$)	15
$R_{available}$	5
The cost of the machine, labor and, material for damage type 1 (\$)	10
The cost of the machine, labor and, material for damage type 2 (\$)	20
The cost of the machine, labor and, material for damage type 3 (\$)	30
The cost of the machine, labor and, material for damage type 4 (\$)	40
The cost of the machine, labor and, material for damage type 5 (\$)	50
$D_{max}(\%)$	50

Table 26 shows resource constraints regarding the machine used for each damage type. For damage type 1, machine number one is required. For damage type 2, machine number one and machine number two are required. For damage type 3, the machine number one, machine number two and machine number three are required. For damage type 4, machine number one, machine number two, machine number three and machine number four are required. For damage

type 5, the machine number one, machine number two, machine number three, machine number four and machine number five are required.

Table 26: Resource Constraint for Case II

<i>Resource</i>	<i>Resource Usage for Each Damage Type</i>				
Machine #	damage type 1	damage type 2	damage type 3	damage type 4	damage type 5
<i>1</i>	<i>1</i>	<i>1</i>	<i>1</i>	<i>1</i>	<i>1</i>
<i>2</i>	<i>0</i>	<i>1</i>	<i>1</i>	<i>1</i>	<i>1</i>
<i>3</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>1</i>	<i>1</i>
<i>4</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>	<i>1</i>
<i>5</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>0</i>	<i>1</i>

Figure 19 shows the result of the numerical analysis. 50 out of 100 part damage levels are not greater than 50%. The cost of repair and inventory of the 50 parts were calculated. The result is that the optimal damage level is 10% costing \$1,100 totally. \$150 will be saved if not replacing all 50 repairable parts (which will cost \$1,250 totally). \$4,400 will be saved if not repairing all 50 parts (which will cost \$5,500 totally). A screenshot of a display interface of the optimal solution is shown in Figure 20.

Figure 19: Result of Case II (Numerical Analysis)

The 'Display II' window shows the following parameters and results:

Damage Level(%)	10
Damage :	1
Amount:	1
Total Repairable Parts:	10
Repair Flag:	1
Repair Time(min):	10
Repair Cost M1:	10
Repair Cost M2:	0
Repair Cost M3:	0
Repair Cost M4:	0
Repair Cost M5:	0
Total Repair Cost:	100
Spare Required:	40
Inventory Cost:	25
Total Inventory Cost:	1000
Total Repair and Inventory Cost (\$):	1100

On the right side, there are buttons for 'New', 'Delete', 'Restore', 'Find Prev', 'Find Next', 'Criteria', and 'Close'. A status bar at the top right indicates '2 of 101'.

Figure 20: A screenshot of a display interface of the optimal solution (Case II)

Case II - LP Trial#1-4

The setting for the LP is as follows.

Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the LP algorithm (Table 27 and Table 28), the total repair cost is \$1,100. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 40.

Table 27: Optimal Cost (Case II - LP Trial#1-4)

Name	Original Value	Final Value
Total Cost(\$)	1190	1100

Table 28: Optimal Solution (Case II - LP Trial#1-4)

Name	Cell Value
Amount T1	10
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	40

Case II - EA Trial#1

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the EA algorithm (Table 29 and table 30), the total repair cost is \$1,160. The number of parts for repair type one (T1) is 6. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 44.

Table 29: Optimal Cost (Case II - EA Trial#1)

Name	Original Value	Final Value
Total Cost(\$)	0	1160

Table 30: Optimal Solution (Case II - EA Trial#1)

Name	Cell Value
Amount T1	6
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	44

Case II - EA Trial#2

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 31 and Table 32), the total repair cost is \$1,190. The number of parts for repair type one (T1) is 4. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 46.

Table 31: Optimal Cost (Case II - EA Trial#2)

Name	Original Value	Final Value
Total Cost(\$)	0	1190

Table 32: Optimal Solution (Case II - EA Trial#2)

Name	Cell Value
Amount T1	4
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	46

Case II – EA Trial#3

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 33 and Table 34), the total repair cost is \$1,205. The number of parts for repair type one (T1) is 3. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 47.

Table 33: Optimal Cost (Case II - EA Trial#3)

Name	Original Value	Final Value
Total Cost(\$)	0	1205

Table 34: Optimal Solution (Case II - EA Trial#3)

Name	Cell Value
Amount T1	3
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	47

Case II – EA Trial#4

In this trial, the time setting (Maximum Time without improvement) is changed from 30 to 43200(12x60x60) in order to check if the result obtained could be improved. The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	43200
Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the EA algorithm (Table 35 and Table 36), the total repair cost is \$1,100. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 40.

Table 35: Optimal Cost (Case II - EA Trial#4)

Name	Original Value	Final Value
Total Cost(\$)	40	1100

Table 36: Optimal Solution (Case II - EA Trial#4)

Name	Cell Value
Amount T1	10
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	40

The optimal cost solutions and their execution times obtained by the numerical analysis, the LP and the EA algorithm are compared in Table 37. By the LP algorithm, the optimal cost solution is 1,100 with a 10% optimal damage level. The execution times in four trials are less than one minute. By the numerical analysis, the optimal cost solution is 1,100 with a 10% optimal damage level. This result is as same as the result obtained by the LP algorithm. The execution times in four trials are less than one hour. By the EA algorithm, the results from four trials are not all the same. In trial one, the execution time is less than 1 minute 31 seconds and 5 milliseconds. The optimal cost solution is 1,160. In trial two, the execution time is less than 1 minute 31 seconds and 2 milliseconds. The optimal cost solution is 1,190. In trial three, the execution time is less than 1 minute 31 seconds and 8 milliseconds. The optimal cost solution is 1,205. In trial four, the execution time is less than 19 hours 19 minutes 44 seconds and 306 milliseconds. The optimal cost solution is 1,110 with a 10% optimal damage level, as same as the results obtained from the numerical analysis and the LP algorithm.

Table 37: Method/Result Comparison of Case II

Method	Trial#	Optimal Cost Solution (Corresponding Damage Level)	Execution Time (HH:MM:SS.mmm)
Numerical Analysis	1	1100(10)	Less than 01:00:00.000
	2	1100(10)	Less than 01:00:00.000
	3	1100(10)	Less than 01:00:00.000
	4	1100(10)	Less than 01:00:00.000
LP	1	1100(10)	Less than 00:01:00.000
	2	1100(10)	Less than 00:01:00.000
	3	1100(10)	Less than 00:01:00.000
	4	1100(10)	Less than 00:01:00.000
EA	1	1160(The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:31.005
	2	1190(The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:31.002
	3	1205 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:31.008
	4	1100 (10)	Less than 19:19:44.306

6.3 Case III Multiple Machines (Various Machine Costs)

In case III (a single machine and multiple machines required for repairing), 100 data are uniformly distributed into 10 bins that are [0%, 10%], [10%, 20%], [20%, 30%], [30%, 40%], [40%, 50%], [50%, 60%], [60%, 70%], [70%, 80%], [80%, 90%], [90%, 100%]. The histogram is shown in Figure 21. The dataset used to test the proposed model contains 100 entries of arrival parts (N) with damage data. For damage level [0%,10%] is assigned to damage type 1 that require machine#1. For damage level [10%,20%] is assigned to damage type 2 that require machine#1 and machine#2. For damage level [20%,30%] is assigned to damage type 3 that require machine#1, machine#2 and machine#3. For damage level [30%,40%] is assigned to damage type 4 that require machine#1, machine#2, machine#3 and machine#4. For damage level [40%,50%] is assigned to damage type 5 that require machine#1, machine#2, machine#3, machine#4 and machine#5.

Figure 21: Histogram of Part Damage Case III

Table 38 presents the use case data including parameter and its value for the numerical study. For inventory cost calculation, an ordering cost ($C_{Ordering}$) is assigned to be \$10 per part and a holding cost ($C_{Holding}$) is assigned to be \$15 per part. There are 5 machines available ($R_{available}$) to be used depending on a damage type. Repair time is assigned to 1 minute. The cost of the machine, labor, and material for damage types 1, 2, 3, 4 and 5 are assigned to be \$10, \$60, \$180, \$400 and \$750 respectively. The maximum acceptable damage for repairing is assigned to be 50%.

Table 38: Use case data including parameter and its value for numerical study Case III

Parameter	Value
N	100
$C_{Ordering}$ (\$)	10
$C_{Holding}$ (\$)	15
$R_{available}$	5
The cost of the machine, labor, and material for damage type 1 (\$)	10
The cost of the machine, labor, and material for damage type 2 (\$)	60
The cost of the machine, labor, and material for damage type 3 (\$)	90
The cost of the machine, labor, and material for damage type 4 (\$)	400
The cost of the machine, labor, and material for damage type 5 (\$)	750
$D_{max}(\%)$	50

Figure 22 shows the result of the numerical analysis. 50 out of 100 part damage levels are not greater than 50%. The cost of repair and inventory of the 50 parts were calculated. The result is that the optimal damage level is 10% costing \$1,100 totally. \$150 will be saved if not replacing all 50 repairable parts (which will cost \$1,250 totally). \$12,900 will be saved if not repairing all 50 parts (which will cost \$14,000 totally). A screenshot of a display interface of the optimal solution is shown in Figure 23.

Figure 22: Result of Case III (Numerical Analysis)

Parameter	Value
Damage Level(%)	10
Damage	1
Amount	1
Total Repairable Parts	10
Repair Flag	1
Repair Time(min)	10
Repair Cost M1	10
Repair Cost M2	0
Repair Cost M3	0
Repair Cost M4	0
Repair Cost M5	0
Total Repair Cost	10
Spare Required	40
Inventory Cost	25
Total Inventory Cost	1000
Total Repair and Inventory Cost (\$)	1100

Figure 23: A screenshot of a display interface of the optimal solution (Case III)

Case III - LP Trial#1-4

The setting for the LP is as follows.

Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the LP algorithm (Table 39 and Table 40), the total repair cost is \$1,100. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 40.

Table 39: Optimal Cost (Case III - LP Trial#1-4)

Name	Original Value	Final Value
Total Cost(\$)	0	1100

Table 40: Optimal Solution (Case III - LP Trial#1-4)

Name	Cell Value
Amount T1	10
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	40

Case III - EA Trial#1

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 41 and Table 42), the total repair cost is \$1160. The number of parts for repair type one (T1) equals to 6. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 44.

Table 41: Optimal Cost (Case III - EA Trial#1)

Name	Original Value	Final Value
Total Cost(\$)	0	1160

Table 42: Optimal Solution (Case III - EA Trial#1)

Name	Cell Value
Amount T1	6
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	44

Case III - EA Trial#2

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 43 and Table 44), the total repair cost is \$1,160. The number of parts for repair type one (T1) is 6. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 44.

Table 43: Optimal Cost (Case III - EA Trial#2)

Name	Original Value	Final Value
Total Cost(\$)	0	1160

Table 44: Optimal Solution (Case III - EA Trial#2)

Name	Cell Value
Amount T1	6
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	44

Case III - EA Trial#3

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 45 and Table 46), the total repair cost is \$1,175. The number of parts for repair type one (T1) is 5. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 45.

Table 45: Optimal Cost (Case III - EA Trial#3)

Name	Original Value	Final Value
Total Cost(\$)	0	1175

Table 46: Optimal Solution (Case III - EA Trial#3)

Name	Cell Value
Amount T1	5
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	45

Case III – EA Trial#4

In this trial, the time setting (Maximum Time without improvement) is changed from 30 to 43200(12x60x60) in order to check if the result obtained could be improved. The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	43200
Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the EA algorithm (Table 47 and Table 48), the total repair cost is \$1,100. The number of parts for repair type one (T1) is 10. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 40.

Table 47: Optimal Cost (Case III - EA Trial#4)

Name	Original Value	Final Value
Total Cost(\$)	0	1100

Table 48: Optimal Solution (Case III - EA Trial#4)

Name	Cell Value
Amount T1	10
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	40

The optimal cost solutions and their execution times obtained by the numerical analysis, the LP and the EA algorithm are compared in Table 49. By the LP algorithm, the optimal cost solution is 1,100 with a 10% optimal damage level. The execution times in four trials are less than one minute. By the numerical analysis, the optimal cost solution is 1,100 with a 10% optimal damage level. This result is as same as the result obtained by the LP algorithm. The execution times in four trials are less than one hour. By the EA algorithm, the results from four trials are not all the same. In trial one, the execution time is less than one minute. The optimal cost solution is 1,160. In trial two, the execution time is less than one minute. The optimal cost solution is 1,160. In trial three, the execution time is less than one minute. The optimal cost solution is 1,175. In trial four, the execution time is less than 12 hours. The optimal cost solution is 1,100 with a 10% optimal damage level, as same as the results obtained from the numerical analysis and the LP algorithm.

Table 49: Method/Result Comparison of Case III

Method	Trial#	Optimal Cost Solution (Corresponding Damage Level)	Execution Time (HH:MM:SS.mmm)
Numerical Analysis	1	1100(10)	Less than 01:00:00.000
	2	1100(10)	Less than 01:00:00.000
	3	1100(10)	Less than 01:00:00.000
	4	1100(10)	Less than 01:00:00.000
LP	1	1100(10)	Less than 00:01:00.000
	2	1100(10)	Less than 00:01:00.000
	3	1100(10)	Less than 00:01:00.000
	4	1100(10)	Less than 00:01:00.000
EA	1	1160 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:00.000
	2	1160 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:00.000
	3	1175 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:01:00.000
	4	1110 (10)	Less than 12:00:00.000

6.4 Case IV Multiple Machines (Various Machine Costs and Unequal Bin of Arrival Parts)

In case IV (a single machine and multiple machines required for repairing), 100 data are randomly distributed into 10 bins that are $[0\%, 10\%]$, $[10\%, 20\%]$, $[20\%, 30\%]$, $[30\%, 40\%]$, $[40\%, 50\%]$, $[50\%, 60\%]$, $[60\%, 70\%]$, $[70\%, 80\%]$, $[80\%, 90\%]$, $[90\%, 100\%]$. The histogram is shown in Figure 24. The dataset used to test the proposed model contains 100 entries of arrival parts (N) with damage data. For damage level $[0\%, 10\%]$ is assigned to damage type 1 that require machine#1. For damage level $[10\%, 20\%]$ is assigned to damage type 2 that require machine#1 and machine#2. For damage level $[20\%, 30\%]$ is assigned to damage type 3 that require machine#1, machine#2 and machine#3. For damage level $[30\%, 40\%]$ is assigned to damage type 4 that require machine#1, machine#2, machine#3 and machine#4. For damage level $[40\%, 50\%]$ is assigned to damage type 5 that require machine#1, machine#2, machine#3, machine#4 and machine#5.

Figure 24: Histogram of Part Damage Case IV

Table 50 presents the use case data including parameter and its value for the numerical study. For inventory cost calculation, an ordering cost ($C_{Ordering}$) is assigned to be \$10 per part and a holding cost ($C_{Holding}$) is assigned to be \$15 per part. There are 5 machines available ($R_{available}$) to be used depending on a damage type. Repair time is assigned to 1 minute. The cost of the machine, labor, and material for damage type 1, 2, 3, 4 and 5 are assigned to be \$10, \$60, \$180, \$400 and \$750 respectively. The maximum acceptable damage for repairing is assigned to be 50%.

Table 50: Use case data including parameter and its value for numerical study Case IV

Parameter	Value
N	100
$C_{Ordering}$ (\$)	10
$C_{Holding}$ (\$)	15
$R_{available}$	5
The cost of the machine, labor, and material for damage type 1 (\$)	10
The cost of the machine, labor, and material for damage type 2 (\$)	60
The cost of the machine, labor, and material for damage type 3 (\$)	90
The cost of the machine, labor, and material for damage type 4 (\$)	400
The cost of the machine, labor, and material for damage type 5 (\$)	750
$D_{max}(\%)$	50

Figure 25 shows the result of the numerical analysis. 51 out of 100 part damage levels are not greater than 50%. The cost of repair and inventory of the 51 parts were calculated. The result is that the optimal damage level is 10% costing \$1,155 totally. \$120 will be saved if not replacing entirely 51 repairable parts (which will cost \$1,275 totally). \$9,145 will be saved if not repairing all 51 parts (which will cost \$10,300 totally). A screenshot of a display interface of the optimal solution is shown in Figure 26.

Figure 25: Result of Case IV (Numerical Analysis)

Display	
Damage Type:	1
Damage Type(Bin):	10
Damage Level (%):	9
Amount:	1
Total Repairable Parts:	8
Repair Flag:	1
Repair Time(minute):	10
Repair Cost M1(\$):	10
Repair Cost M2(\$):	0
Repair Cost M3(\$):	0
Repair Cost M4(\$):	0
Repair Cost M5(\$):	0
Total Repair Cost (\$):	10
Accumulative Repair Cost (\$):	80
Spare Required:	43
Inventory Cost (\$):	25
Total Inventory Cost (\$):	1075
Total Repair and Inventory Cost (\$):	1155

Figure 26: A screenshot of a display interface of the optimal solution (Case IV)

Case IV - LP Trial#1-4

The setting for the LP is as follows.

Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the LP algorithm (Table 51 and Table 52), the total repair cost is \$1,155. The number of parts for repair type one (T1) is 8. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 43.

Table 51: Optimal Cost (Case IV - LP Trial#1-4)

Name	Original Value	Final Value
Total Cost(\$)	0	1155

Table 52: Optimal Solution (Case IV - LP Trial#1-4)

Name	Cell Value
Amount T1	8
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	43

Case IV - EA Trial#1

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 53 and Table 54), the total repair cost is \$1,200. The number of parts for repair type one (T1) is 5. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 46.

Table 53: Optimal Cost (Case IV - EA Trial#1)

Name	Original Value	Final Value
Total Cost(\$)	0	1200

Table 54: Optimal Solution (Case IV - EA Trial#1)

Name	Cell Value
Amount T1	5
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	46

Case IV - EA Trial#2

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 55 and Table 56), the total repair cost is \$1,170. The number of parts for repair type one (T1) is 7. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 44.

Table 55: Optimal Cost (Case IV - EA Trial#2)

Name	Original Value	Final Value
Total Cost(\$)	0	1170

Table 56: Optimal Solution (Case IV - EA Trial#2)

Name	Cell Value
Amount T1	7
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	44

Case IV – EA Trial#3

The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	30
Constraint Precision	0.0000001
Integer Optimally(%)	1

According to the result obtained by the EA algorithm (Table 57 and Table 58), the total repair cost is \$1,170. The number of parts for repair type one (T1) is 7. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 44.

Table 57: Optimal Cost (Case IV - EA Trial#3)

Name	Original Value	Final Value
Total Cost(\$)	0	1170

Table 58: Optimal Solution (Case IV - EA Trial#3)

Name	Cell Value
Amount T1	7
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	44

Case IV – EA Trial#4

In this trial, the time setting (Maximum Time without improvement) is changed from 30 to 43200(12x60x60) in order to check if the result obtained could be improved. The properties settings for the evolutionary approach are as follows.

Convergence	0.0001
Mutation Rate	0.075
Population Size	100
Random Seed	0
Maximum Time without improvement	43200
Constraint Precision	0.0000001
Integer Optimally (%)	1

According to the result obtained by the EA algorithm (Table 59 and Table 60), the total repair cost is \$1,155. The number of parts for repair type one (T1) is 8. The number of parts for repair type two (T2) is 0. The number of parts for repair type three (T3) is 0. The number of parts for repair type four (T4) is 0. The number of parts for repair type five (T5) is 0. The number of inventory parts is 43.

Table 59: Optimal Cost (Case IV - EA Trial#4)

Name	Original Value	Final Value
Total Cost(\$)	0	1155

Table 60: Optimal Solution (Case IV - EA Trial#4)

Name	Cell Value
Amount T1	8
Amount T2	0
Amount T3	0
Amount T4	0
Amount T5	0
Amount Inventory	43

The optimal cost solutions and their execution times obtained by the numerical analysis, the LP and the EA algorithm are compared in Table 61. By the LP algorithm, the optimal cost solution is 1,155 with a 10% optimal damage level. The execution times in four trials are less than one minute. By the numerical analysis, the optimal cost solution is 1,155 with a 10% optimal damage level. This result is the same as the result obtained by the LP algorithm. The execution times in four trials are less than one hour. By the EA algorithm, the results from four trials are not all the same. In trial one, the execution time is less than three minutes. The optimal cost solution is 1,200. In trial two, the execution time is less than three minutes. The optimal cost solution is 1,170. In trial three, the execution time is less than three minutes. The optimal cost solution is 1,170. In trial four, the execution time is less than 19 hours 35 minutes 39 seconds 186 milliseconds. The optimal cost solution is 1,100 with a 10% optimal damage level, as same as the results obtained from the numerical analysis and the LP algorithm.

Table 61: Method/Result Summary (Case IV)

Method	Trial#	Optimal Cost Solution (Corresponding Damage Level)	Execution Time (HH:MM:SS.mmm)
Numerical Analysis	1	1155(10)	Less than 01:00:00.000
	2	1155(10)	Less than 01:00:00.000
	3	1155(10)	Less than 01:00:00.000
	4	1155(10)	Less than 01:00:00.000
LP	1	1155(10)	Less than 00:01:00.000
	2	1155(10)	Less than 00:01:00.000
	3	1155(10)	Less than 00:01:00.000
	4	1155(10)	Less than 00:01:00.000
EA	1	1200(The obtained optimal solution is not as good as the numerical analysis)	Less than 00:03:00.000
	2	1170 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:03:00.000
	3	1170 (The obtained optimal solution is not as good as the numerical analysis)	Less than 00:03:00.000
	4	1155(10)	Less than 19:35:39.186

6.5 Summary and Preview

A numerical study was conducted for the illustration of the developed decision-making approach since the cost data from a private company is confidential and cannot be disclosed.

According to the results obtained from the data used for the numerical study, different levels of damage affect the cost incurred. It is possible that repairing all repairable parts is not the best operation solution in terms of cost optimization. In case I, repairing all repairable parts costs \$1,500 while replacing all repairable parts costs \$1,250 and the optimal solution costs only \$1,050. In case II, repairing all repairable parts costs \$5,500 while replacing all repairable parts costs \$1,250 and the optimal solution costs only \$1,100. In case III, repairing all repairable parts costs \$14,000 while replacing all repairable parts costs \$1,250 and the optimal solution costs only \$1,100. In case IV, repairing all repairable parts costs \$10,300 while replacing all repairable parts costs \$1,275 and the optimal solution costs only \$1,155.

In addition, the linear programming is applicable for this problem scope and can give an optimal solution within a minute, faster than the numerical analysis and the evolutionary solver. According to the results, comparing optimal solutions together with execution time, the evolutionary solver cannot always provide the optimal solution as good as the optimal solution obtained from the linear programming. The evolutionary approach might be a good option to deal with high dimensional and complicated multi-objective optimization problems while execution time is not a major concern.

The next chapter presents a summary of this thesis including the contributions of the work. Limitations of the research and directions of future work are presented at the end of the thesis also.

Chapter 7 Conclusion

This thesis presents a data driven decision-making methodology for remanufacturing. In this chapter, a presentation comes to an end. Section 7.1 summarizes the research study and highlights research contributions. Finally, section 7.2 discusses the limitations and possible directions for future work.

7.1 Summary and Contributions

The importance of product recovery and repair in remanufacturing for a sustainable society is highlighted in Chapter 1. The global industry for remanufacturing is growing at an annual double-digit rate. The United State produced forty-three billion US dollars in remanufactured goods supporting one hundred and eighty thousand full-time jobs. The current five-year plan for China has identified remanufacturing as a growth area and is being encouraged by the introduction of legislation and standardization. In Singapore, the aerospace maintenance, repair, and overhaul sector makes up a significant component of the local remanufacturing landscape. Other industries that have sizeable and growing local remanufacturing operations include oil and gas, industrial equipment and automotive. Recovering the right item at the right time especially a high-value product could lead to several benefits such as cost saving, resource saving. A decision on recovering a high-value product such as a High-Pressure Compressor Stage 3 Stator Vane could make a difference in cost saving. Generally, a product is manufactured and then used until its end of life phase; when holders discard the product. Product recovery is one way to contribute to sustainability. Instead of disposing of End-Of-Life products, we can reduce waste and a new manufactured product volume by considering other recovery alternatives such as remanufacturing. The product recovery is cost-effective. A recovered component can be cheaper than a new manufactured one. It can decrease the number of natural resource consumptions. It can reduce pollutant emissions and negative environmental impacts. Selecting a recovery option is crucial. Different recovering option selection results in different outputs. Traditionally, decision makers select a recovery option based on their experiences. A

remanufacturing restores worn-out products to like-new products, also ensuring to meet manufacturing standards and specifications. A remanufacturing can lead to economic, environmental and societal sustainability. A remanufacturing can save costs and resources while reducing waste. An important stage of the remanufacturing process is a component assessment procedure. A component assessment is a labor-intensive and time-consuming task. In remanufacturing, there is a process that requires critical decision makings called part sentencing. It is a procedure that determines if a component of a product or part is to be repaired. It is commonly found executed manually by skilled operators. The process is limited to consideration of the physical conditions of end-of-life parts. In an operational environment, there are many factors involved such as the number of skilled operators, the number of machines available, resource constraints. Due to various part conditions, resource constraints, human and machine limitations, the cost of repairing is sometimes higher than the cost of replacement with spare parts. There are two questions. First, since a traditional assessment process considers physical conditions, how to provide a quantitative method to justify repairing the end of life parts? Second, since the cost of repairing is high, is repairing all repairable parts always the best solution to manage end of life parts? The objective of the research includes (1) to investigate the part sentencing decision-making process and (2) to develop a decision-making method for repair decisions that could assist in part sentencing by assessing the acceptability of End-Of-Life parts in remanufacturing.

A critical literature review is outlined in Chapter 2. In short, a comprehensive decision-making model for the automobile sector was developed by Ahmed, et al. (2016). The integrated approach based on the DEMATEL, AHP, and fuzzy AHP was proposed to evaluate End-Of-Life options. The proposed methodology required expert opinions to assist in making a strategic decision. While Tan, et al. (2016) focused on life extension and repair decision making for the offshore sector. A combination of a DELPHI, AHP, Grey theory and fuzzy assessment method or DHGF was proposed. Expert opinions were required as well. The approaches in existing studies that are related to decision-making methods that consider a repair option require expert

opinions. Regarding advantages and disadvantages of different evaluation models, AHP is one of the most commonly used methods for solving multi-criteria decision-making problems and excellent in identifying criteria and sub-criteria in a decision hierarchy and assigning a ranking to the alternative options through pairwise comparison matrices. However, the decision-making is based on personal perspectives. Subjectivity is strong. For the Fuzzy evaluation model, it offers a quantitative description method for a vague situation but the decision-making is also based on personal perspectives. The subjectivity is also strong. Even the DHGF was developed to improve the decision making by reducing the subjectivity but a great deal of calculation is needed. There is room for improvement regarding repair decisions with repair and inventory cost concerns. The difference in this research study comparing to the previous research is that this research focuses on the decision-making model for cost optimization by additionally considering repair cost and inventory cost. To achieve the objective number one: to investigate the part sentencing decision-making process, the author worked on investigating a part sentencing flow, by collecting data from an assessment manual and check sheets in the remanufacturing site and further reviewing papers. To be able to answer question number one: how to provide a quantitative method to justify repairing the end of life parts? and to achieve the objective number two: to develop a decision-making method for repair decisions that could assist in part sentencing by assessing the acceptability of End-Of-Life parts in remanufacturing, the author found out decision-making factors, by reviewing journal and conference papers until 2014. Since the research could be refined and additionally updated the author further conducted the questionnaire, asking domain experts and analyzing the result using a statistic calculation. The author developed a decision-making model, by constructing the generalized cost model and building a linear programming model for the cost optimization problem for jet engine parts. Last but not least, to answer question number two: Is repairing all repairable parts always the best solution to manage End-Of-Life parts, the author conducted a numerical study by using the developed model with 100 data records.

Decision-making factors are critical when making an important decision. Reviewing the state-of-art decision-making factors and further conducting a survey in the remanufacturing site were executed in Chapter 3. Study results reveal that recovery cost and processing time are factors that get lots of attention.

Realizing the importance of understanding a process flow of part sentencing by examining the component assessment manual and check sheets, a simulation model for making a repair decision was developed and described in Chapter 4. Simulation studies achieve 100% similarity comparing to the part sentencing results obtained from domain experts on site.

As the question number one: how to provide a quantitative method to justify repairing End-Of-Life parts? the author built a linear programming model for the cost optimization problem in Chapter 5. The main theoretical contribution of the research study is the development of a quantitative decision-making model by building a linear programming mathematical model for the cost optimization problem to assist in making repair decisions in remanufacturing. Repair cost derives from the machine cost, labor cost and material cost which are varied by repairing time and a damage level. While inventory cost derives from the ordering cost and the holding cost. The objective of the proposed model is to minimize cost incurring in repair and inventory.

In Chapter 6 the author conducted a numerical study to find out the answer to question number two: Is repairing all repairable parts always the best solution to manage End-Of-Life parts? and demonstrate how to apply the proposed decision-making model to assess the acceptability of End-Of-Life parts. Different scenarios demonstrated in numerical studies reveal that with inventory concerns, selecting a repair option for all repairable parts is not always the best optimal solution in terms of cost optimization. In case I a discrete uniform distribution of damage with a single machine required for different damage types, the optimal cost solution is \$1,050 with a 20% optimal damage level. Repairing all repairable parts costs \$1,500 while replacing all repairable parts costs \$1,250. \$200 will be saved if not replacing all repairable parts. \$450 will be saved if not repairing all repairable parts. In case II a discrete uniform distribution

of damage with a single machine and multiple machines required for different damage types, the optimal cost solution is \$1,100 with a 10% optimal damage level. Repairing all repairable parts costs \$5,500 while replacing all repairable parts costs \$1,250. \$150 will be saved if not replacing all repairable parts. \$4,400 will be saved if not repairing all repairable parts. In case III a discrete uniform distribution of damage with a single machine and multiple machines required for different damage types and various machine costs, the optimal cost solution is \$1,100 with a 10% optimal damage level. Repairing all repairable parts costs \$14,000 while replacing all repairable parts costs \$1,250. \$150 will be saved if not replacing all repairable parts. \$12,900 will be saved if not repairing all repairable parts. In case four a discrete random number of damages with a single machine and multiple machines required for different damage types and various machine costs, the optimal cost solution is \$1,155 with a 10% optimal damage level. Repairing all repairable parts costs \$10,300 while replacing all repairable parts costs \$1,275. \$120 will be saved if not replacing all repairable parts. \$9,145 will be saved if not repairing all repairable parts.

In summary, there are 3 major accomplishments which are (1) the examination of part sentencing in remanufacturing and the development of a simulation model of End-Of-Life parts repair decision, (2) the investigation of non-trivial decision-making factors regarding product recovery option selection, and (3) the development of a decision-making model to minimize repair and inventory costs. This work addresses the repair decision of returned parts. The main objective of this work is to provide quantitative decision rules for justification of the repairing of the returned parts. The proposed method consists of a decision-making model that, given a set of parameters, determines the optimal damage point. The application of the system to possible scenarios is demonstrated through numerical studies. The numerical study demonstrates how to apply the proposed decision-making model to assess the acceptability of End-Of-Life parts and enable identification of the optimal solution. The optimal solution shows the cost saving when comparing repair and replacement options.

For the potential application, the research concept can be deployed to various industrial applications which include multinational original equipment manufacturers in areas such as aerospace, automotive and marine regarding restoration of components to serviceable condition and remanufacturing of products, small and medium enterprises about improvements of remanufacturing operational process and optimization of remanufacturing for implementation in various industries.

7.2 Limitations of the Research and Directions for Future Work

The current application has focused on developing a decision-making methodology and establishing a fundamental understanding and knowledge in the area of repair decision for remanufacturing. Moving forward, the challenge is to characterize a repair technology that could be more complex.

The findings could be validated by other companies using practical assessments and also other parts/products. In addition to the aerospace industry, this generic concept for repair decision in remanufacturing could also be applied to other sectors.

The concern that business enterprises focus on economic activities while ignoring impacts on the environment is growing [188]. The environmental issues have received more attention, also the businesses face increasing pressure to make the supply chain more environmental friendly [189-191]. Environmental factors become necessary to take into consideration since concerns on the harmful consequences of supply chain activities on the environment [191]. To develop ways in which industrial development and environmental protection can coexist is the big challenge [192]. One critical concern in the sustainability literature is the compatibility of sustainability and economic growth [193]. More research on developing a framework to capture the essence of dynamics is needed [194]. The idea that organizations should be analyzed based on their resources is put forward [195]. The resources including all assets, information, knowledge enable the organization to conceive of to improve

efficiency and effectiveness [196]. In the field of operations and supply chain management, the resource becomes received considerable attention [197]. According to Christmann [198], environmental management can significantly lead to cost advantage. Therefore, environmental concerns could be considered for repair decisions.

In order to make a realistic business decision and carry out the corporate social responsibility (CSR), profitability and environmental impact based on the recovery option are assessed. The profitability of business mainly depends on the selling price, cost and market demand (number unit of sold). Return volume and condition of parts are the factors that impact on cost. Environmental impact is another key factor in deciding the recovery option. Depending on the product condition, resource consumption such as usage of electricity in operation (machined usage), and raw material has a large impact on the environment. To make sustainable decision making, any one of the criteria considered separately would not provide a complete picture [82]. Criteria are not meant to stand alone as a decision-making tool. Criteria are meant to form part of multiple criteria analysis along with other decision-making tools such as a cost-benefit analysis and an environmental assessment.

In the future, minimizing the return volume to lower repairing costs also could be studied to better improve part recovery efficiency. To further enhance the proposed methodology, other methods could be adopted to improve the reliability of the proposed methodology and provide more valuable information. AHP is the highly used technique to calculate the relative weightings of the criteria. The weighted value could be considered additionally.

Publications

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"Kanchanasri, P., Moon, S.K., and Ng, G.K.L., "Decision making criteria for sustainable remanufacturing," *Toward Sustainable Operations of Supply Chain and Logistics Systems*, Springer International Publishing Switzerland, pp. 153–160, 2015.

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Appendices

Appendix A: High Pressure Compressor Stage 3 Stator Vane

A High Pressure Compressor Stage 3 Stator Vane is a component of a turbofan aircraft engine. The Trent 800 (Figure 27) is a high-bypass turbofan aircraft engine. It is manufactured by Rolls-Royce Plc. It consists of eight-stage low pressure (LP) and six-stage high pressure (HP) compressor. Figures 28-32 are HPC Stg 3 vanes in different views.

Figure 27: Rolls-Royce Trent 800 on a British Airways 777(Kobayashi-Hillary)

Figure 28: HPC Stage 3 (1)

Figure 29: HPC Stage 3 (2)

Figure 30: HPC Stage 3 (3)

Figure 31: HPC Stage 3 (4)

Figure 32: HPC Stage 3 (5)

Appendix B: Sample Data

Table 62: Sample Data Numerical Study Case I – III (Sorted)

Part ID	Damage Type	Damage Level (%)
PID001	1	1
PID002	1	2
PID003	1	3
PID004	1	4
PID005	1	5
PID006	1	6
PID007	1	7
PID008	1	8
PID009	1	9
PID010	1	10
PID011	2	11
PID012	2	12
PID013	2	13
PID014	2	14
PID015	2	15
PID016	2	16
PID017	2	17
PID018	2	18
PID019	2	19
PID020	2	20
PID021	3	21
PID022	3	22

PID023	3	23
PID024	3	24
PID025	3	25
PID026	3	26
PID027	3	27
PID028	3	28
PID029	3	29
PID030	3	30
PID031	4	31
PID032	4	32
PID033	4	33
PID034	4	34
PID035	4	35
PID036	4	36
PID037	4	37
PID038	4	38
PID039	4	39
PID040	4	40
PID041	5	41
PID042	5	42
PID043	5	43
PID044	5	44
PID045	5	45
PID046	5	46
PID047	5	47
PID048	5	48
PID049	5	49

PID050	5	50
PID051	0	51
PID052	0	52
PID053	0	53
PID054	0	54
PID055	0	55
PID056	0	56
PID057	0	57
PID058	0	58
PID059	0	59
PID060	0	60
PID061	0	61
PID062	0	62
PID063	0	63
PID064	0	64
PID065	0	65
PID066	0	66
PID067	0	67
PID068	0	68
PID069	0	69
PID070	0	70
PID071	0	71
PID072	0	72
PID073	0	73
PID074	0	74
PID075	0	75
PID076	0	76

PID077	0	77
PID078	0	78
PID079	0	79
PID080	0	80
PID081	0	81
PID082	0	82
PID083	0	83
PID084	0	84
PID085	0	85
PID086	0	86
PID087	0	87
PID088	0	88
PID089	0	89
PID090	0	90
PID091	0	91
PID092	0	92
PID093	0	93
PID094	0	94
PID095	0	95
PID096	0	96
PID097	0	97
PID098	0	98
PID099	0	99
PID100	0	100

Table 63: Sample Data of Case Study IV (Sorted)

Part ID	Damage Type	Damage Level (%)
PID001	1	2
PID002	1	2
PID003	1	3
PID004	1	3
PID005	1	4
PID006	1	5
PID007	1	5
PID008	1	9
PID009	2	11
PID010	2	12
PID011	2	12
PID012	2	13
PID013	2	14
PID014	2	15
PID015	2	15
PID016	2	16
PID017	2	17
PID018	3	21
PID019	3	21
PID020	3	23
PID021	3	23
PID022	3	24
PID023	3	25
PID024	3	25
PID025	3	25

PID026	3	25
PID027	3	26
PID028	3	28
PID029	3	29
PID030	3	30
PID031	4	32
PID032	4	33
PID033	4	33
PID034	4	35
PID035	4	36
PID036	4	36
PID037	4	36
PID038	4	37
PID039	4	37
PID040	4	38
PID041	4	38
PID042	5	41
PID043	5	41
PID044	5	41
PID045	5	43
PID046	5	43
PID047	5	44
PID048	5	46
PID049	5	48
PID050	5	49
PID051	5	49
PID052	0	51

PID053	0	52
PID054	0	53
PID055	0	54
PID056	0	54
PID057	0	55
PID058	0	55
PID059	0	56
PID060	0	56
PID061	0	57
PID062	0	58
PID063	0	60
PID064	0	60
PID065	0	60
PID066	0	61
PID067	0	61
PID068	0	66
PID069	0	67
PID070	0	68
PID071	0	71
PID072	0	71
PID073	0	73
PID074	0	74
PID075	0	76
PID076	0	78
PID077	0	79
PID078	0	80
PID079	0	82

PID080	0	83
PID081	0	84
PID082	0	84
PID083	0	85
PID084	0	87
PID085	0	88
PID086	0	88
PID087	0	88
PID088	0	89
PID089	0	91
PID090	0	91
PID091	0	91
PID092	0	93
PID093	0	94
PID094	0	95
PID095	0	95
PID096	0	96
PID097	0	97
PID098	0	98
PID099	0	98
PID100	0	99

Appendix C: A Survey Form

Research: Decision Making for Product Recovery Option Selection

Thank you for participating in the research of an intelligent decision making for product recovery option selection. Your comment is important. The research aims to develop a decision making method to assist product/part recovery option selection (ex. remanufacture/repair). In order to identify the best recovery alternative, key decision criteria and rules are to be explored. The research focuses on extracting key information to decide if the product/part is worth to be recovered. The research consists of three sections:

1. An importance of decision criteria: to identify key decision criteria for product/part recovery option selection
2. Participant comments: to extract further key decision criteria (if any) and decision rules that should be considered for product recovery option selection
3. Participant information: for acknowledgement and reference (if required)

Acknowledgement: Advanced Remanufacturing & Technology Centre, Singapore

Thank you and best regards,

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1. An importance of criteria to decide if a product/part should be recovered or not

	Not important(0)	Low(1)	Medium(2)	High(3)	Very important(4)
Return product volume	Return product volume Not important(0)	Return product volume Low(1)	Return product volume Medium(2)	Return product volume High(3)	Return product volume Very important(4)
Demand/ market need/customer need	Demand/ market need/customer need Not important(0)	Demand/ market need/customer need Low(1)	Demand/ market need/customer need Medium(2)	Demand/ market need/customer need High(3)	Demand/ market need/customer need Very important(4)
Product reliability	Product reliability Not important(0)	Product reliability Low(1)	Product reliability Medium(2)	Product reliability High(3)	Product reliability Very important(4)
Before recovery product quality	Before recovery product quality Not important(0)	Before recovery product quality Low(1)	Before recovery product quality Medium(2)	Before recovery product quality High(3)	Before recovery product quality Very important(4)
Product design (ease of disassembly)	Product design (ease of disassembly) Not important(0)	Product design (ease of disassembly) Low(1)	Product design (ease of disassembly) Medium(2)	Product design (ease of disassembly) High(3)	Product design (ease of disassembly) Very important(4)
Cost	Cost Not important(0)	Cost Low(1)	Cost Medium(2)	Cost High(3)	Cost Very important(4)
Inventory cost	Inventory cost Not important(0)	Inventory cost Low(1)	Inventory cost Medium(2)	Inventory cost High(3)	Inventory cost Very important(4)
Material cost	Material cost Not important(0)	Material cost Low(1)	Material cost Medium(2)	Material cost High(3)	Material cost Very important(4)
Landfill cost	Landfill cost Not important(0)	Landfill cost Low(1)	Landfill cost Medium(2)	Landfill cost High(3)	Landfill cost Very important(4)
Logistic cost - location, transportation, collecting	Logistic cost - location, transportation, collecting Not important(0)	Logistic cost - location, transportation, collecting Low(1)	Logistic cost - location, transportation, collecting Medium(2)	Logistic cost - location, transportation, collecting High(3)	Logistic cost - location, transportation, collecting Very important(4)
Machine cost including maintenance	Machine cost including maintenance Not important(0)	Machine cost including maintenance Low(1)	Machine cost including maintenance Medium(2)	Machine cost including maintenance High(3)	Machine cost including maintenance Very important(4)
Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc.	Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc. Not important(0)	Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc. Low(1)	Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc. Medium(2)	Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc. High(3)	Processing cost by machine - disassembly, repair/restoration, remanufacture, disposal etc. Very important(4)
Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc.	Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc. Not important(0)	Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc. Low(1)	Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc. Medium(2)	Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc. High(3)	Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc. Very important(4)

2. Decision criteria importance ranking (1: Most important-22: Least important, N/A if not important)

Return product volume

▼

☐ N/A

Demand/ market need/customer need

▼

☐ N/A

Product reliability

▼

☐ N/A

Before recovery product quality

▼

☐ N/A

Cost

▼

☐ N/A

Inventory cost

▼

☐ N/A

Material cost

▼

☐ N/A

Landfill cost

▼

☐ N/A

Logistic cost - location, transportation, collecting

☐ N/A

Machine cost including maintenance

☐ N/A

Processing cost by machine – disassembly, repair/restoration, remanufacture, disposal etc.

☐ N/A

Processing time by machine - disassembly, repair/restoration, remanufacture, disposal etc.

☐ N/A

Machine capability/ failure

☐ N/A

Labour – number of operators/manpower

☐ N/A

Labour – skilled operators/decision makers

☐ N/A

Labour cost/Processing cost by people – disassembly, repair/restoration, remanufacture, disposal etc.

☐ N/A

Processing time by people - disassembly, repair/restoration, remanufacture, disposal etc.

▼

☐ N/A

Legislation

▼

☐ N/A

Carbon/gas emission – CO₂, SO₂ etc.

▼

☐ N/A

Heat emission

▼

☐ N/A

Product useful life time

▼

☐ N/A

Natural resource consumption – material, fuel, energy, electricity etc.

▼

☐ N/A

Research Participant Comments

Participant comments: to extract further key decision criteria (if any) and decision rules that should be considered for product recovery option selection.

3. What are other key decision criteria that should be considered if products should be recovered (if any)?

4. What are decision rules that should be considered if products should be recovered? (Ex. 1. Crack length is not over X millimeters. 2. repair cost is not over 70% of new manufactured product/part cost. 3. Electricity usage is not over X kWh a day)

5. Contact Information

Name:

Company:

Country:

Email Address:

Phone Number:

6. Your job title (ex. Technical Manager, Inspector, System Engineer)

7. About how long have you been in your current position?

Years:

Months: