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# A Fuzzy Inference System Approach for Evaluating the Feasibility of Product Remanufacture

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# A FUZZY INFERENCE SYSTEM APPROACH FOR EVALUATING THE FEASIBILITY OF PRODUCT REMANUFACTURE

by

Thomas Aming'a Omwando

A Dissertation Submitted in  
Partial Fulfillment of the  
Requirements for the Degree of

Doctor of Philosophy  
in Engineering

at

The University of Wisconsin – Milwaukee

December 2016

## ABSTRACT

# A FUZZY INFERENCE SYSTEM APPROACH FOR EVALUATING THE FEASIBILITY OF PRODUCT REMANUFACTURE

by

Thomas Aming'a Omwando

The University of Wisconsin–Milwaukee, 2016

Under the Supervision of Professor Wilkistar Otieno

In the recent past, efforts have been made in enhancing sustainable manufacturing aimed at protecting the environment and saving natural resources. Among the efforts that have been explored include strategies to ensure responsible end-of-life product management so as reduce the impact on the environment and achieve effective use of resources. Towards this end, reduce, reuse and recycle product disposal strategies have found a lot of consideration in manufacturing. Of the product reuse strategies, remanufacturing has been widely applied owing to its unique feature of rendering the remanufactured product as good as new. For remanufacturers, this strategy leads to provision of quality products comparable to new their new counterparts at a reduced cost. Remanufacturing also leads to a sustainable environment through energy and material savings, as well as minimized solid wastes.

Remanufacturing however, poses challenges related to collection of the returns or cores, manufacturing process planning, resource allocation, warranty estimation and redistribution. These challenges are due to product and process complexities, customer requirements, and uncertainties associated with product take back and the remanufactured products' market-base. Key among these challenges is the remanufacturing process which is complicated, labor intensive with varying process times. In most cases the routing of these processes is stochastic in nature, based on the condition of the returned product. There is also the negative perception among consumers that remanufactured products are less superior to new ones, which calls for the need to allocate preferably longer warranty periods for the remanufactured product to induce confidence in the consumer while at the same time keeping the warranty costs low.

The objectives of this study were informed by challenges faced by a local remanufacturing firm. They include: (1) a detailed study of the current remanufacturing process of the firm's products; (2) identification of bottlenecks in the process to make recommendations for improvement; (3) develop a decision support system for assessing product remanufacture; (4) assess warranty allocation options for remanufactured product reuse.

The study revealed that there are bottlenecks in the current remanufacturing process and suggested an improvement to enhance efficiency. This bottlenecks include overutilization of some of the process centers such as the diagnostic testing and the after-repair testing centers which lead to the product spending more time in the system than necessary. To improve the system performance the capacities of the bottleneck centers

were increased which yielded significant reduction in the time the product spends in the system.

The key contribution of this dissertation is the development of a decision support system based on a bi-level fuzzy linguistic computing approach. This model integrates qualitative and quantitative product attributes in determining the remanufacturability of a product. The fuzzy-based model established remanufacturability metric, herein referred to as an index, is applied to assess the feasibility of remanufacturing two products that were used as a case study. A number of warranty scenarios are considered to ascertain the impact of different warranty periods and policies on the cost of warranty. The results show that the additional warranty cost for product reuse is a function of the period of first use and the residual life of the product.

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To  
my parents,  
my wife,  
and my children

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# CHAPTER 1: INTRODUCTION

## 1.1 Sustainable Manufacturing

The need to conserve the environment for future generations has created the impetus for governments to set up and enforce environmental laws. In order to comply with the legislations and avoid the concomitant liabilities, companies are continually challenged to integrate Design for the Environment (DfE) programs [1]. These strategies encompass aspects such as Reduced Energy Consumption, Reduced Usage of Virgin Raw Materials, Design for Disassembly and Remanufacture, Green Manufacturing, Environmentally Conscious Manufacturing, Inverse Manufacturing, Sustainable Manufacturing, Sustainable Production, Reuse, Recycling and Recovery Business Plans [2], [3], [4], [5]. Varied as the terms describing these initiatives may seem, the thoughts and driving themes behind them are similar. Through these techniques, industries are seeking opportunities to lower their production costs, increase their profit margins, and satisfy the ever-increasing consumer demands while limiting and mitigating the negative environmental risks of their processes and products.

Initially, DfE strategies focused on environmental concerns. However, over the years the concerns have become all-inclusive, subsuming social, legal and economic concerns affecting governments, industries and consumers globally. Figure 1 shows the trend in Municipal solid waste generation in the USA over the past 6 decades. According to the Environmental Protection Agency (EPA), the amount of Municipal Solid Wastes (MSW) generated by each person in the U.S. alone has increased from 2.7 to 4.4 pounds per day between 1960 and 2013 before recycling [6]. This means that each year an average American throws away about 1,606 pounds of trash, much of it being products

and packaging. By age 50, one would have thrown away 80,000 pounds of solid waste, which is equivalent to the weight of a Boeing 737 [7]. This results in about 254 million tons of waste generated by material before recycling in the US in 2013 [6], out of which an equivalent of 34.1% is either recycled or composted, and close to 60% of the solid wastes produced end up in landfills. Figure 2 shows the categorization of solid waste and their percentages in the U.S. alone.

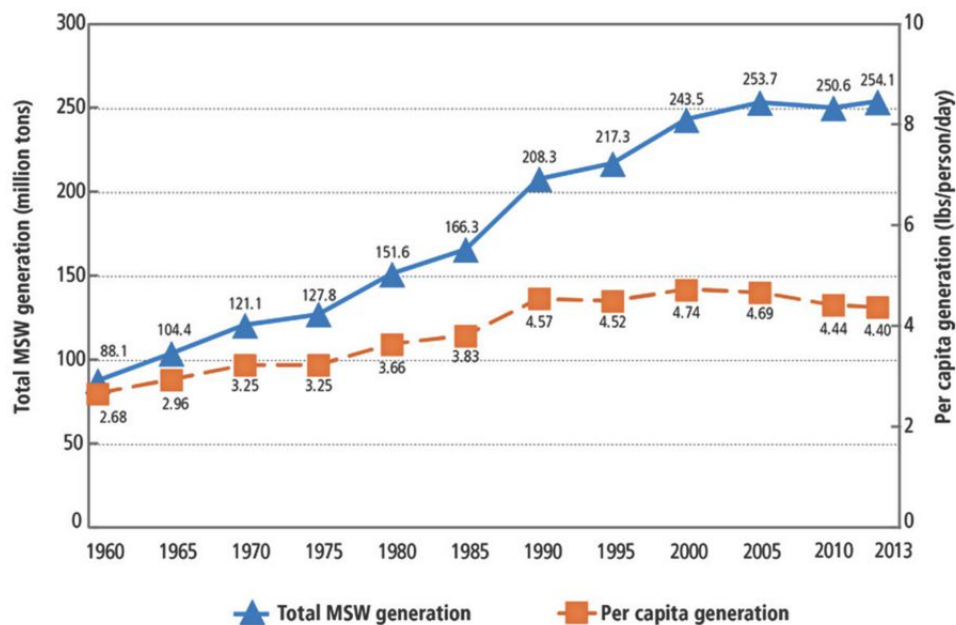
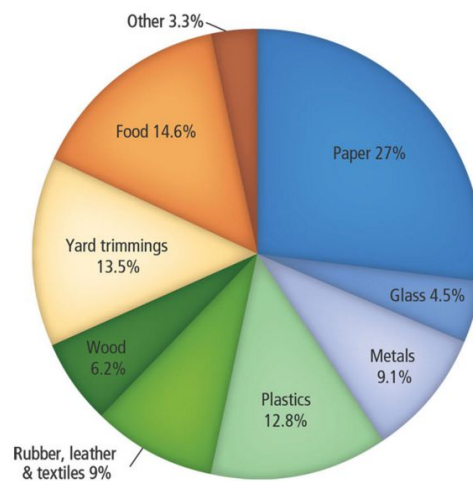


Figure 1: MSW Generation Rates 1960 to 2013 [6]

## Environmental Concerns

Key among the drivers of sustainability is environmental concerns. With a steadily growing population and the demand for goods and services, there is pressure on the environment especially causing grievous pollution and waste problems [3], [5]. Scarcity of space for landfill and the rising waste processing costs contributes into degeneration

of the situation [8]. Product stewardship efforts aim to encourage manufacturers and retailers to take increasing responsibility to reduce the end-of-life-cycle impacts of a product and its packaging. These impacts include energy and materials consumption, air and water emissions, the amount of toxins in the product, worker safety, and waste disposal.



**Figure 2: Total MSW Generation (by material) in the US in 2013 [6]**

One of the approaches previously employed in addressing environmental concerns was the end of pipe treatment of industrial wastes. It has however become apparent that there are environmental issues to be addressed throughout the life cycle of a product spanning from material acquisition, product manufacture, use and disposal or end of life. Hence, the need for an entire life cycle approach in addressing environmental concerns.

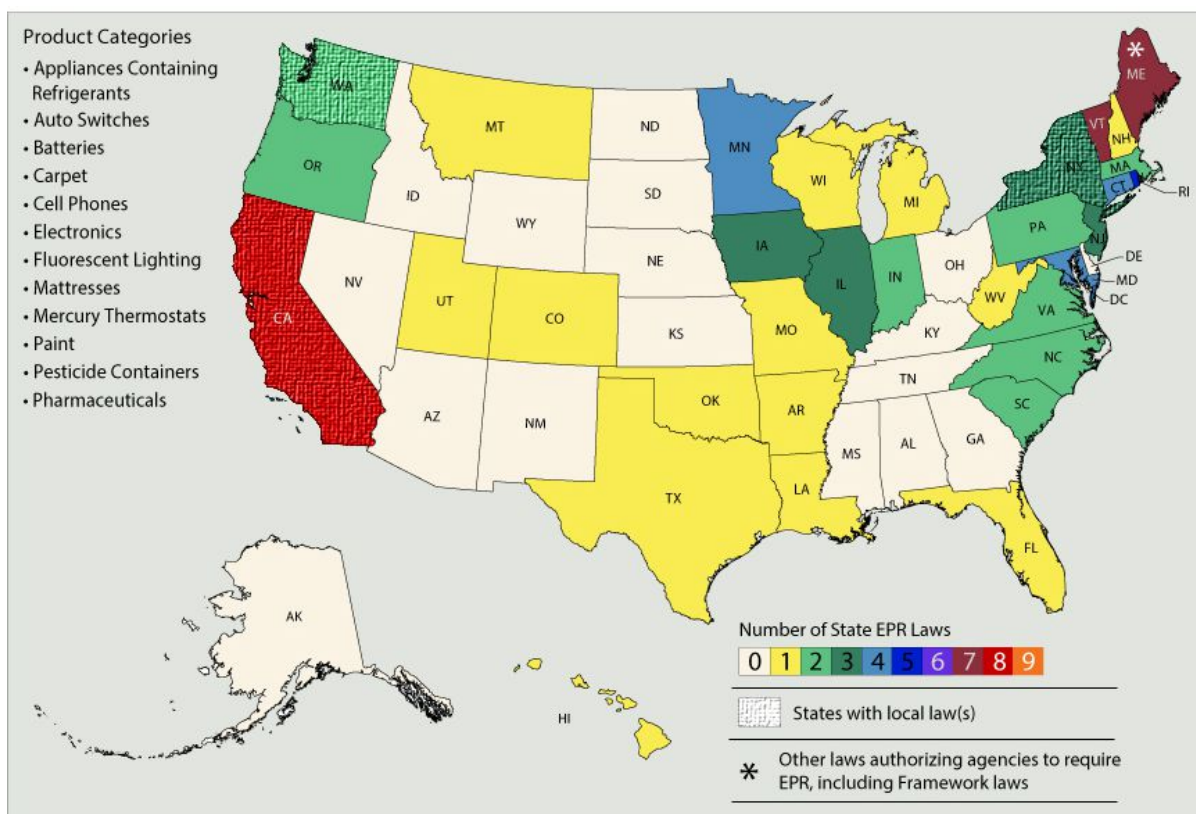
### ***Social Pressure***

Consumers and the society in general have put pressures on industries to go green and manufacture products that are not only of high quality but also of superior environmental performance. This is because a lot of health issues have been raised due to environmental problems emanating from some production processes, products and the associated wastes. For this reason, projects and industries in most developed countries have adopted the Triple Bottom Line concept in fostering sustainability [9]. Industries are therefore required to have a broader picture in their decisions and activities to encompass the environmental and social aspect in their corporate strategy. Hence terms like green manufacturing have been applied by most industries to depict their environmental image which plays well into a company's corporate image and competitiveness [10].

### ***Legislation pressure***

There is increasing pressure especially from governments and environmental agencies for manufacturers to reduce, reuse and recycle their products [10]. Further, international and national legislation on industrial production and waste management make producers accountable for the end of life treatment of their products [11], [12]. By moving away from end-of-pipe regulations, such as the Clean Air Act, the Clean Water Act, and the Resource Conservation Recovery Act, the latest regulations put more emphasis on producers' responsibility [11], [12]. For instance, stringent product take back laws in Europe [13], [14], recyclability laws in Japan [15], the Extended Producers' Responsibility (EPR) Law, the Integrated Product Policy (IPP), Environmentally Superior Products (ESP), and Sustainable Product and/or Service Development (SPSD) [13], [14],

the Waste Avoidance and Resource Recovery Act in New South Wales Australia [15] and the pollution prevention and minimization laws in the US [16], have to some extent impacted the growth of the remanufacturing sector. The United States envision some form of cap and trade program aimed at reducing CO<sub>2</sub> by 83% by the year 2050 [17]. As of January 2016 a number of legislations were in place in various states of the US concerning the Extended Producer Responsibility (EPR) which directs all those involved in the life cycle of a product to take responsibility for the health and environmental impacts that result from the production, use, and end-of-life management of a product [18], [19]. Figure 3 shows the current map of the EPR laws by state in the US as of January, 2016.



**Figure 3: Extended Producer Responsibility State laws as of January 2016, [19]**

These environmental policies oblige producers to take responsibility for the whole life cycle of their products, in particular at the end-of-life (EOL), either by enforcing penalties or introducing incentives [20]. Consequently, manufacturers must take-back their old products at the end of the lifetime or subcontract to a third party. Although these regulations are gradually being implemented, manufacturers have to prepare themselves with strategies for product end of life management in order to gain an upper edge in the future global market.

### ***Economic Advantages***

Apart from the environmental benefits of the take-back regulations, the take-back of used products also offer huge financial benefits [2], [10], [21]. In fact, the main driver for businesses to move towards sustainable manufacturing is its economic advantage [3], [11]. Initially, the financial benefits could be attained through incentives and tax reductions due to less hazardous waste. However, a giant hidden opportunity comes from material and energy recovery as well as from the potential of reusing products for a second “lifetime” [21].

## **1.2 Remanufacturing as an End of Life Strategy**

Remanufacturing is the process of returning a used product or some of its components to “as-good-as-new” condition. It is a restorative process it is most viable for products that have a high replacement cost or valuable components that can be cost-effectively reused or reconditioned. This practice has existed for close to a century with the automotive industry having a leading history through the remanufacturing operation commonly referred to as “engine rebuilding.” Remanufacturing dates back to the Second

World War when due to the prevailing conditions, rebuilding of old automotive engines and weapons was established to keep up with their demand [22].

The motivation behind this practice largely varies but encompasses ethical responsibility, legislation, profit maximization, securing of spare parts, source of under-warranty products, customer orientation, market share and brand protection [9]. Remanufacturing companies save between 40 and 60% of the cost of manufacturing a new product with a saving of about 20% on the energy required to produce a new product [23]. These profit margins scale up with the size of the company. Therefore, remanufacturing enables the development of a circular economy of any industry [24], rendering it a feasible alternative to sustainable smart growth of the local, national and global economy. Currently, there are more than 6600 remanufacturing companies in the USA alone [21].

### **1.3 Challenges in Remanufacturing**

The decision as to whether a product that has reached its first EOL and is suitable to be remanufactured largely depends on the degree of its remanufacturability. It is therefore imperative that an EOL product's remanufacturability be carefully analyzed. The remanufacturability of an EOL product varies considerably due to several factors including but not limited to its design structure, production and assembly quality, operating environment and level of damage to its components [25].

There is scarcity of literature addressing the remanufacturability evaluation of a product. The most recent is Yanbin et al., [25] who proposed a methodology for evaluating the remanufacturability of used machine tool. In their work, they used the analytical

hierarchical process (AHP) method to determine the weighting of each index for technological feasibility, economic feasibility and environmental benefits of machine tool remanufacturing. Subramanian et al., [26] modeled two design attributes of the product using a multi-dimensional measure of environmental performance (such as energy efficiency) during product use, and a measure of product remanufacturability, modeled as the fraction of the product that can be recovered after use. Nasr et al. [27] developed a methodology and system for assessing remanufacturability of an apparatus. In their work the methodology assesses the remanufacturing options of an item based on determination of the overall condition for the item—whether the item satisfies operation specifications and a determination of a risk priority for the item to identify which of the remanufacturing options are viable. Dixit [28] developed a conceptual product remanufacturing index which gives a fair outlook of efforts required to remanufacture a product considering all the major aspects of product after life, including disassembly, recycling and other damage correction efforts at the design stage of the product. His model was used to determine the remanufacturability index of an electric stapler, ETF X50.

Challenges that limit the establishment and institutionalization of a successful remanufacturing system are inextricably linked to internal and external drivers that can be categorized into design, logistical, financial, environmental and legal aspects of any remanufacturing system. Studies by Lundmark et al. [29] has identified three key areas of challenges in remanufacturing, viz, the collection, manufacturing process and redistribution related challenges.

In the collection aspect, there is lack of balancing in supply and demand. There is



lack of control in the quality and quantity of the core returns due to uncertain nature of the life of the products, product life stages, the rate of technological change and the stochastic return patterns caused by the unpredictable product disposer behavior [30], [31]. Further, the timing and quantities of returns make forecasting of demand for remanufactured products challenging which is compounded by technological changes. The remanufacturing process on the other hand is complicated, labor intensive with varying process times. In most cases the routing of these processes is stochastic in nature based on the condition of the returned product.

Further, most products are not designed for remanufacture and there is a low degree of automation if any in most cases. Design for remanufacture—DfR (also referred to as design for multiple life-cycles) is a strategy that optimizes remanufacture through product architecture strategies that ensure increased recovery value and ease of remanufacture [32]. Sundin and Bras [33] addressed this challenge by developing the RemPro matrix that relates a product's properties to remanufacturing activities.

The third major challenge is redistribution of the remanufactured products. This is caused by uncertainty in demand for remanufactured products which is compounded by the fact that these products serve a wide range of small niche markets which are largely different from each other. There is also the negative perception among consumers that remanufactured products are less superior to manufactured ones [30]. Market reaction subsumes factors such as consumer behavior towards purchasing remanufactured products (demand determinant), end-of-life product return volume, return quality and delays.

In their paper, Hazen et al. [34] provided an empirical justification for quality and

cost estimation of remanufactured products and present a discussion of quality ambiguity and its effects on consumer behavior. Organizational reaction is indicated by companies' understanding of the value (or loss) associated with remanufacturing, price analysis and warranty decisions. Ferrer and Whybark [35] presented models for evaluating the economics of retreading used tires as a case scenario considering the steps in the entire remanufacturing process and aberrations such as single or multiple tire recovery.

Legal issues including the definition of product integrity as being “as-good-as-new”, government eco-design incentives and disposal fees [36], and ownership of the intellectual property developed to improve products' design for remanufacture, and to improve the performance of remanufactured products are all determined to highly affect the success of a remanufacturing program especially when third party independent remanufacturers are involved.

#### **1.4 Objectives of the Dissertation**

This study is based on a collaborative research with a partnering multi-national remanufacturing company. One of the major challenges addressed in this study is the need for a decision support system that will determine the feasibility of a product for remanufacture. In addition, there is need to equip technicians and inspectors on the production floor with a tool to determine the remanufacturability of a product as soon as it is received and inspected. Hence, the objectives of this thesis are;

- 1) Study and analyze performance metrics of the current remanufacturing process of a case study plant with the aim of developing a performance evaluation simulation model to analyze and evaluate remanufacture of end of life products.

- 2) Develop a fuzzy inference based remanufacturability metric herein referred to as an index, which incorporates product attributes, core supply uncertainties, labor requirements and the environmental impacts of the product returns.
- 3) Assess the cost of warranty allocation options for remanufactured products.

## **1.5 Dissertation Outline**

This dissertation is composed of four more chapters. Chapter two provides a literature review of fuzzy systems and how they have been applied in various fields. Chapter three presents a theoretical background of the fuzzy linguistic approach and explains the fuzzy linguistic concept that is used to determine the remanufacturability index. It also shows how the fuzzy linguistic terms are established for use in the proposed fuzzy inference system for determining the remanufacturability index. Chapter four deals with data collection, preprocessing and performance evaluation of the current remanufacturing process at the case study plant. The performance evaluation is done using a ProModel simulation software to establish equipment and resource utilization in the current setting. Chapter five presents the application of fuzzy inference system for determination of remanufacturability index. Chapter six presents the results of the work that has been done on establishing the remanufacturability index of selected case study product families from the remanufacturing company. Chapter seven looks at the determination of cost of warranty for reuse of remanufactured products.

## CHAPTER 2: LITERATURE REVIEW

### 2.1 Fuzzy Systems

Fuzzy decision systems have been used in a variety of areas including evaluation, multi-objective optimization, machine design, control theory, and pattern recognition, in addition to solving numerous managerial decisions. For example, using a combination of fuzzy analytic hierarchy process and zero one goal programming, Firouzabadi et al. [37] developed a decision support methodology to address the strategy selection problem, in which a single or aggregated “go or no-go” decision has to be made considering multiple stakeholders. Their model takes into account adverse tangible and intangible criteria, resource limitations and goal constraints and suggests an aggregated model that resolves conflicting criteria from different stakeholders. Pan [38] applied a fuzzy Analytical Hierarchical Process (AHP) model to handle issues of uncertainty and vagueness that are a challenge to the conventional AHP method, especially in the selection of design alternatives. To address the imprecision inherent in subjective judgment, the author used triangular and trapezoidal fuzzy numbers and the  $\alpha$ -cut concept. He applied the max-min aggregation and center of gravity defuzzification approach to derive fuzzy weights for the respective criterion and the  $\alpha$ -cut concept to model decision environment related uncertainties.

In the location selection arena, Kuo et al. [39] used a fuzzy environment to propose group decision-making based on the fuzzy hierarchical Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). To deal with uncertainty, subjectivity and imprecise data, they used linguistic variables to assess each alternative against each criterion. Further, Kengpol et al. [40] applied fuzzy AHP and TOPSIS to model a decision

support system for avoiding flood in a solar power plant site selection. Their model integrates quantitative and qualitative variables in order to take into account both environmental and social needs on a TOPSIS platform.

Fuzzy systems have also been used to evaluate and select the best alternative among choice projects, industries, and processes. For example Huang et al. [41] applied fuzzy AHP methodology to evaluate expert judgments in selecting a government sponsored research and development project for funding. They employed fuzzy AHP simulation to understand variations in expert judgement under different decision risks. Gumus [42] used fuzzy AHP and TOPSIS to evaluate and select the most appropriate hazardous waste transportation firm. In another study Sambasivian and Fei [43] used the AHP approach to evaluate and determine the factors critical to the successful implementation of ISO 14001-based environmental management system. Also, Sun [44] used an integration of fuzzy AHP and TOPSIS methods model to evaluate the performance of top notebook computer original design manufacturing (ODM) companies using manufacturing, supply chain, innovation, financial, human resource, and service quality capabilities as the system attributes.

Dagdeviren and Yuksel [45] developed a Fuzzy AHP based decision model to enhance safety management through determination of the level of faulty behavior risk in work systems. In particular, they used pairwise comparison with triangular fuzzy numbers to determine which factors are responsible for faultier behavior in the work system. Chen et al. [46] on the other hand used a combination of fuzzy AHP and multi-criteria decision making to determine the weighting of subjective/perceptive judgments in expatriate assignment decision-making.

In the area of inventory classification Cakir and Canbolt [47] proposed a web-based fuzzy AHP to categorize inventory items by demand. Their methodology integrates fuzzy concepts with real inventory data to capture uncertainties associated with criteria evaluation to optimize the inventory replenishment priority. In another classification study, Bozbura et al. [48] applied a fuzzy AHP technique to improve the quality of the prioritization of human capital measurement indicators such as talent, strategic integration, cultural relevance, leadership and knowledge management. Their study showed that of the several human capital indicators they studied, using knowledge to creating results, employees' skills index, sharing and reporting knowledge and the level of success of training programs are the four key measurement indicators of the human capita in Turkey. In identifying customer needs/requirements and order characteristics, Lin and Chang [49] proposed a framework that integrates AHP and TOPSIS technique to evaluate the final price. Their approach employed triangular fuzzy numbers and linguistic variables to classify buyers to inform the decision whether to produce an order with priority, decline it or apply a mixed integer programming model to rank the orders for segmented pricing.

Our study hinges on the application of fuzzy AHP models in a decision making optimization processes. To this end, Sharma et al. [50] used AHP method to optimize the selection of delivery network design for a distribution center. During the process of subjective evaluation of new product development (NPD) performance, there are risks of information loss when dealing with heterogeneous information

To accommodate the challenges of heterogeneity and information loss during the process of subjective evaluation, Wang [51] used a 2-tuple fuzzy linguistic computing

approach to manipulate the heterogeneous integration processes based on a managerial group decision making scenario. More recently Wang and Chan [52] presented a model that evaluates alternative designs for remanufacturing. Their model integrates a fuzzy extent analysis based on a hierarchical framework and TOPSIS methodology to support a front-end rationale of product design selection from a remanufacturing perspective.

The contribution of our work is the use of fuzzy decision systems to determine the remanufacturability of returned products also referred to as cores. In order to evaluate remanufacturing performance more appropriately, it is important that remanufacturers consider both quantitative and qualitative aspects. The quantitative factors include measurable product aspects such as the supply of returned products and demand of remanufactured products. On the other hand, the qualitative aspects or factors often include subjective judgments of product remanufacturability by multiple decision-makers or experts. However, similar to the case of a new product development [51], measurement of the level of remanufacturability of a product is subject to varying degree of uncertainty, fuzziness and information heterogeneity. Hence the determination of a product's remanufacturability is best approached as a multi-criteria decision-making problem. Table 1 is a summary of the researchers who have applied Fuzzy AHP and TOPSIS in a variety of applications.

**Table 1: Summary of Literature Review**

<b>Author</b>	<b>Year</b>	<b>Application</b>	<b>Methodology</b>
Firouzabadi et al.	2008	Strategy selection problem	Combined fuzzy AHP and zero-one goal programming
Pan	2008	Selection of design alternatives	Fuzzy AHP
Kuo et al.	2007	Location selection problem	Fuzzy hierarchical TOPSIS
Kengpol et al.	2013	Solar power plant site selection	Fuzzy AHP and TOPSIS
Gumus	2009	Evaluation of expert judgement	Fuzzy AHP and TOPSIS
Sambasivian and Fei	2008	Evaluation of success ISO 14001 critical factors for success	Fuzzy AHP
Sun	2010	Company performance evaluation	Fuzzy AHP and TOPSIS
Dagdeviren and Yuksel	2008	Decision making in behavior based safety management	Fuzzy AHP
Chen et al.	2008	Decision making in expatriate assignment	combination of fuzzy AHP and multi-criteria decision making
Cakir and Canbolt	2008	Inventory classification	Web-based fuzzy AHP
Bozbura et al.	2007	Prioritization of human capital indicators	Fuzzy AHP technique
Lin and Chang	2008	Evaluation of customer needs and order characterization	AHP and TOPSIS technique
Sharma et al.	2008	Optimization of network delivery method	AHP method
Wang	2009	Performance evaluation	2-tuple fuzzy linguistic
Wang and Chan	2013	Evaluation of product design	Integrated fuzzy approach



## CHAPTER 3: FUZZY LINGUISTIC APPROACH

### 3.1 Introduction

Whereas most purely quantitative methods represent information numerically, most real world cases involving individual perceptions are vague and imprecise and thus best represented qualitatively. Linguistic assessment is one of the qualitative methods that have widely been applied in many applications. In this approach, for each term set, appropriate linguistic descriptors are chosen dependent on the granularity of certainty of the linguistic variables. Typically, linguistic models constitute assigned odd cardinal values, with the mid value representing the mid assessment and the rest of the assessment values symmetrically distributed around the mid value.

According to Herrera and Martinez [53], assessment values normally have a cardinality of  $7 \pm 2$ , which is the optimal range of elements the human mind is able to process. To generate linguistic terms and their semantics, we directly supply the terms set across the variables scale. Membership functions are then used to describe a fuzzy number in the  $[0,1]$  interval that assigns a degree of the semantic value.

Membership functions typically used are, Gaussian, Bell-shaped, Sigmoidal, polynomial based and piecewise linear functions. The Gaussian membership function is given by Equation (1).

$$f(x; \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (1)$$

Where, the parameter  $\sigma$  is the width of the curve and  $c$  locates distance from the origin. This membership function is characterized by non-zero and smooth features at all points. Figure 4 illustrates the shape and characteristics of this membership function.

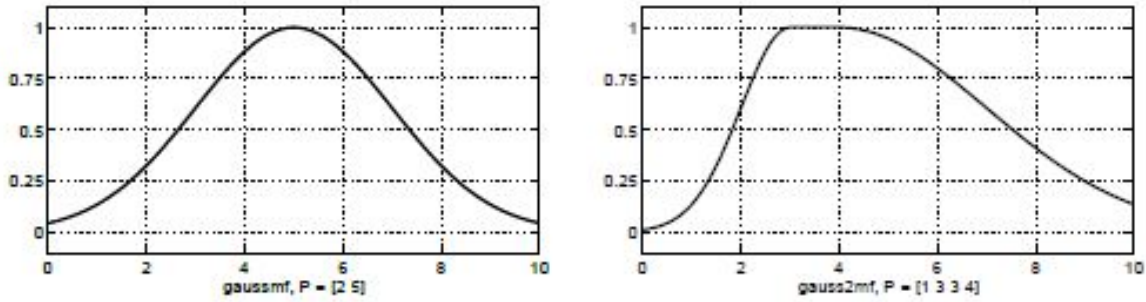


Figure 4: The Gaussian membership function

The bell-shaped MFs. Unlike the Gaussian membership function that has only two parameters, the generalized bell membership function is specified by three parameters as expressed by Equation (2).

$$f(x; a, b, c) = \frac{1}{1 + \left| \frac{x - c}{a} \right|^{2b}} \quad (2)$$

Where, the parameter  $a$  is the width of the curve,  $c$  locates the center of the curve and  $b$  is usually a positive value. Figure 5 illustrates the bell-shaped MF which also exhibits smooth and non-zero at all points.

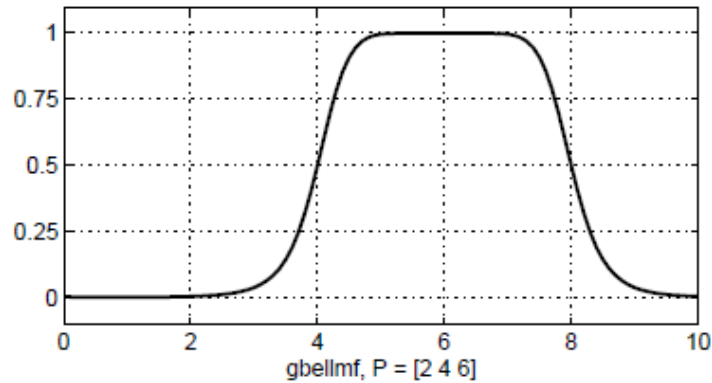


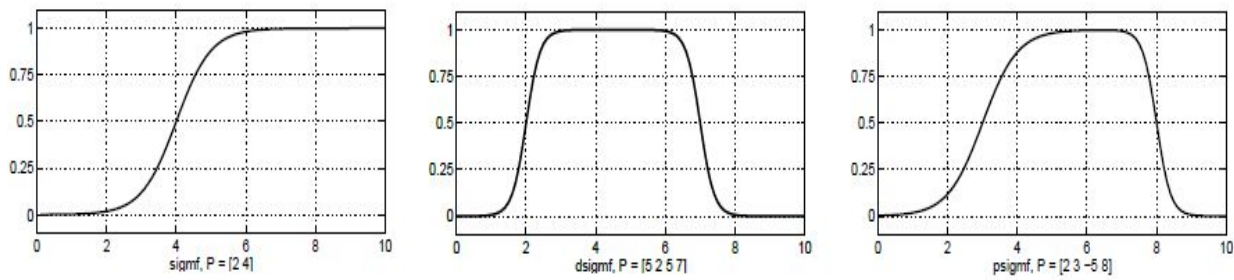
Figure 5: The bell-shaped membership function

Gaussian and bell-shaped membership functions are mainly used in fuzzy sets because of their smoothness and concise notations. Despite these attributes these two membership functions are unable to fit in applications that require asymmetric membership functions.

The sigmoidal membership function is either open left or open right or asymmetric and closed. The general expression of this MF is given by Equation (3).

$$f(x; a, c) = \frac{1}{1 + e^{-(x-c)}} \quad (3)$$

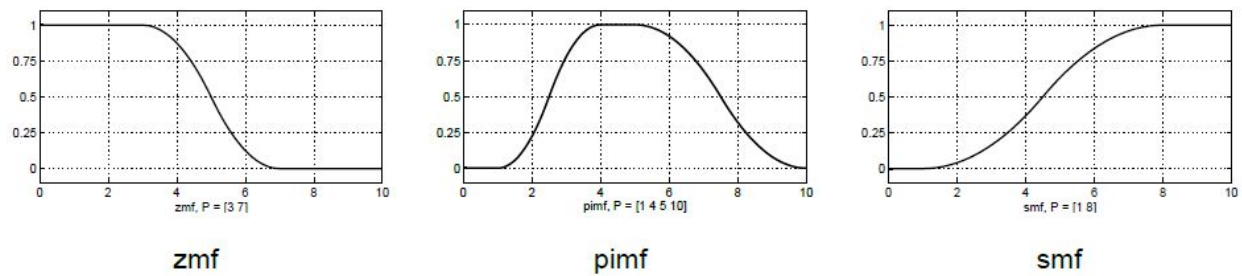
Where, the parameter  $a$  is determines the steepness of the function and  $c$  locates the distance from the origin. The parameter,  $a$  can be negative for open left or positive for open right representing the extreme negative and extreme positive linguistic terms. The symmetrical or asymmetrical but closed MF are constructed using either the difference or the product of the open left and open right MFs. Figure 6 is an illustration of the shapes of the sigmoidal family of membership functions which are also non-zero and smooth at all points.



**Figure 6: The sigmoidal membership function**

Polynomial based MFs come in a variety of shapes. Figure 7 shows the common ones, that is; zmf, which is open to the left; smf, which is opens to the right; and Pi function which is zero on both extremes with a rise in the middle. The polynomial functions are

smooth but not non-zero at all points

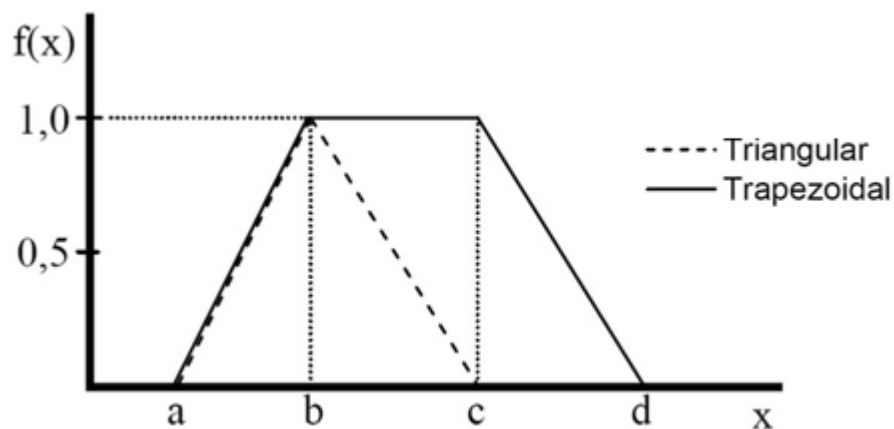


**Figure 7: Polynomial membership functions**

Piecewise linear membership functions. These MFs are formed using straight lines. Figure 8 illustrates the triangular and trapezoidal membership functions which are the most commonly used in these family of MFs. Equation (4) describes the shape of the trapezoidal membership function.

$$f(x; a, b, c, d) = \max \left\{ \min \left( \frac{x - a}{b - a}, 1, \frac{d - x}{d - c} \right), 0 \right\} \quad (4)$$

Where, a and d locate the feet of the trapezoid and b and c locate the shoulders.



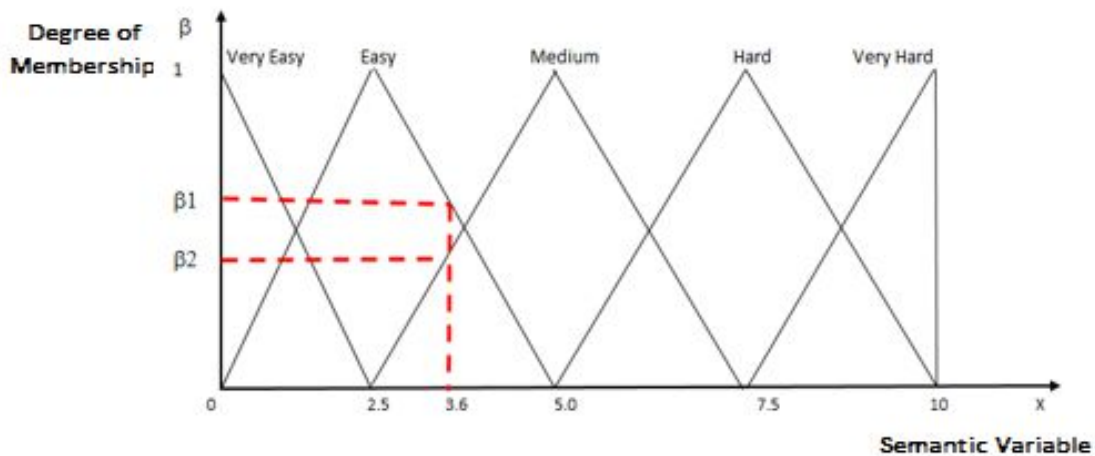
**Figure 8: Linear Triangular and Trapezoidal Membership Functions**

A triangular membership function is a special case of a trapezoidal MF with parameter  $d = b$ . Equation (5) describes the shape of this function.

$$f(x; a, b, c) = \max \left\{ \min \left( \frac{x - a}{b - a}, \frac{b - x}{b - c} \right), 0 \right\} \quad (5)$$

The piecewise linear MFs have extensively been used due to their computational efficiency and ease of application [54].

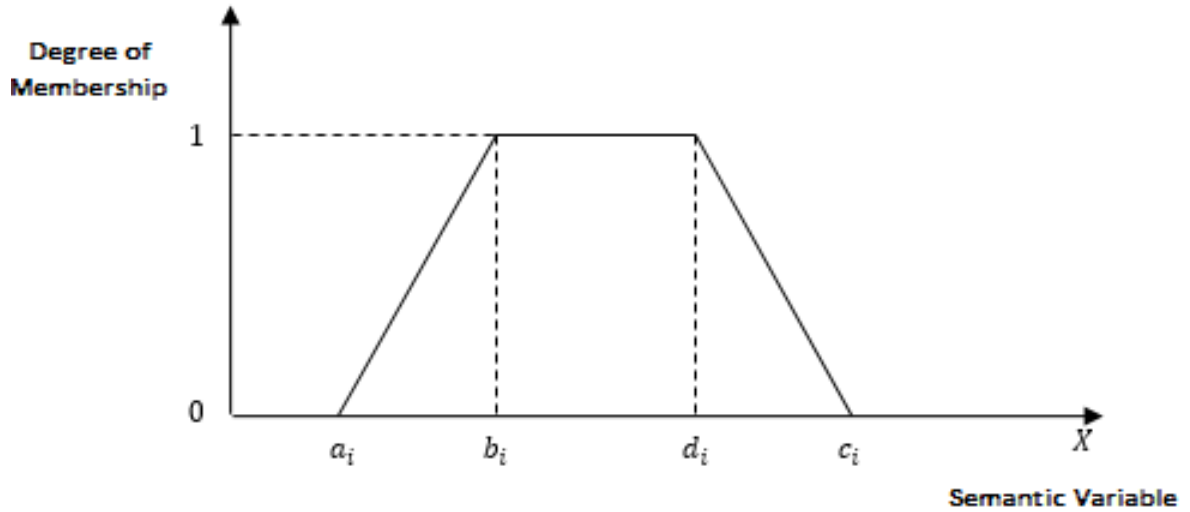
For instance, the levels of a variable named “cleaning a product” contain {very easy, easy, medium, hard and very hard} as the linguistic terms, which can be mapped onto a semantics variable on an ordinal scale. Let the level, “easy” be describable by the values [0 to 5] on a scale of 0 to 10. Suppose a technician determines that the level of cleaning required is 3.6. Membership functions (MFs) are used to describe this fuzzy number in the [0, 1] interval that assigns a degree of membership to the semantic value 3.6, into the “easy” linguistic term. Figure 9 is a schematic representation of the assignment of degree membership to levels of a qualitative variable.



**Figure 9: Schematic representation of the assignment of degree of membership**

Membership functions typically used include triangular, trapezoidal, Gaussian, polynomial curves and sigmoid. Triangular and trapezoidal MFs have been extensively used due to their computational efficiency and ease of application [54]. Figure 10 illustrates a linear trapezoidal MF using the cleaning example described above.

Trapezoidal MFs are represented by 4-tuple parameter vectors  $(a_i, b_i, c_i, d_i)$  to capture the details of linguistic assessments. Parameters  $a_i$  and  $c_i$  are the left and right limits of the trapezoidal membership function of the “EASY” linguistic term. Hence the values of  $a_i$  and  $c_i$  are 1 and 4 respectively, whose membership values vary linearly. On the other hand, the parameters  $b_i$  and  $d_i$  are the inner limits (in this case 2 and 3) that describe the interval where the membership value is 1.



**Figure 10: Linear Trapezoidal Membership Function**

The triangular membership function is a special case of a trapezoidal function in which  $b_i = d_i$ . Let  $\lambda$  be an input numeric value assigned to a product attribute such as “how clean the product is”, where  $\lambda \in [0, 1]$ . Let  $F(S_T)$  be a basic fuzzy term set in  $S_T$  such

that  $F(S_T)$  is described by the vector  $\{s_0, \dots, s_g\}$ . The fuzzy process seeks to determine the degree to which the numerical value  $\lambda$  belongs to each term  $S_i$ . To do so, each fuzzy term  $S_i$  is represented on a trapezoidal MF by parameters  $\{a_i, b_i, c_i, d_i\} \in [0, 1]$  (the interval  $[0, 1]$  is only being used for explanatory purposes). However, it is expected that the input variables may at times be non-homogeneous i.e. numerical, non-numerical and interval. The following sections are included to illustrate how each of these types of input variables are assigned into a predefined set of fuzzy terms [55].

### 3.1.1 Making Input Variables Homogenous

#### *Transformation of crisp numerical input variables into fuzzy numbers*

Consider a function  $\tau_{ST}$  (Equation 1) that transforms the input numerical value  $\lambda \in [0, 1]$  into a basic fuzzy term set  $F(S_T)$ . The transformation is done by determining a degree of membership  $\beta$  (Equation 2), for the input variable  $\lambda$  into each term  $S_i$  in the linguistic terms of  $S_T$ .

$$\tau_{ST}: [0,1] \rightarrow F(S_T),$$

$$\tau_{ST}(\lambda) = \{(s_0, \beta_0), \dots, (s_g, \beta_g)\}, \quad s_i \in S_T \text{ and } \beta_i \in [0,1] \quad (6)$$

$$\beta_i = \mu_{s_i}(\lambda) = \begin{cases} 0 & \text{if } \lambda \notin \text{support}(\mu_{s_i}(\lambda)), \\ \frac{\lambda - a_i}{b_i - a_i} & \text{if } a_i \leq \lambda \leq b_i, \\ 1 & \text{if } b_i \leq \lambda \leq d_i, \\ \frac{c_i - \lambda}{c_i - d_i} & \text{if } d_i \leq \lambda \leq c_i. \end{cases} \quad (7)$$

In this case  $\mu_{s_i}(\lambda)$  is the trapezoidal membership function.

For illustrative purposes, a set of seven fuzzy terms  $S_T$  is assigned the following linguistic terms.

$$S_T = \{s_0 = N, s_1 = VL, s_2 = L, s_3 = M, s_4 = H, s_5 = VH, s_6 = P\}$$

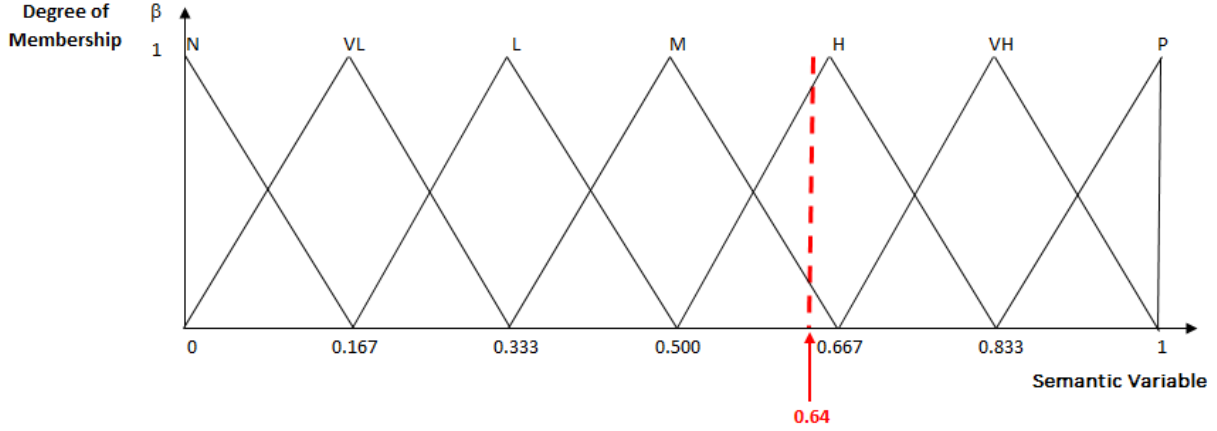
Where N, VL, L, M, H, VH, and P stand for none, very low, low, medium, high, very high and perfect respectively in the basic linguistic term set. Since the trapezoidal membership function is general, we use it in this illustration, in conjunction with the foregoing term set described using a triangular membership function and each term  $S_i$  is defined by the following parameters  $\{a_i, b_i, c_i\}$  of  $S_T$  in  $[0,1]$  as follows. In this case where  $b_i = d_i$ .

$$s_0 = (0,0,0.167), s_1 = (0,0.167,0.333), s_2 = (0.167,0.333,0.5), s_3 = (0.333,0.5,0.667),$$

$$s_4 = (0.5,0.667,0.833), s_5 = (0.667,0.833,1), s_6 = (0.833,1,1)$$

Let an attribute be assessed to have a numerical value of  $\lambda = 0.64$  on a scale of  $[0, 1]$ . This value is mapped on the basic term set to determine the degree of membership in the linguistic term set  $S_T$  (following Equations 1 to 3). Figure 11 illustrates the mapping assessed value on to the basic linguistic term set.





**Figure 11: Numerical term transformation into  $S_T$**

The following equations are iterations of Equation 3 to determine the degree of membership of  $\lambda = 0.64$  into each fuzzy term.

$$s_0, \beta_0 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0}{0 - 0}, 1, \frac{0.167 - 0.64}{0.167 - 0} \right), 0 \right] = 0$$

$$s_1, \beta_1 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0}{0.167 - 0}, 1, \frac{0.333 - 0.64}{0.333 - 0.167} \right), 0 \right] = 0$$

$$s_2, \beta_2 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0.167}{0.333 - 0.167}, 1, \frac{0.5 - 0.64}{0.5 - 0.333} \right), 0 \right] = 0$$

$$s_3, \beta_3 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0.333}{0.5 - 0.333}, 1, \frac{0.667 - 0.64}{0.667 - 0.5} \right), 0 \right] = 0.16$$

$$s_4, \beta_4 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0.5}{0.667 - 0.5}, 1, \frac{0.833 - 0.64}{0.833 - 0.667} \right), 0 \right] = 0.84$$

$$s_5, \beta_5 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0.667}{0.833 - 0.667}, 1, \frac{1 - 0.64}{1 - 0.833} \right), 0 \right] = 0$$

$$s_6, \beta_6 = \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] = \text{Max} \left[ \text{Min} \left( \frac{0.64 - 0.833}{1 - 0.833}, 1, \frac{1 - 0.64}{1 - 1} \right), 0 \right] = 0$$

Therefore, the fuzzy set obtained for this attribute is

$$\tau_{ST}(0.64) = \{(s_0, 0), (s_1, 0), (s_2, 0), (s_3, 0.16), (s_4, 0.84), (s_5, 0), (s_6, 0)\}$$

This therefore means that the assessed attribute belongs only to the medium( $s_3$ ), and

high ( $s_4$ ) descriptors with 16%, and 84% degrees of membership respectively.

### *Transformation of interval input variables into fuzzy numbers*

In instances where the input variable  $\lambda$  is provided as an interval, it is transformed into fuzzy term sets using. Let  $I_i = [\underline{i}, \bar{i}]$  be an interval value in  $[0,1]$ . It is assumed that the interval value has a representation inspired in the membership function set ( $S_T$ ) [55] as in Equation (8):

$$\mu_i(\lambda) = \begin{cases} 0 & \text{if } \lambda < \underline{i} \\ 1 & \text{if } \underline{i} \leq \lambda \leq \bar{i} \\ 0 & \text{if } \bar{i} < \lambda \end{cases} \quad (8)$$

The transformation function is

$$\begin{aligned} \tau_{IST}: I &\rightarrow F(S_T) \\ \tau_{IST}(\lambda_i) &= \{(s_k, \beta_k) \mid k \in \{0, \dots, g\}\} \quad \forall \lambda_i \in I \\ s_i, \beta_i &= \text{Max} \left[ \text{Min} \left( \frac{\lambda - a_i}{b_i - a_i}, 1, \frac{c_i - \lambda}{c_i - d_i} \right), 0 \right] \end{aligned} \quad (9)$$

In the case where the lower limit,  $\underline{i}$ , and the upper limit,  $\bar{i}$ , of the interval value are within the same membership function then the degree of membership is determined using the “OR” operator. Figure 12 shows an instance where an attribute that is assessed as an interval value,  $I = [0.21, 0.35]$  is mapped in the basic linguistic term set.

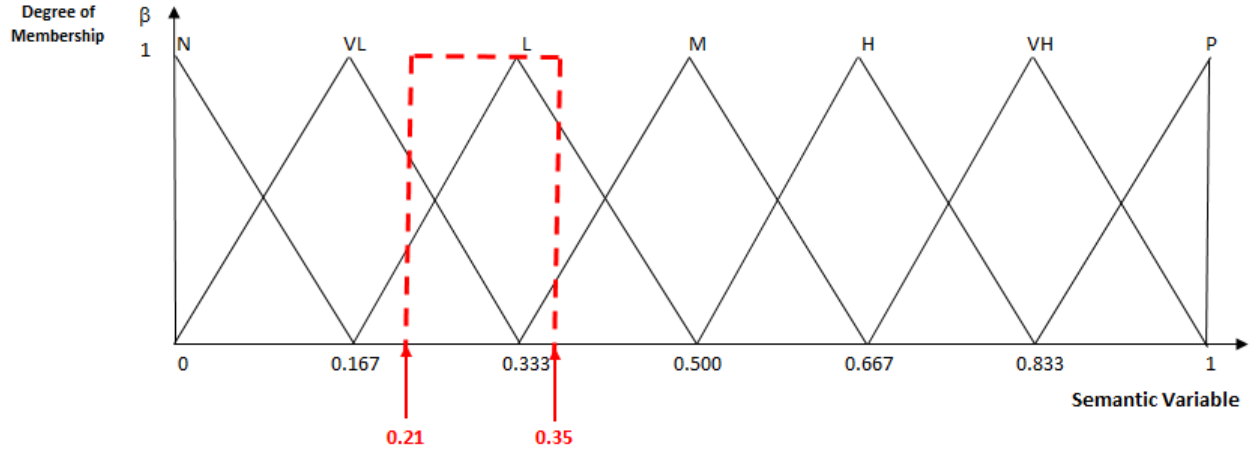


Figure 12: Interval term transformation into ( $S_T$ ).

The following equations are iterations of Equation (9) and the OR operator to determine the degree of membership of  $\lambda$ , ( $I = [0.21, 0.35]$ ) into each fuzzy term.

$$\begin{aligned}
 s_0, \beta_0 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0}{0-0}, 1, \frac{0.167-0.21}{0.167-0} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0}{0-0}, 1, \frac{0.167-0.35}{0.167-0} \right), 0 \right] \right\} = 0 \\
 s_1, \beta_1 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0}{0.167-0}, 1, \frac{0.333-0.21}{0.333-0.167} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0}{0-0}, 1, \frac{0.167-0.35}{0.167-0} \right), 0 \right] \right\} = 0.74 \\
 s_2, \beta_2 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0.167}{0.333-0.167}, 1, \frac{0.5-0.21}{0.5-0.333} \right), 0 \right] \right\} \mid \{1\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0.167}{0.333-0.167}, 1, \frac{0.5-0.35}{0.5-0.333} \right), 0 \right] \right\} = 1 \\
 s_3, \beta_3 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0.333}{0.5-0.333}, 1, \frac{0.667-0.21}{0.667-0.5} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0.333}{0.5-0.333}, 1, \frac{0.667-0.35}{0.667-0.5} \right), 0 \right] \right\} = 0.1 \\
 s_4, \beta_4 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0.5}{0.667-0.5}, 1, \frac{0.833-0.21}{0.833-0.667} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0.5}{0.667-0.5}, 1, \frac{0.833-0.35}{0.833-0.667} \right), 0 \right] \right\} = 0 \\
 s_5, \beta_5 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0.667}{0.833-0.667}, 1, \frac{1-0.21}{1-0.833} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0.667}{0.833-0.667}, 1, \frac{1-0.35}{1-0.833} \right), 0 \right] \right\} = 0 \\
 s_6, \beta_6 &= \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.21-0.833}{1-0.833}, 1, \frac{1-0.21}{1-1} \right), 0 \right] \right\} \mid \left\{ \text{Max} \left[ \text{Min} \left( \frac{0.35-0.833}{1-0.833}, 1, \frac{1-0.35}{1-1} \right), 0 \right] \right\} = 0
 \end{aligned} \tag{10}$$

Therefore, the fuzzy set obtained for this attribute is

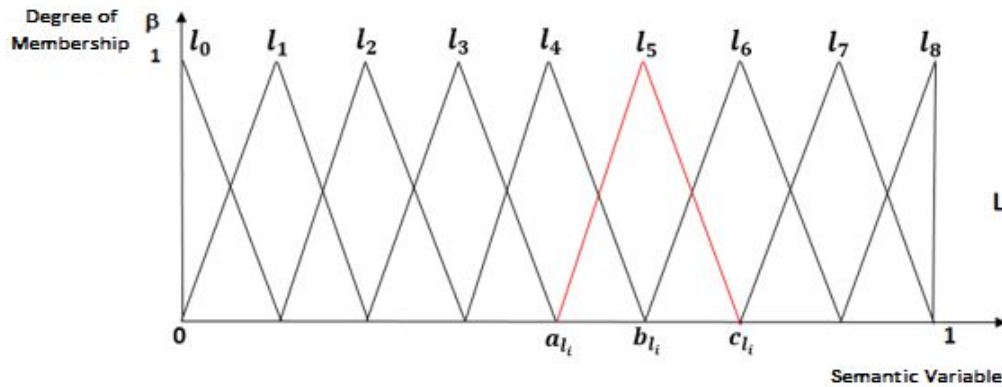
$$\tau_{IST}([0.21, 0.35]) = \{(s_0, 0), (s_1, 0.74), (s_2, 1), (s_3, 0.1), (s_4, 0), (s_5, 0), (s_6, 0)\}$$

In this example the assessed attribute belongs to the very low( $s_1$ ), low( $s_2$ ) and medium ( $s_3$ ) descriptors with 0.74, 1 and 0.1 degrees of membership respectively.

#### *Transformation of linguistic input variables into fuzzy numbers*

For linguistic data sets, a transformation is applied to obtain a fuzzy set in terms of the basic linguistic term set as follows.

Let  $L_T = \{l_0, \dots, l_p\}$  be a non-homogenous set of linguistic terms that can be used to describe the input variable. Also, let  $S_T = \{s_0, \dots, s_g\}$  be a unified linguistic set predefined expressions in the fuzzy model. Let  $a_{l_i}, b_{l_i}, c_{l_i}$  and  $d_{l_i}$  be the parameters of the triangular membership functions of a linguistic term set for an assessed attribute to be transformed to a basic linguistic term set with parameters  $a_i, b_i, c_i$ . Figure 13 represents the linguistic term sets of the assessed attribute be transformed while Figure 14 represents basic linguistic term set. The interrelation between the two sets is such that the cardinality of the later subsumes all possible elements of the former.



**Figure 13: Linguistic term set ( $L_T$ )**

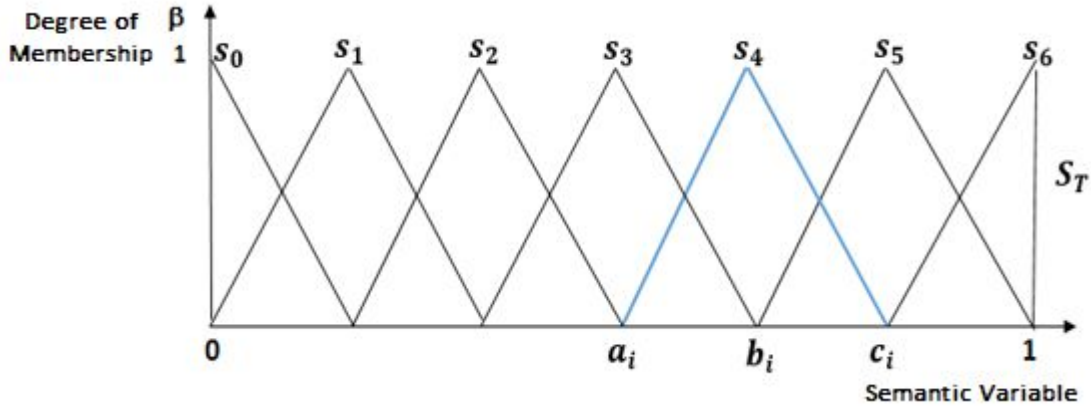


Figure 14: Unified Linguistic Set ( $S_T$ )

For any point of the linguistic label mapped on the basic term set, the input variable  $\lambda$  is determined using Equation (11) as follows:

$$\lambda = \begin{cases} \frac{c_{l_i}b_i - b_{l_i}a_i}{(c_{l_i} - b_{l_i} + b_i - a_i)} & \text{if } a_i \leq \lambda \leq b_i, \\ 1 & \text{if } \lambda = b_i, \\ \frac{(c_i b_{l_i} - b_i a_{l_i})}{(c_i - b_i + b_{l_i} - a_{l_i})} & \text{if } b_i \leq \lambda \leq c_i. \end{cases} \quad (11)$$

Then a linguistic transformation function  $\tau_{LS_T}$  used to unify the non-homogeneous terms  $L$  into  $S_T$  is described as [29]:

$$\tau_{LS_T}(l_i) = \{(s_k, \beta_k) \mid k \in \{0, \dots, g\}\} \quad \forall l_i \in L$$

$$\beta_k = \mu_{s_i}(\lambda) = \begin{cases} 0 & \text{if } \lambda \notin \text{support}(\mu_{s_i}(\lambda)), \\ \frac{c_{l_i}b_i - b_{l_i}a_i - a_i(c_{l_i} - b_{l_i} + b_i - a_i)}{(b_i - a_i)(c_{l_i} - b_{l_i} + b_i - a_i)} & \text{if } a_i \leq \lambda \leq b_i, \\ 1 & \text{if } \lambda = b_i, \\ \frac{c_i(c_i - b_i + b_{l_i} - a_{l_i}) - (c_i b_{l_i} - b_i a_{l_i})}{(c_i - b_i)(c_i - b_i + b_{l_i} - a_{l_i})} & \text{if } b_i \leq \lambda \leq c_i. \end{cases} \quad (12)$$

$$\beta_k = \max_{\lambda} \min \{\mu_{l_i}(\lambda), \mu_{s_k}(\lambda)\} \quad (13)$$

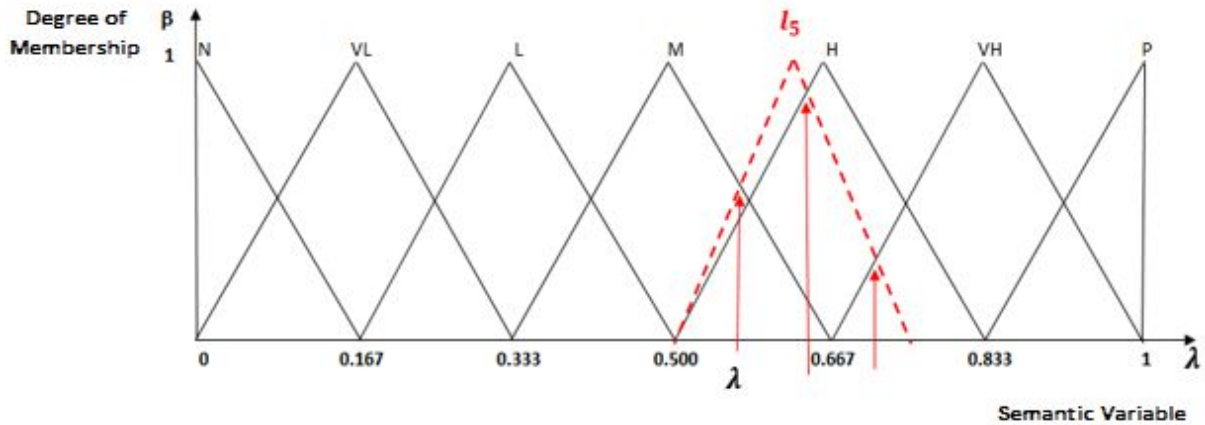
Where  $(S_T)$  is the set of fuzzy sets defined in  $S_T$ , and  $\mu_{l_i}(\cdot)$  and  $\mu_{s_k}(\cdot)$  are the membership functions of the fuzzy sets associated with the terms  $l_i$  and  $s_k$  respectively.

Therefore, the result of  $\tau_{LS_T}$  for any linguistic value of  $L$  is a fuzzy set defined in  $S_T$ .

For instance, if we have a linguistic term set  $L = \{l_0, l_1, \dots, l_8\}$  with 9 labels having the following semantics associated with them.

$$l_0 = (0,0,0.125), l_1 = (0,0.125,0.25), l_2 = (0.125,0.25,0.375), l_3 = (0.25,0.375,0.5), l_4 = (0.375,0.5,0.625) \\ l_5 = (0.5,0.625,0.75), l_6 = (0.625,0.75,0.875), l_7 = (0.75,0.875,1) \text{ and } l_8 = (0.875,1,1)$$

Figure 15 illustrates how the assessed attribute's linguistic term set is mapped on to the basic term set.



**Figure 15: Linguistic term transformation into  $(S_T)$**

For the label  $l_5$  the degree of membership of the variable values are determined as illustrated in the following iteration.

$$s_i, \beta_i = \text{Max} \left[ \text{Min} \left( \frac{c_i b_i - b_i a_i - a_i (c_i - b_i + b_i - a_i)}{(b_i - a_i)(c_i - b_i + b_i - a_i)}, 1, \frac{c_i (c_i - b_i + b_i - a_i) - (c_i b_i - b_i a_i)}{(c_i - b_i)(c_i - b_i + b_i - a_i)} \right), 0 \right] \quad (14)$$

$$s_3, \beta_3 = \text{Max} \left[ \text{Min} \left( \frac{0.75 * 0.667 - 0.625 * 0.333 - 0.333(0.75 - 0.625 + 0.50 - 0.333)}{(0.50 - 0.333)(0.75 - 0.625 + 0.50 - 0.333)}, 1, \frac{0.667(0.667 - 0.50 + 0.625 - 0.50) - (0.667 * 0.625 - 0.50 * 0.50)}{(0.667 - 0.50)(0.667 - 0.50 + 0.625 - 0.50)} \right), 0 \right] = 0.5714$$

Similarly,  $s_4, \beta_4 = 0.8571$  and  $s_5, \beta_5 = 0.2857$

Hence for label  $l_5$  the transformation yields the fuzzy set,

$$\tau_{ST}(l_5) = \{(s_0, 0), (s_1, 0), (s_2, 0), (s_3, 0.5714), (s_4, 0.8571), (s_5, 0.2857), (s_6, 0)\}$$

Hence the assessed attribute belongs to the medium( $s_3$ ), high ( $s_4$ ) and very high( $s_5$ ) descriptors with 57.1%, 85.7% and 28.6% degrees of membership respectively in the basic linguistic term set.

### 3.2 Fuzzy Model Architecture and Inferencing

Mendel [56] provides a detailed description of the structure of a general fuzzy inference system (FIS). We construct a FIS applied to the power control drives remanufacturing scenario based on Mendel's generalized form. Figure 16 shows the FIS for our case which is composed of four important performance indicators—namely, technical remanufacturability indicator (TRI), the economic remanufacturability indicator (ERI), resource utilization indicator (RUI) and environmental effect indicator (EEI). These four models which are generated from the first four models are then aggregated to form the remanufacturability indicator (RI) model. For each of the five fuzzy models the evaluation process proceeds in four steps namely, fuzzification, inferencing, composition and defuzzification.

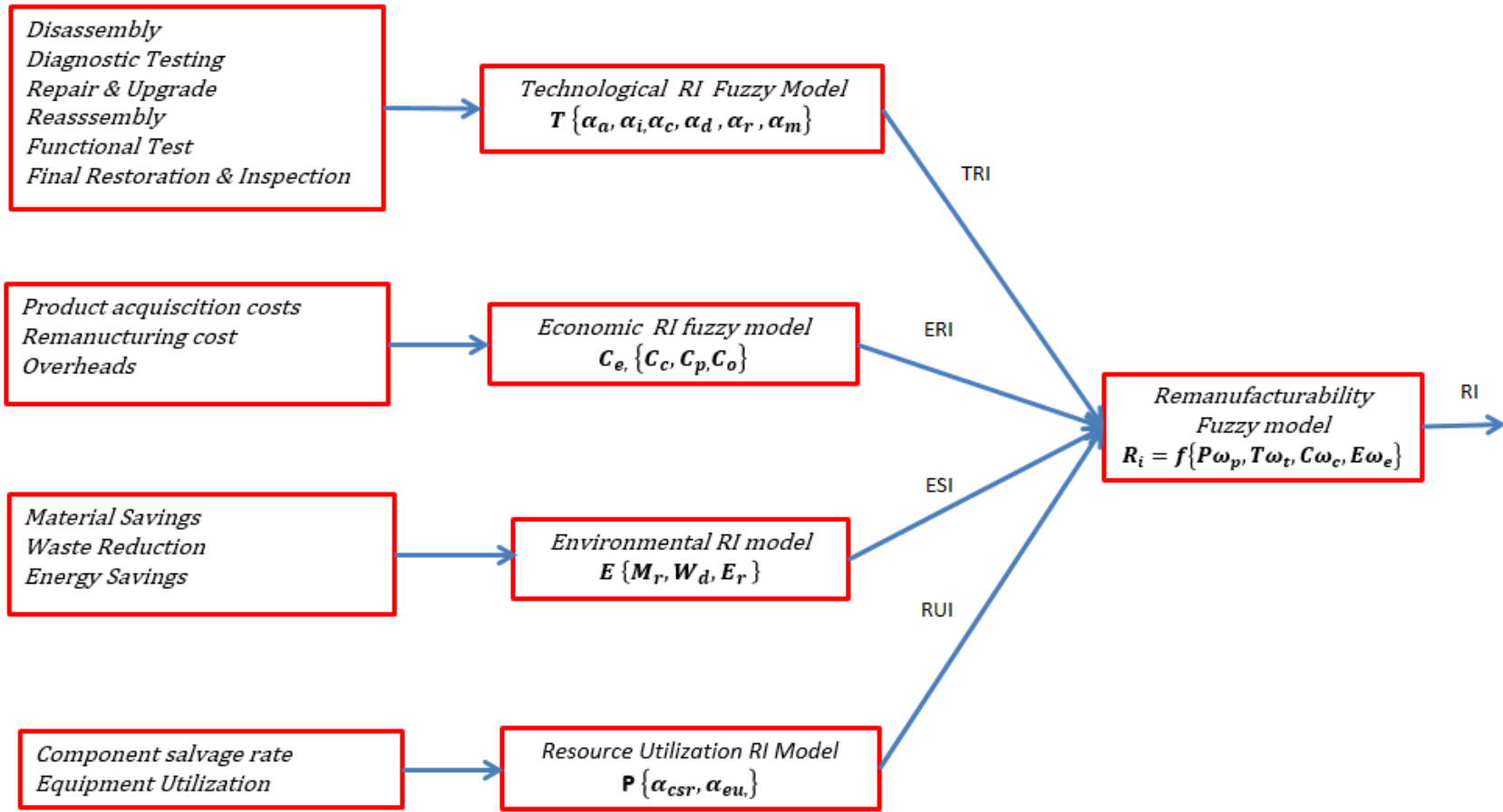
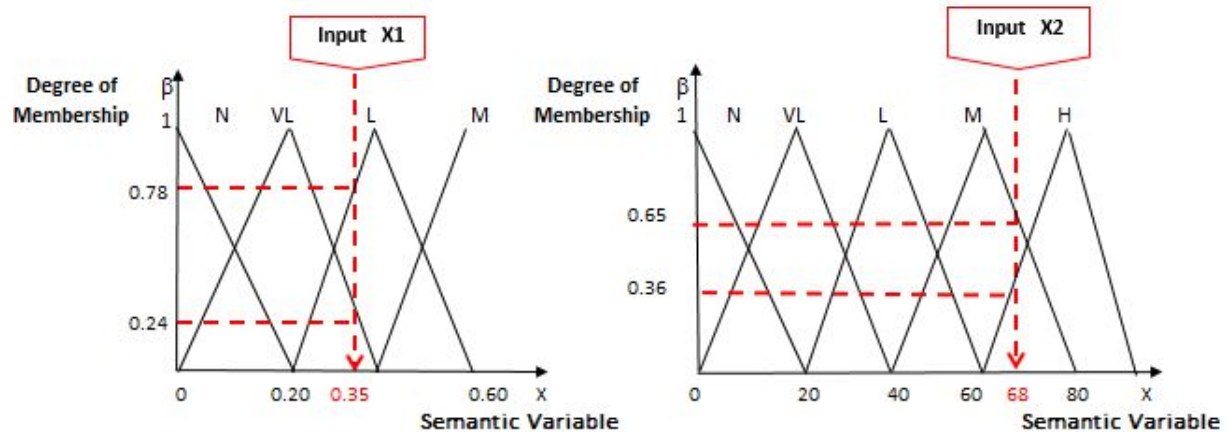


Figure 16: FIS System Architecture



We summarize the stages of FIS in this section as follows:

To understand the fuzzification stage, we will first introduce the term “rule”. Rules in our case are determined by the membership of an input variable into a subset of the basic fuzzy terms  $s_i$ . For instance, a rule may be stated as a set of premises, where one premise could be that: “Disassembly = low AND Diagnostic Testing = High.” Generally, we express a rule  $i$  as  $R_i: \{X_1 \text{ is } S_1, \text{ and } X_2 \text{ is } S_2 \dots \text{ and } X_k \text{ is } S_k\}$ . *Fuzzification* therefore involves applying membership functions defined on the input variables ( $\lambda$ ) to determine the degree of truth for each rule for a given input variable using Equations (1), (2), and (3). If a rule's premise has a nonzero degree of truth (i.e. if the rule applies) then the rule is said to “FIRE”. Figure 17 illustrates the fuzzification stage of the FIS system. Fuzzification is important because it enables the activation of the fuzzy rules. The output of the fuzzification stage (which is the input to the inferencing stage) is the set of rules that are fired/activated) by the given input variable.



**Figure 17: Input Variable Fuzzification (considering two ranges of input variables X)**

*Inferencing* stage involves the computation of the truth value for each premise of

the rule, and its application to the outcome of each rule. The rules which take the form of an “if–then” format describe the relationship between the linguistic variables of each of the performance factors for each sub–model. A typical fuzzy rule inference is generally expressed as: If  $X_1$  is  $S_1$ , and  $X_2$  is  $S_2$ ... and  $X_k$  is  $S_k$ ), then  $Y$  is  $Z_i$ . Where  $S_1, S_2, \dots$ , and  $S_k$  are the fuzzy sets corresponding to the input linguistic variables  $X_1, X_2, \dots$ , and  $X_k$  respectively while  $Z_i$  is the fuzzy set corresponding to the output linguistic variable  $Y$ . The inferencing stage results in one fuzzy subset to be assigned to each output variable for each rule e.g. “then  $Y$  is  $Z_i$ ”. The process of evaluating fuzzy rules involves the determination of the degree of truth (degree of membership) of the premise of rule  $R_i$ . The degrees of membership for  $X_1, X_2, \dots$ , and  $X_k$  are  $\beta_1, \beta_2, \dots$ , and  $\beta_k$  respectively. Just as humans use different types of inferential procedures in decision making, fuzzy inference systems use different fuzzy logic inferential procedures. The most commonly used are MIN, PRODUCT, and MAX inferential procedures. However, the MIN and PRODUCT are the most preferred in engineering applications because their implications do not violate common engineering sense [56, 57]. In MIN inferencing, the output membership function is clipped off at a height corresponding to the rule premise's computed degree of truth. In which case, the overall degree of truth of the premise takes the minimum value among the individual degrees of truth [58]. In PRODUCT inferencing, the output membership function is scaled by the rule premise's computed degree of truth. Figure 18 illustrates the inferencing approach for rule  $R_i$ , using the MIN (AND) and MAX (OR) operators. This implies that for rule  $R_i$ , the degree of membership  $\beta$  of its consequent linguistic variable  $Y_i$  is equal to the overall degree of membership,  $\beta_i$  of its premise.

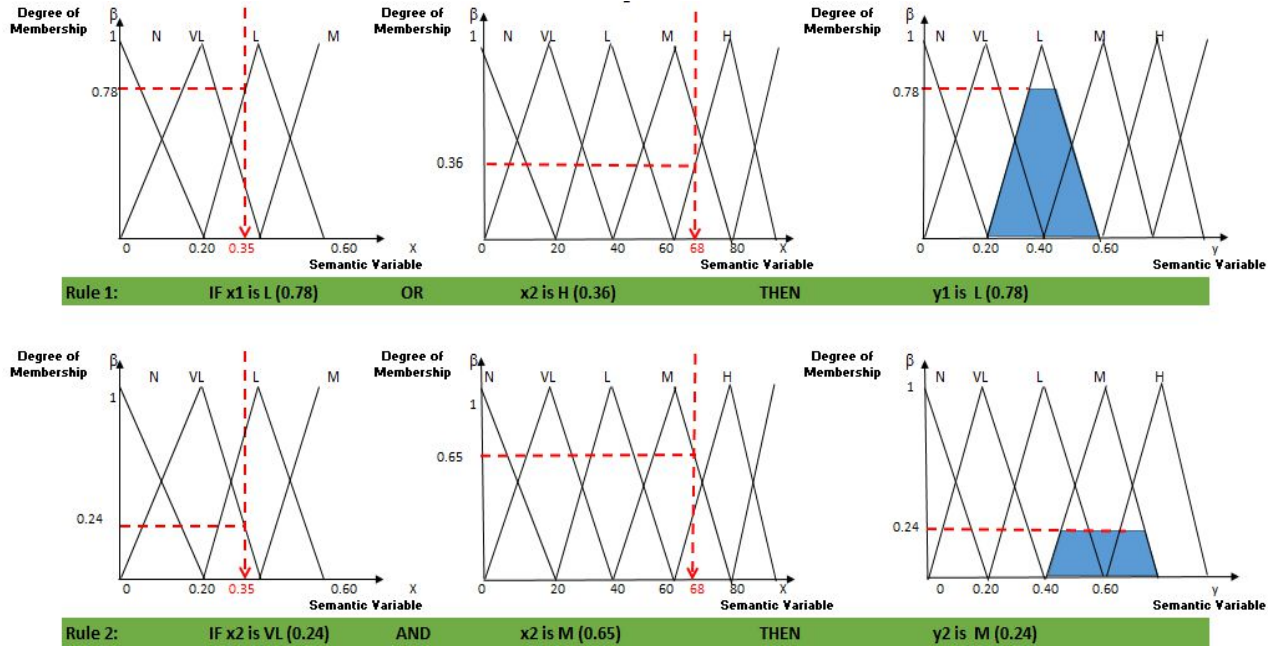
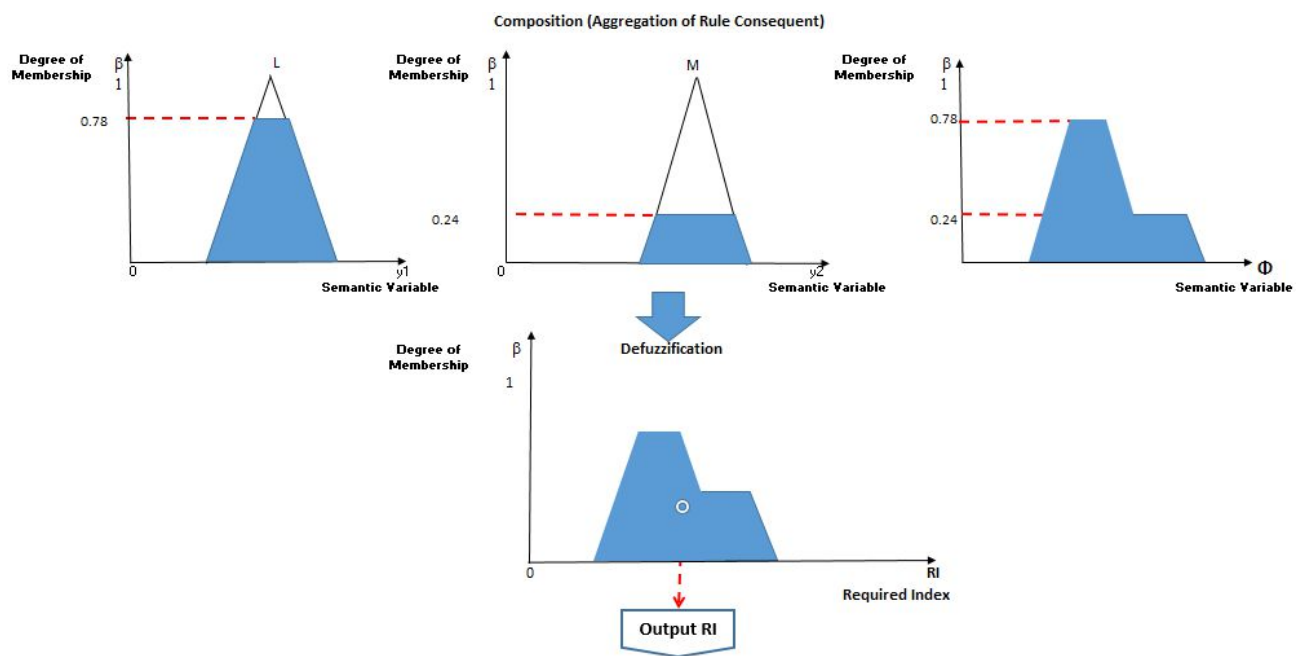


Figure 18: FIS Inferencing

Two types of FISs are widely used in a variety of applications namely, Mamdani and Sugeno models. The former was introduced by Mamdani [59] in boiler and steam engine control systems that used experienced human operators' linguistic control rules. This method has found vast application in decision systems. On the other hand, the Sugeno methodology, has widely been used in control problems particularly involving dynamic nonlinear systems such as robot operations [60] as well as optimization and adaptive techniques. In this work the Mamdani fuzzy inference method is used because it captures expert knowledge and, allows for subjective and intuitive descriptions in a more human like manner.

*Composition*, which is the next step in the FIS evaluation involves combining the fuzzy subsets assigned to each output variable  $Y_i$  for each rule  $R_i$ , to form a single fuzzy subset for the aggregate output variable  $Y$ . Usually MAX or SUM functions are used in the composition section [56]. Using the SUM function, the combined output fuzzy subset

is constructed by taking the pointwise sum of all the fuzzy subsets ( $Z_i$ ) assigned to the output variable ( $Y$ ) from the inference section. In MAX composition, the combined output fuzzy subset is constructed by taking the pointwise maximum over all the fuzzy subsets assigned to the variable by the inference rule. Figure 19 illustrates the composition and fuzzification process. For each of the sub-models we consider each of the attributes according to the domains described earlier for evaluating the remanufacturability index. The attribute inputs are aggregated fuzzy to determine an output which represents the remanufacturability indicator for the model.



**Figure 19: FIS Composition and Defuzzification**

*Defuzzification* is used to convert the fuzzy output set (symbol) from the composition section to a crisp real number value for the relevant metric under consideration. A number of defuzzification methods are available for use which include, Maximum, Min of Maxima, Centroid (Center of Gravity, (COG)), Height and Modified Height defuzzification. Of this only two (CENTROID and MAXIMUM methods) are

commonly used [57]. In the CENTROID method, the crisp value is determined by finding the value at the center of gravity of the membership function for the fuzzy value. On the other hand, in the MAXIMUM method, the crisp value is chosen as the maximum truth value of the variables' fuzzy subset. This method uses the presumption that points outside the max are not optimal and therefore ignores all the information concerning the membership function that is not crisp maximal. The choice of the defuzzification method depends on the nature of analysis and the preferences in the decision-making environment. In this work, the centroid method is adopted because it's the most commonly used in engineering applications [61]. To obtain a numerical value that supports the output fuzzy set, we apply ( $\chi$ ) function [55] using Equation (15) as follows;

$$\chi: (S_T) \rightarrow [0, g]$$

$$\chi(S_T) = \chi(\{(s_i, \beta_i), \quad i = 0, \dots, g\}) = \frac{\sum_{i=0}^g i\beta_i}{\sum_{i=0}^g \beta_i} = \omega \quad (15)$$

Where,  $\beta_i$  is the degree of membership at the given domain of  $\beta \in [0, 1]$  in the aggregated output fuzzy region of the output linguistic variable Y.

To obtain the required indicator, we first apply a ( $\Delta$ ) functions to transform the  $\omega \in [0, g]$  into two 2-tuples that support this information using equation (16),

$$\Delta: [0, g] \rightarrow \{S_T y[0,1]\} y \{S_T y[0,1]\}$$

$$\Delta(\chi(S_T)) = \Delta(\omega) = \{(s_h, 1 - \gamma), (s_{h+1}, \gamma)\} \quad (16)$$

Where,

$$h = \text{trunc}(\omega) \text{ and } \gamma = \omega - h$$

Finally, we determine the required remanufacturability index using Equation (17)

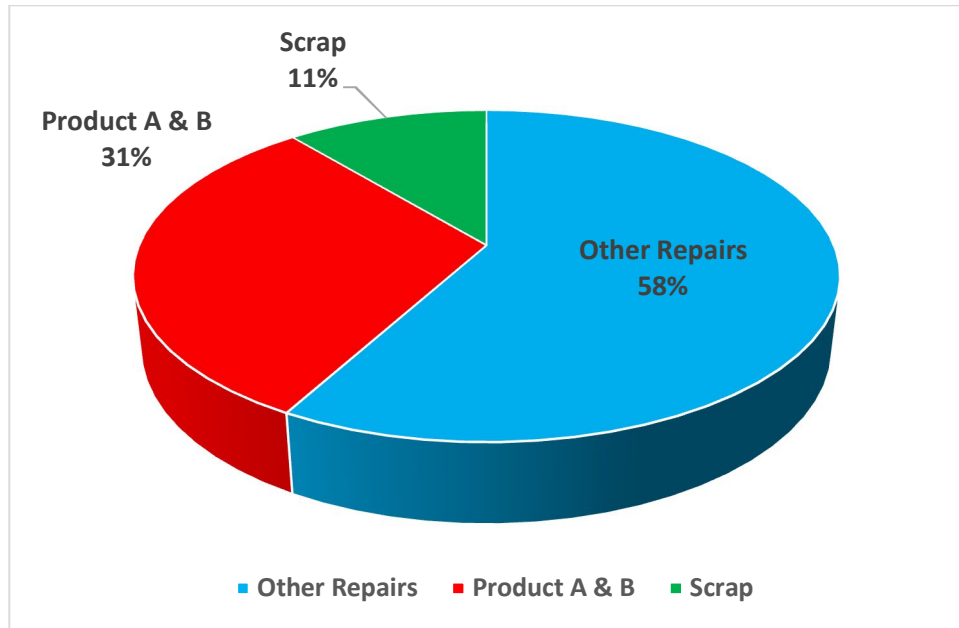
$$RI = y = k\{(s_h, 1 - \gamma), (s_{h+1}, \gamma)\} = CV(s_h) * (1 - \gamma) + CV(s_{h+1}) * \gamma \quad (17)$$

Where,  $CV(s_h)$  and  $CV(s_{h+1})$  are the characteristic values of the linguistic labels  $(s_h)$  and  $(s_{h+1})$  of the output variable respectively.

## CHAPTER 4: DATA COLLECTION, AND PLANT PERFORMANCE EVALUATION USING PROMODEL SIMULATION

### **4.1 Remanufacturability of Used Control Drives**

The case study plant has been remanufacturing control drives in the region for over a decade. The setting up of the facility was motivated by environmental concerns as well as profit maximization. The facility has been growing over the years with cores of control drives being received at the plant increasing annually. At the time this data was collected the remanufacturing plant was receiving 32,117 products annually. Figure 20 shows that, of the cores received and remanufactured, two product families accounted for 31% while the rest of the product types combined accounted for 58%. The products are usually received with various degrees of damage or malfunction. About 11% of them may not be renewed or remanufactured and thus this portion of the products are disassembled to redeem parts that can be reused while those that cannot be reused in their original form are recycled. Most of the products that arrive at the plant are either those recently supplied and are covered by warranties but fail in the field and the field servicemen are not able to repair on site, or those products previously sold but need to be renewed or upgraded for reuse by customers or sale as remanufactured products. Other reasons for take back include products that are damaged during transportation. The plant also remanufactures third party products.



**Figure 20: Distribution of Cores received at the plant Dec 2012 - Nov 2013**

## **4.2 Data Collection and Input Analysis**

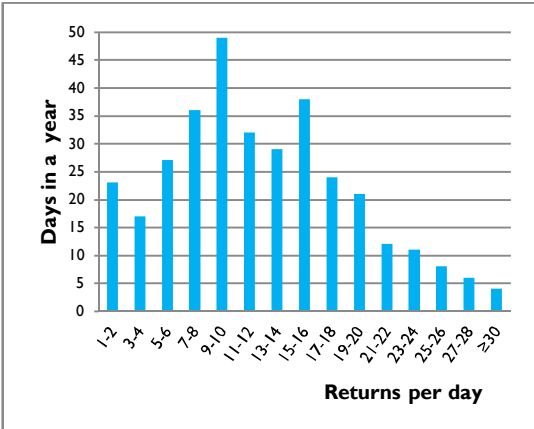
We obtained the data used in this study from an OEM remanufacturing plant. We studied the system in order to identify the characteristics and operations of the system under study. We then identified the principal inputs to feed into the simulation model. Our model is based on two products families herein referred as Product A and Product B, given that they account for the highest percentage of the cores remanufactured at the plant.

Compared to manufacturing, control drive remanufacturing process is more complex because of uncertainties caused by variability in the availability and condition of returned control drives, warranty status of the products, material, geometry and structural restrictions as well as software migration [62]. Product return dynamics is an important aspect of remanufacturing. Figure 21 shows the trend of returns for products A and B in

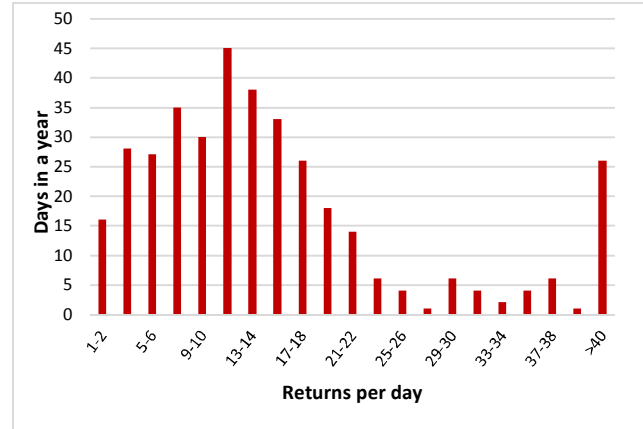


terms of the number of product returns per day. It is evident that there is a high variability in the product returns for both product streams. When a remanufacturing plant receives product returns at unpredictable rates and highly variable quality the remanufacturing operations become more complex to plan, manage and control [63].

The company receives approximately 4,195 of product A cores annually. Using the ProModel probability distribution fitting feature, the core inter-arrival time distribution is determined to be Weibull with a shape parameter  $\alpha$ , of 1.73 and a scale parameter  $\beta$ , of 13.2 hours (Appendix I). Therefore, in this study, Weibull (1.73, 13.2) is used to model the inter-arrival time for product A. For product B, approximately 6,000 cores are received annually. The data significantly fits the exponential distribution, with a mean arrival rate of 12 products daily. This translates to one core per hour for a 12-hour work day, hence the exponential distribution Expo (60 min) is assigned to model the inter-arrival time for product B. These findings are intuitive given that product arrival rate is a surrogate indicator of the rate of failure which can indeed be modeled as a Weibull distribution (in the case of aging failures as indicated by a  $\beta > 1$ ). In addition, when the Weibull shape parameter  $\beta = 1$ , the failure rate is said to be constant (random failures during normal usage), and thus reduces into an exponential distribution. One other important correlation that can be drawn from the inter-arrival rate is that, while product A has been in the market for more than 10 years, product B is relatively new and has been in the market for less than 5 years. Thus, product A may already have started to experience maturity failures (phase III of a typical reliability bathtub curve) while product B exhibits phase II failures. Depending on the outcome of the sorting process, some returns are marked for remanufacture while others are scrapped.



a) *Product A Returns*



b) *Product B Returns*

**Figure 21: Variability in quantity of returns for: (a) Product A and (b) Product B**

Figure 22 illustrates the steps involved in the remanufacture of control drives. These include: receiving, inspection and sorting, disassembly, cleaning, diagnostic testing, part reconditioning and upgrading, reassembly, testing, and final restoration and inspection. Firstly, the discarded control drives are completely disassembled, and the reusable parts cleaned, reconditioned, and put into the inventory. The remanufactured control drives are reassembled using reconditioned parts and subassemblies (and when necessary, new parts are procured).

The warranty status of the returned product highly affects the profitability of a remanufacturing firm. Once returns have been sorted and cleared for remanufacture, their warranty status is ascertained. For a product to be considered warrantable it must be within 24 months of manufacturing, must have been used by the customer and must not be physically damaged by the customer. Upon verification of the warranty status, the personnel at the receiving section assigns a bar code to the unit for easy tracking of repair

history and order status.

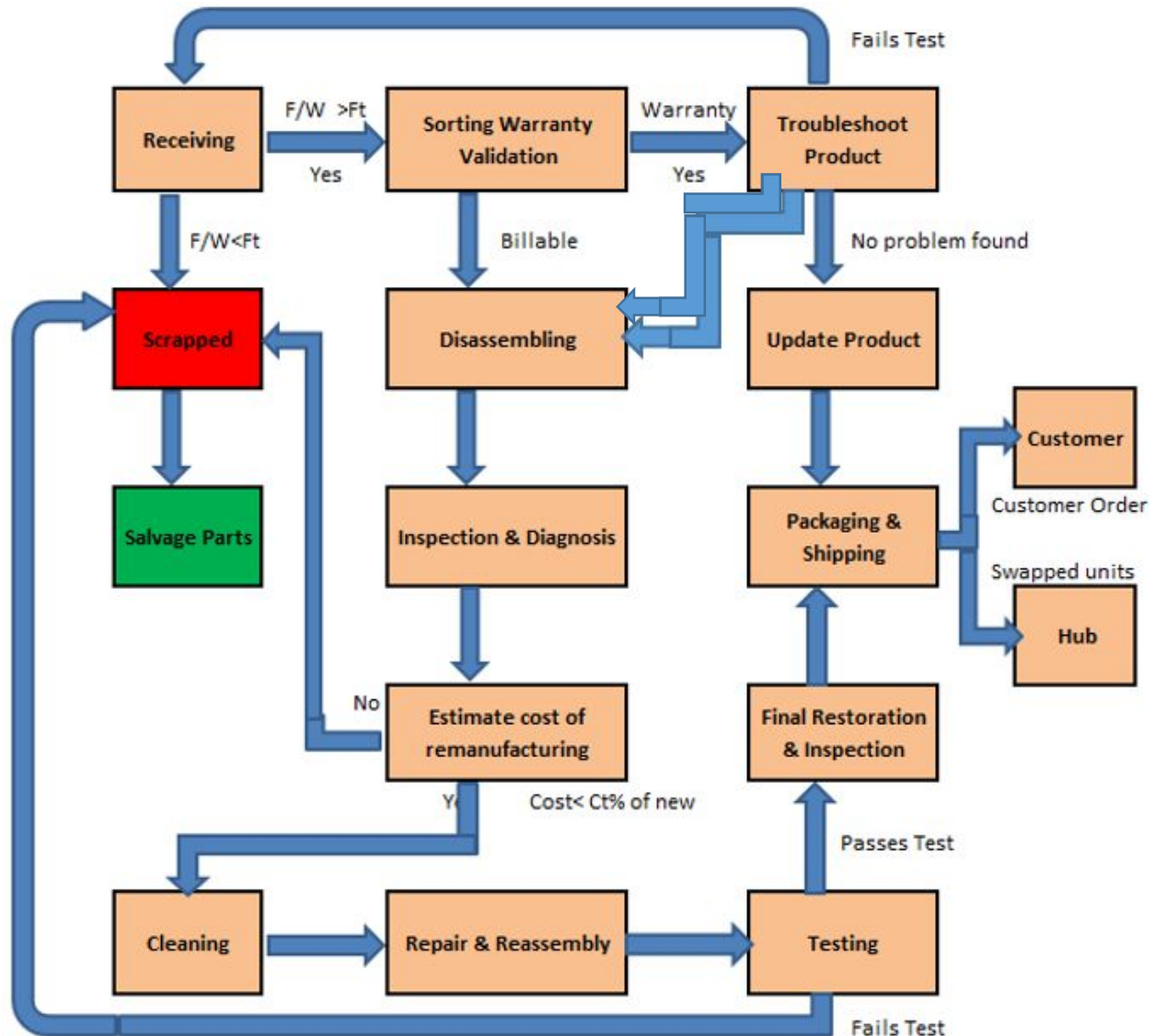
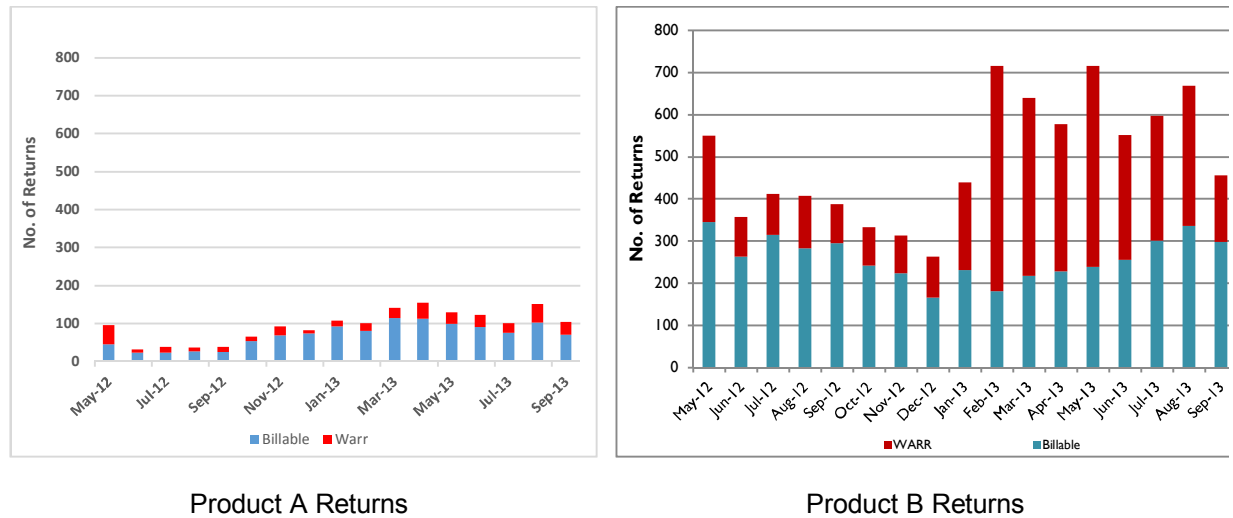


Figure 22: Control Drive Remanufacturing Process

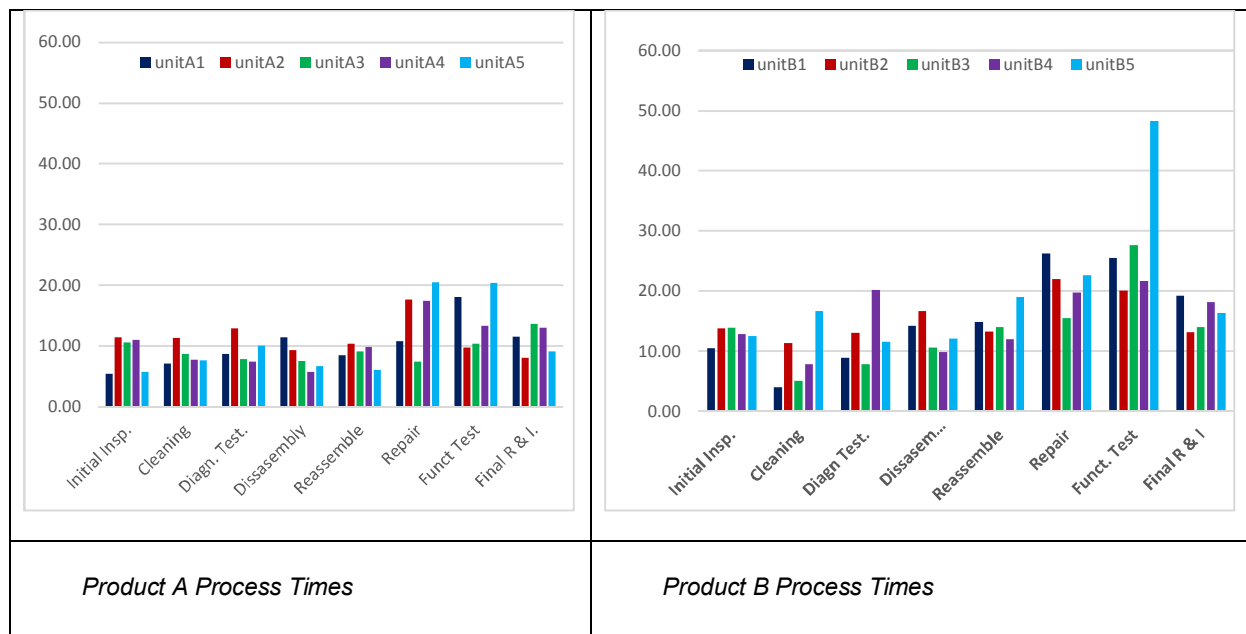
Figure 23 shows the distribution in the number of billable and warranty returns for products A and B. Of the two products, product A has a healthy return profile since much fewer warranty returns are received compared to billable returns. Product B on the other hand has a highly variable return pattern with some instances showing more warranty returns than billable returns—which is typical for products that are in the early market

phase. Since warranty returns have to be remanufactured to as good as new condition at the remanufacturer's expense and returned to the customer, a high number of warranty returns implies a high financial burden on the remanufacturing plant.



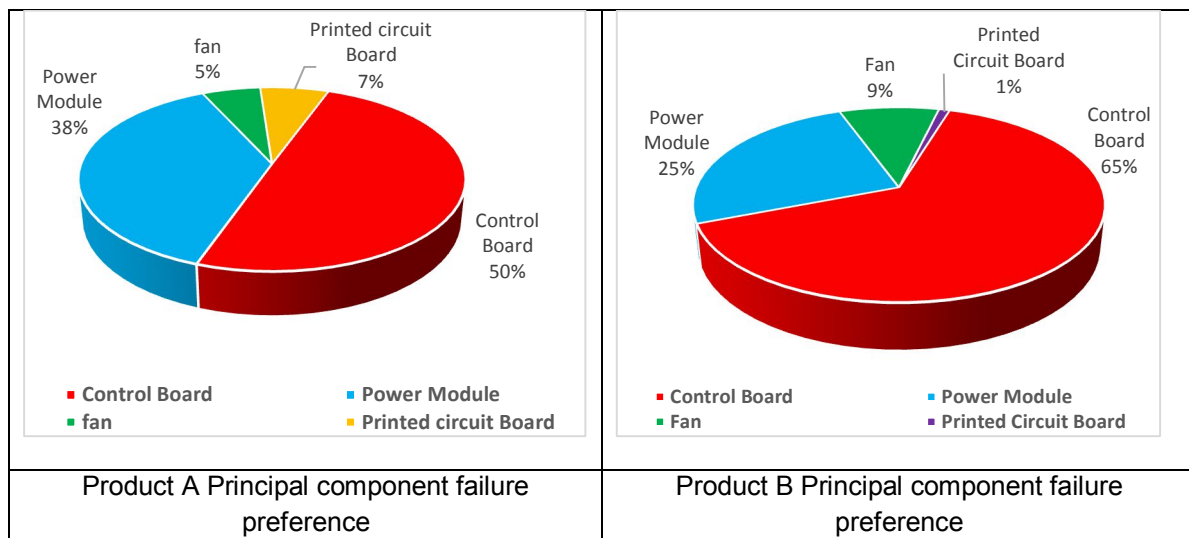
**Figure 23: Variability in billable and warranty returns for: (a) Product A and (b) Product B**

Upon verification of the warranty status, the returns go through the remanufacturing process. Unlike conventional manufacturing in which the products follow a dedicated process from raw material processing through to the final assembly point with almost constant production time, remanufacturing process times are extremely variable. To understand the variability in process times, we carried out detailed remanufacturing process and time observations at the remanufacturing plant. Five units of each product were considered and the processing times from start to finish recorded. Figure 24 shows the distribution of the process times observed for the two product streams. It was observed that there is high variability in the processing times for both units with the repair and functional test processes exhibiting very high levels of variability.



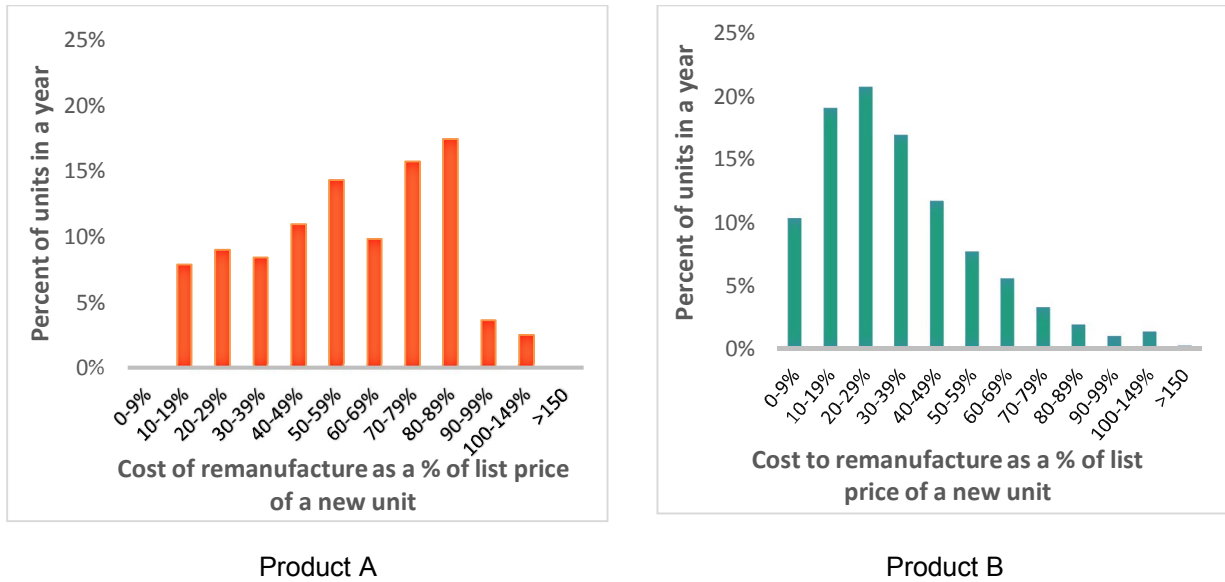
**Figure 24: Distributions of Processing Times for Product A and Product B**

During the inspection of the returns for remanufacture certain conditions must be fulfilled to warrant replacement of parts otherwise the whole unit is replaced and the return scrapped for parts and material recovery. For a unit to be remanufactured, it should be free from corrosion or extreme contamination, have a working power module, and be free from severe burns, dents or discoloration. The principal components of a control drive are the power module also known as switching power supply (SPS) board, control board (CB), printed circuit board (PCB) and the cooling fan. These together with the relays are the most commonly replaced parts in remanufacturing of control drives. Figure 25 shows the percentage distribution of the failure rates of the principal components for a total of 4195 product A returns and 6124 product B returns. It was observed that for both products, the control boards account for the highest percentage of failures at almost 50% and 65% for product A and B respectively followed by the power modules.



**Figure 25: Failure Preference of Principal component parts of returns for Product A and B**

By remanufacturing, the residual value of the used control drives can be fully used and the performance of remanufactured control drives restored to be as good as new. In addition, the cost of remanufactured drives may at times be as high as 120% of the cost of new ones. Figure 26 provides a summary of the cost of remanufacture as a proportion of the cost of new drives. According to the experts at the company, a control drive is feasible for remanufacture if the cost of remanufacturing a unit is less than 60% of the cost of the equivalent new product.



**Figure 26: Variability in the Cost of Remanufacture as a Source of Uncertainty**

### 4.3 Performance Evaluation Simulation Model

#### *Process flow and requirements.*

In our model, we considered two product families, A and B because these products account for the highest percentage of the cores received and remanufactured in the facility, representing 31% of the total cores received and processed in the plant annually. There is an 80% chance of the returned products being repairable, and a 20% chance of the returned products being unrepairable, hence disassembled to salvage reusable parts. Of the salvaged parts, 75% are reusable and 25% not reusable and hence are scrapped for recycling or disposal. Table 2 shows details of the system's processing zones and their production capacity for each of the two product families.

**Table 2: Details of activity times and location capacities**

Processes	Location	Service Time (Min)		Capacity	
		Product A	Product B	Product A	Product B
1	Arrival	Weib(1.73, 13.2)	Expo(60)		
2	Registration	Norm(5,1.5)	Norm (5,1.5)	1	1
3	Diagnostic testing	Norm (14.5, 5)	Norm (10, 2.5)	1	1
4	Repairing	Norm (22, 3.5)	Norm (14, 484)	2	1
5	Cleaning	Norm (10.5, 5)	Norm (8,1.8)	2	1
6	Finished product Testing	Norm (31.5, 9.5)	Norm (16.5, 4.5)	1	1
7	Disassembling	Norm (14,3.5)	Norm (9.5, 2.5)	2	1
8	Finished product Storage	Norm (90, 30)	Norm (90, 30)	Inf.	Inf.
9	Final restoration and inspection	Norm (16,5)	Norm (12,2.5)	2	1
10	Sorting	Norm (5, 2.5)	Norm (5,2.5)	1	1
11	Scrap	Norm (4, 1)	Norm (4, 1)	1	1

The process model presented in this work represents one of the actual control drive remanufacturing processing lines of the company in the case study. Figure 27 shows the model layout of the remanufacturing plant. In evaluating the system, system performance measures of interest were identified as:

- Average time products spent in the system
- Number of parts reused
- Number of parts scraped
- Percentage of new parts used to repair products
- Percentage utilization of the resources



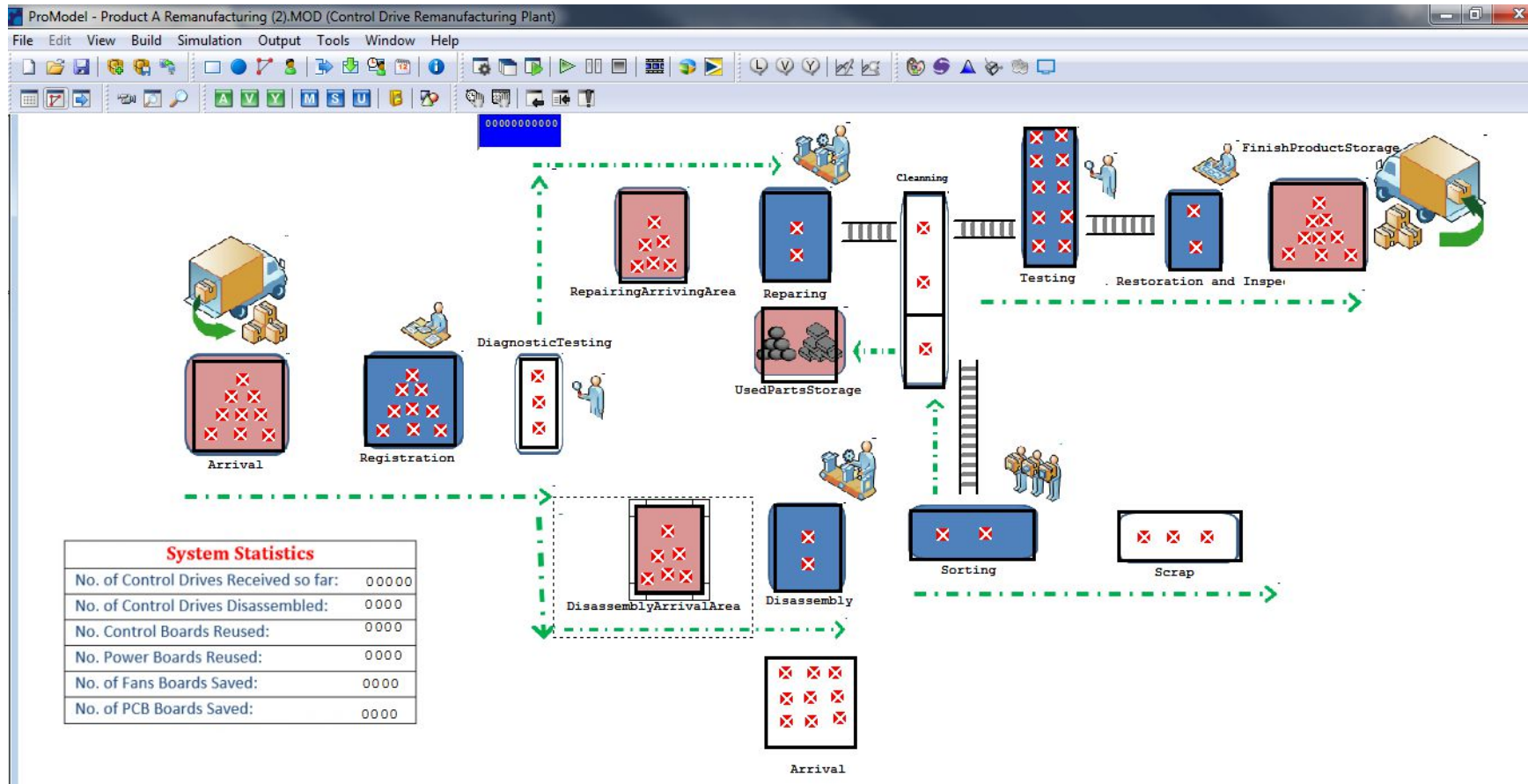


Figure 27: ProModel View of the Remanufacturing Process Layout

The elements of the model consist of 20 locations, 6 entities, 3 arrivals and 14 global variables. The global variables are used to track the number of cores received, the number of component parts reused, number of component parts scrapped and the number of remanufactured units exiting the system.

#### **4.4 Model Verification and Validation**

The model was run with animation to see if the products followed the processing sequence as specified in the model. We checked the execution of the send concept at the disassembly section and the join command at the assembly part of the process and verified that they were working. We also carried out a 95% confidence interval analysis of the key performance metrics and established that the model results were within the expected output. The results are presented in the appendices section.

#### **4.5 ProModel Simulation Experiment Results**

Each of the work cells operates on two 8-hour shifts a day. Therefore, the model runs for 96 hours which represents one week's operations for 16 hours a day, 6 days a week. Six replications were performed for each simulation for product A and B and detailed results of the averages, standard deviations and the 95% confidence intervals of the key system performance measures are presented in Appendices I, II and III. Table 3 shows the average time each entity (core/component part) spends in the system. This time represents the sum of the average time the product spends in operation and the average time the entity is blocked in the system. The results show that the average time a control drive spends in the system is 194 minutes for product A and 743.5 minutes for

product B. The unrepaired control drive takes the least amount of time in the system because once this entity reaches the disassembly section it is disassembled into four component parts, that is, the control board, power board unit, fan and PCB boards. This implies that at that point the control drive entity exits the system and is replaced by the four new entities which are the constituent components of a control drive.

These entities are then channeled to the sorting section to determine reusability and if they are reusable they are cleaned and stored to await a need to arise for them to be used in repairing a control drive in the repair section.

**Table 3: Experimentation Results for Product System Entities**

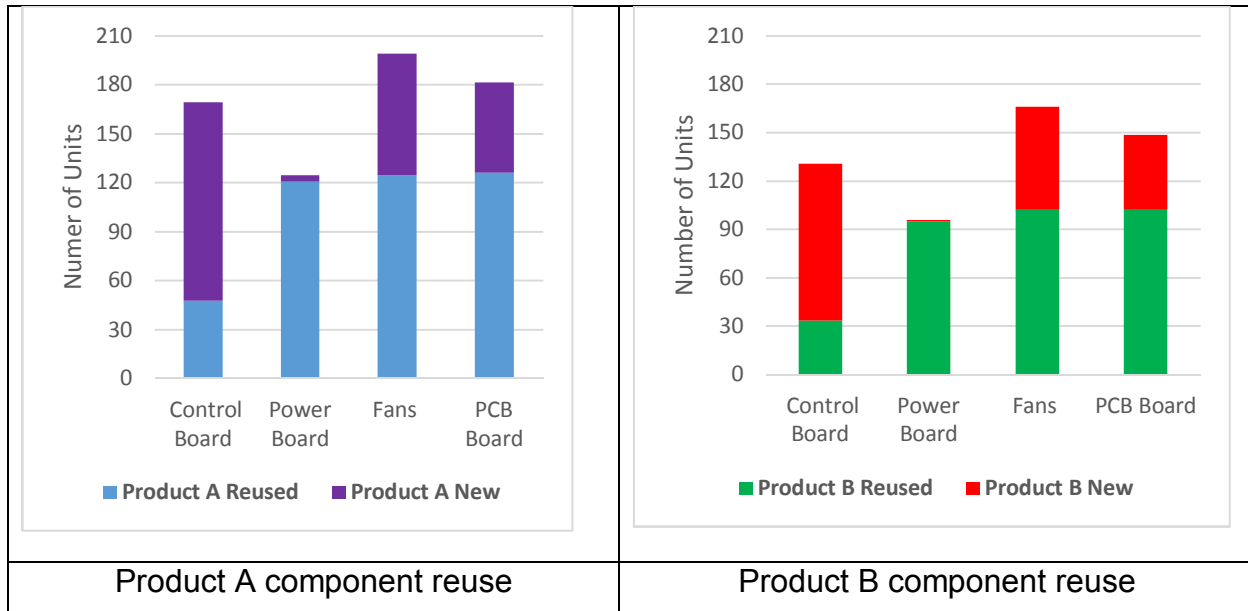
Entity	Total Exits		Ave. time in System		Ave. time in operation		Ave. time blocked	
	A	B	A	B	A	B	A	B
Control Drive	308	251	193	516	167	222	27	294
Control Board	106	85	2753	2925	22	14	5	3
Power Board	98	87	2841	2870	19	15	4	3
Fan	163	129	2907	2872	25	20	6	5
PCB Board	158	129	2881	2957	25	19	6	5
Unrepaired Control Drive	165	133	35	299	25	33	10	265

Global variables are used to track the number of items exiting a given process. Appendix III has the full details of the system statistics for the global variables. Table 4 shows the average values of the global variables tracked in this model and their respective values for product A and B.

**Table 4: Experimentation results for variables**

<b>Variables</b>	<b>Current Value</b>	
	<b>A</b>	<b>B</b>
Number of control drives received	486	428
Number of control drives disassembled	166	133
Number control boards reused	48	33
Number of power boards reused	121	95
Number of fans reused	124	102
Number of PCB board reused	126	102

The simulation results indicate that approximately 34% of product A and 31% of product B control drives arriving in the facility are disassembled to recover parts for reuse. The rest of the returns are thus repairable. For most of the component parts the number of new parts used to repair the control drives is fewer than the number of reused parts. Figure 28 shows a comparison of the number of new and reused component parts used in the repair of the control drive. Thus, for both product A and B, most of the control drives are returned due to failure of control boards in the field. It was reported that on diagnosing the returned control drive, if the power board is found faulty, the unit is disassembled to recover other usable parts, otherwise it is remanufactured. Since most of the parts are reused in remanufacturing the returns, there are substantial savings in terms of materials, energy and labor realized that would have been used if only new parts were used in the repair of the cores.



**Figure 28: Component Reuse for Both Product A and B**

Table 5 is a summary of the percent utilization and total entries for each location. The statistics show that utilization for most of the locations is over 50% for both product families. However, the diagnostic testing and the functional testing centers have very high utilization levels of more than 80% in both cases. This may be attributed to the fact that testing takes more time and sometimes prompts for a retest if a unit fails the initial test.

**Table 5: Experimentation Results for Process Locations**

Process	Capacity		Total Entries		Average time per entry		Average Content		% Utilization	
	A	B	A	B	A	B	A	B	A	B
Registration	1	1	485	399	8.3	14.2	0.7	1.0	70.2	98.6
Diagnostic Testing	1	1	485	398	10.0	14.4	0.8	1.0	84.1	99.6
Repairing	2	2	395	330	14.5	22.8	1.0	1.3	49.7	65.4
Cleaning	1	1	393	328	8.6	11.5	0.6	0.7	58.5	65.4
Testing	2	2	393	325	17.4	31.7	1.2	1.8	59.3	89.3
Final Restoration and Inspection	1	1	315	256	12.0	16.0	0.7	0.7	65.6	70.9
Disassembly	2	2	166	133	9.5	13.9	0.3	0.3	13.6	16.1

Generally, the current system indicates a situation where the registration, diagnostic testing center, testing and final restoration and inspection sections are over utilized with over 70% utilization whereas other zones are underutilized. The system is therefore not balanced and will need some improvement to ensure proper utilization of locations to enhance a balanced remanufacturing process. We therefore carry out a modification to address the bottleneck areas especially the diagnostic testing and the testing process.

Given that the diagnostic testing center and the after-repair testing center are highly technical processes the control drive spends most of the time in this processes. We therefore consider a scenario of an increased capacity of the diagnostic testing for both product A and B from 1 to 2. We also increased the capacity of registration for product B from 1 to 2 but retained the capacity of registration for product A at 1. We maintained the testing resources for product A at 2 but increased that of product B to 3. The main implication to this arrangement is that more space will be required in the testing center for product B to setup the testing of the extra 1 units. Once the control drive test is set running the technicians only need to check for output data from the computer connected to the testing system. Table 6 shows the current and suggested capacities for the new scenario. The results of the modifications of the model are presented in Table 7 and Table 8.

**Table 6: Possible system variations**

Process	Current Capacity		New Capacity (after Modification)	
	A	B	A	B
Registration	1	1	1	2
Diagnostic Testing	1	1	2	2
Repairing	2	2	2	2
Cleaning	1	1	1	1
Testing	2	2	2	3
Final Restoration and Inspection	1	1	1	1
Disassembly	2	2	2	2

**Table 7, Experimentation results for entities of the modified system**

Entity	Total Exits		Ave. time in System		Ave. time in operation		Ave. time blocked	
	A	B	A	B	A	B	A	B
Control Drive	317	259	186	227	168	208	18	20
Control Board	102	120	2953	2849	25	18	6	4
Power Board	100	50	2906	2783	24	12	6	2
Fan	163	142	2803	2877	27	21	7	5
PCB Board	162	135	2840	2858	27	21	7	6
Unrepaired Control Drive	167	146	25	34	24	33	1	1

Table 7 presents the results of the entities of the modified system. The new results show that there is an overall improvement in the performance of the system. For instance, average time a control drive spends in the system reduced from 193 minutes to 186 minutes for product A and from 516 minutes to 227 minutes for product B. This is a significant improvement especially for product B in which the time was reduced by more than 50%. At the same time the time the control drive is blocked in the system reduced from 294 minutes to just 20 minutes which is more than 93% reduction. The number of control drives exiting the system has also increased for both product A and B. There is therefore an overall improvement in the performance of both systems. This could reduce lead time and enhance customer satisfaction.

Table 8 shows that the percent utilization of the various locations or process center for both product A and product B are balanced. This is attributed to the removal of the bottlenecks especially in the diagnostic testing and the testing centers that were causing system blockage. Bottlenecks caused control drives spend more time in the system than necessary.

Generally, the new system indicates an improved scenario with more Control drives being repaired and Control drives spending less time in the system

**Table 8: Experimentation Results for Process Locations**

Process	Capacity		Total Entries		Average time per entry		Average Content		% Utilization	
	A	B	A	B	A	B	A	B	A	B
Registration	1	2	494	418	5.1	5.8	0.4	0.4	43.8	50.9
Diagnostic Testing	2	2	493	417	10.0	14.4	0.9	1.0	42.7	52.3
Repairing	2	2	405	328	14.7	22.0	1.0	1.3	51.6	62.6
Cleaning	1	1	403	326	8.6	10.5	0.6	0.6	60.1	59.5
Testing	2	3	403	326	17.9	32.1	1.2	1.8	62.4	60.6
Final Restoration and Inspection	1	1	322	264	12.1	15.5	0.7	0.7	67.4	71.3
Disassembly	2	2	167	147	9.5	13.9	0.3	0.4	13.7	17.7

#### 4.6 Discussion and Conclusion

In the current system, more especially for product B, the registration, diagnostic testing and the after-repair testing centers are over utilized, whereas the other locations are underutilized, and the number of products shipped is relatively low. Varying the capacities of these centers significantly improved the system performance.

The time a control drive spends in the system has also been reduced by 3.6% for product A and 56% for product B. This is a tremendous improvement indicating that



cumulatively a lot of time will be saved if a whole year's operation is considered given the number of to control drives that will be serviced/remanufactured. The results from this evaluation model are used in assessing the technical attributes and resource utilization part of the fuzzy inference (Section 3.6) for determining remanufacturability index of the control drives.

The number of new component parts used is much fewer than the number of reused component parts used in the repair of the control drives exiting the system. It is evident that there are huge savings in terms of materials, energy and labor that would have been used if only new parts were used in the repair of the control drives. In fact, most companies involved in the remanufacturing activities report savings of more than 20% on energy consumption alone.

## CHAPTER 5: FUZZY INFERENCE SYSTEM FOR DETERMINATION OF REMANUFACTURABILITY INDEX (RI)

### 5.1 Introduction

Figure 16, in Section 2.3 illustrated the architecture of the Fuzzy Inference System architecture used to determine the remanufacturability index (RI) for control panels. In brief, the FIS in our case is composed of four important performance indicators—namely, technical remanufacturability indicator (TRI), economic remanufacturability indicator (ERI), resource utilization indicator (RUI) and environmental effect indicator (EEI) which are aggregated in the remanufacturability indicator ( $R_i$ ) model.

### 5.2 Evaluating the Technical Remanufacturability Indicator (TRI)

As opposed to manufacturing directly from virgin materials, remanufacture of control drives is a complex process given that the cores are received with varied conditions. The variabilities in core quality subsequently affects the quality of remanufactured control drives which is extremely important for the consumers. Some products or parts may not be remanufacturable due to their poor status and some parts may fail during the remanufacturing process. To guarantee that a remanufactured unit can meet consumers' expectations, we evaluate its technological remanufacturability indicator for (TRI). TRI is a measure of the technical burden of remanufacturing taking into consideration the time and level of technical expertise required during the remanufacturing processes. These include assessing the level of technical burden required to disassemble, clean, sort and validate warranty status, troubleshoot, repair or

recondition, reassemble, test functionality and carry out final restoration and inspection of a returned product. In this model these aspects of the remanufacturing process are considered as the variables for the TRI. Based on the percentage of the time it takes accomplish an activity within the remanufacturing process for a unit relative to the similar processing time of a new product, each time dependent variable is assessed in the linguistic term set {very low, low, average, high, very high}. According to industry experts it is expected that for each unit in a given product line, the activity takes between 80% and 120% of the time it takes for a manufactured product. In this case the activity index is considered unfavorable if the remanufacturing process time is more than 120% of the idealized time and quite favorable if it is less than 80% of the idealized time. The activity time is therefore assessed in the linguistic term set represented in Equation (18) as follows:

$$l_i = \begin{cases} l_0 & \text{if } \lambda_i \leq 0.60 \\ l_1 & \text{if } 0.60 < \lambda_i \leq 0.80 \\ l_2 & \text{if } 0.80 < \lambda_i \leq 1.2 \\ l_3 & \text{if } 1.2 < \lambda_i \leq 1.4 \\ l_4 & \text{if } \lambda_i > 1.4 \end{cases} \quad (18)$$

$\lambda_i$  is the proportion of the time taken to carry out activity  $i$  relative to the ideal standard time for that activity respectively while  $l_0, l_1, \dots, l_4$  are elements of the linguistic term set representing very low, low, average, high and very high respectively.

### ***Inspection and Sorting***

Once a unit is received, its history is assessed using its serial number to establish whether the unit had previously been reconditioned/repared. The unit is then visually

inspected for use, contamination, defects, and damage. It is determined whether the power module and (or) control module—two of the principal components of a control drive are recoverable. Feasibility of inspection is evaluated in terms of the proportion of the time taken to diagnose a unit in relation to the ideal standard inspection time using Equation (19) and the linguistic terms are established in the linguistic term set of Equation (18).

$$\lambda_i = \lambda_{ins} = 1 - \frac{\sum_{i=1}^N B_i \times t_{ins}}{T_{ins}} \quad (19)$$

Where,  $t_{ins}$  represents the inspection and sorting time the remanufactured product/module,  $T_{ins}$  is the ideal or standard inspection and sorting time for a manufactured unit, and  $B_i$  represents the billing regime which is taken as 1.0 for a billable unit and 1.2 for a warranty unit. The inspection and sorting indicator is therefore assessed in the linguistic term set  $l_i$  using Equation (18) where  $\lambda_i$  is an intermediate variable for the inspection and criteria.

### **Disassembly**

Upon receipt and inspection of a core, the disassembly acts as the gateway of products, modules and parts to the remanufacturing process [30]. Most products were initially not designed for remanufacture and therefore may pose a challenge to disassemble sometimes taking a considerable amount of time. Depending on the level of difficulty and time taken to disassemble a product a qualitative index is assigned to the product/module. The disassembly index can be determined using expert knowledge based on the fastening structure, quantity of parts, the devices used to disassemble [64]

and level of expertise required. As was established earlier, control drives come in two categories; those that are billable to the customer and those that are under warranty.

Particular to the company in the case study, labor skillset variations and labor allocation poses an additional complexity to the remanufacturing process. In particular, units that are billable can be disassembled by either a technician or an associate while those that are under warranty can only be disassembled by a technician. In this case, a technician has more skills than an associate, implying that units under warranty have a higher technical burden than billable units. Therefore, a factor of 1.2 is applied for warranty units. Thus, the disassembly index is the ratio of the actual total time taken to disassemble all the parts of a product/module to the total idealized time [65] as shown in Equations (20).

$$\lambda_i = \lambda_d = 1 - \frac{\sum_{i=1}^N B_i \times t_i}{T_d} \quad (20)$$

Where,  $t_i$  represents the disassembly time of unit  $i$ ,  $T_d$  is the ideal or standard disassembly time and  $B_i$  represents the billing regime which is taken as 1.0 for a billable unit and 1.2 for a warranty unit. The disassembly indicator is therefore assessed in the linguistic term set  $l_i$  using Equation (18) where  $\lambda_i$  is an intermediate variable obtained from equation (12).

### ***Diagnostic Testing***

After disassembly, diagnostic testing is carried out to establish the cause of failure for the unit. This is a time-intensive non-value-adding process and can sometimes take long and delay remanufacturing due to inspection for damages, corrosion and other

defects of the drive. Feasibility of diagnostic testing is evaluated in terms of the time taken to diagnose as a fraction of the ideal time to test a remanufactured unit. The diagnostic test indicator is therefore assessed in the linguistic term set  $l_i$  in Equation (18) where,  $\lambda_i$  is determined using Equation (21)

$$\lambda_i = \lambda_{DiaT} = 1 - \frac{\sum_{i=1}^N I_i \times t_{DiaT}}{T_{DiaT}} \quad (21)$$

Where,  $t_{DiaT}$  represents the diagnostic time the remanufactured product/module,  $T_{DiaT}$  is the ideal or standard inspection and sorting time,  $\lambda_i$  is an intermediate variable.

### ***Cleaning index***

Depending on the operating environment of the returned control drive, cores/modules may be covered with dust, oil, grease and other contaminants. At this stage, contaminations such as dust, liquid, grease, and corrosion on the unit are removed/cleaned using blowers, dust remover spray, and/or alcohol wipe cloth to ensure that it looks like new. Unwanted labels are removed as well using a heat gun and their residue cleaned with alcohol wipe cloth. Some units may require advanced cleaning using a washing and drying machine. These cleaning methods have different degrees of difficulty and therefore the feasibility of cleaning is evaluated based on the time taken and the complexity of the cleaning method used. Cleaning complexity ranges from simple methods such as blowing, brushing or use of alcohol swipes, washing manually or using parts washer machine and drying them in the oven.

The cleaning indicator is therefore assessed in the linguistic term set  $l_i$  in Equation (18) where,  $\lambda_i$  is determined using Equation (22)

$$\lambda_i = \lambda_{cleaning} = 1 - \frac{\sum_{j=1}^4 t_j \times \theta_j}{\sum_{j=1}^4 t_j} \quad (22)$$

Where,  $t_j$  represents the time taken to wash the parts/modules using the  $j^{th}$  washing method and  $\theta_j$  represents the complexity of the  $j^{th}$  cleaning method.

### **Repair**

We first note that for control drive remanufacture the repair/refurbishing and reassembly activities take place almost simultaneously and there is no clear-cut separation between these processes. To isolate the two processes, we model the reparability of a unit in terms of the proportion of key components/parts reused to the number of key parts in the unit. A product's reparability is a renewal process [66]. Given that returned units come from varying operating conditions, they come with varying quality levels implying that some parts/components may fail the renewal process necessitating the use of new ones [67]. Using the method advanced by Yanbin *et al.* [25], the reparability indicator,  $\lambda_{Rep}$ , for a part/module/product can be obtained by equation (23)

$$\lambda_{Rep} = \frac{Q}{Q_T} \quad (23)$$

Where, Q represents the quantity of key components/ parts that are reused and  $Q_T$  is the quantity of key parts in the unit to be remanufactured. The ratio obtained from the foregoing equation is used to determine the membership function of the score in the linguistic term set for the reparability in the domain represented by Equation (24).

$$l_i = \begin{cases} l_0 & \text{if } 0.00 < \lambda_i \leq 0.20 \\ l_1 & \text{if } 0.20 < \lambda_i \leq 0.40 \\ l_2 & \text{if } 0.40 < \lambda_i \leq 0.60 \\ l_3 & \text{if } 0.60 < \lambda_i \leq 0.80 \\ l_4 & \text{if } 0.80 < \lambda_i \leq 1.00 \end{cases} \quad (24)$$

### **Reassembly**

The assessment score for reassembly is related to fastening components and methods used, reassembly accuracy, quantity of standard parts, reassembly path, and so on. In new product manufacture the assembly process is usually automated or structured to allow specialized assembly points along the assembly line. However, in remanufacturing the process takes place in a cell in which case all the activities are carried out within one cell. Thus the reassembly indicator is the ratio of the actual total time taken to reassemble the product/module to the total idealized time for reassembling a product/module as shown in Equations (25)

$$\lambda_i = \lambda_{Reass} = 1 - \frac{B_f \times t_i}{T_a} \quad (25)$$

Where,  $t_i$  represents the reassembly time of unit,  $T_a$  is the ideal or standard reassembly time and  $B_f$  is a factor to account for the level of expertise required which is 1.0 if it requires an associate and 1.2 if it requires a technician. Based on the percentage of time it takes to reassemble a remanufactured product in relation to the idealized time the reassembly time is assessed in the domain  $l_i$  using the linguistic term set in Equation (18).



## Testing

The warranty of a remanufactured component or product is influenced by its performance both in the factory and in the field. Two types of tests are carried on the units; dielectric test and functional test. The dielectric test, also referred to as Hipot test is used to verify that the insulation of the unit is sufficient to protect users from electrical shock while the functional test is carried out to check whether the remanufactured unit is performing to the required specification. For some products, technicians carry out these tests while in others either a technician or an associate can carry out the test. The testing criterion is therefore determined by considering the testing time and the level of complexity of the test based on the level of expertise required. To evaluate this criterion, five linguistic terms (very high, high, moderate, low, very low) in Equation (18) while the intermediate variable are obtained from Equation (26) as follows.

$$\lambda_i = \lambda_{test} = 1 - \frac{B_f \times t_{test}}{T_{test}} \quad (26)$$

Where,  $t_{test}$  represents the testing time for the remanufactured product/module,  $T_{test}$  is the ideal or standard functional testing time,  $B_f$  is a factor to account for the level of expertise required which is 1.0 for an associate and 1.2 if it requires a technician,  $\lambda_{test}$  is an intermediate variable.

According to industry experts, the testing time for each unit is expected to be between 80% and 120% of the ideal estimated time for testing a remanufactured unit. The testing time is therefore assessed in the linguistic term set  $l_i$  in Equation (18).

### 5.3 Evaluating the Economic Remanufacturability Indicator (ERI)

Remanufacturing costs of control drive  $C_R$  include the cost of core acquisition ( $C_1$ ), the cost of remanufacturing process ( $C_2$ ) and overhead cost incurred ( $C_3$ ) [68]. The core acquisition cost constitutes the cost incurred in delivering the cores to the plant as well as the cost of purchasing or trading in the cores if applicable. The remanufacturing process cost is a combination of labor, replacement parts and consumables used in the process. Remanufacturing overhead costs on the other hand are the operating expenses associated with control drive remanufacturing and they include accounting fees, advertising, depreciation, insurance, interest, legal fees, rent, repairs, supplies, taxes, travel expenses, telephone bills and utilities costs.

The total cost of control drive remanufacturing is the sum of the three cost categories as expressed in Equation (27).

$$C_R = \sum_{i=1}^3 C_i \quad i=1 \dots 3 \quad (27)$$

Since the cost of remanufacturing a product is in many cases less than the cost of manufacturing a new product, the economic index of remanufacturing is determined by calculating the ratio between the cost of remanufacturing and the cost of a new product using Equation (28)

$$\lambda_i = \lambda_e = 1 - \frac{C_R}{C_N} \quad (28)$$

Where  $C_N$  is the list price of a new control drive.

As stated earlier, according to the industry experts the cost of remanufacturing should be less than 60% of the cost of a new product otherwise the product is considered

not feasible for remanufacture and should therefore be replaced with a new unit. We therefore model the economic attribute using remanufacturing cost as a percentage of the list price and assess in the linguistic term set  $l_i$  using Equation (29)

$$l_i = \begin{cases} l_0 & \text{if } 0.00 < \lambda_e \leq 0.40 \\ l_1 & \text{if } 0.40 < \lambda_e \leq 0.60 \\ l_2 & \text{if } 0.60 < \lambda_e \leq 0.80 \\ l_3 & \text{if } 0.80 < \lambda_e \leq 1.0 \\ l_4 & \text{if } \lambda_e > 1.0 \end{cases} \quad (29)$$

#### 5.4 Resource Utilization Indicator (RUI)

At every stage in the remanufacturing process resources are utilized. These resources include the materials or component salvage rate and equipment resources utilization.

##### ***Component salvage rate***

One of the main advantages of remanufacturing is the reduction of the use of virgin materials. By reusing an end of life product in whole or in part, the value embedded in the product or part is recovered and therefore use of virgin materials is avoided [28]. To assess this performance indicator in remanufacturing we use component salvage rate (CSR). This is an important performance indicator because it reduces the total remanufacturing cost which leads to improvement of the plant's return on investment [69]. The CSR is therefore assessed in terms of the proportion of key components/parts reused to the number of key parts in the unit. A product's reparability is a renewal process [66]. Given that returned units come from varying operating conditions, they come with varying

quality levels implying that some parts/components may fail the renewal process necessitating the use of new ones [67]. The aim is to salvage as much as possible and therefore we model the component salvage rate using the evaluation term set  $l_i$  using Equation (31), where, the intermediate variable,  $\lambda_i$ , is obtained using Equation (23)

$$\lambda_i = \lambda_{cs} = \frac{Q}{Q_T} \quad (30)$$

Where,  $Q$  represents the quantity of key components/ parts that are reused and  $Q_T$  is the quantity of key parts in the unit to be remanufactured. The higher the proportion of key components reused the higher the component salvage rate.

$$l_i = \begin{cases} l_0 & \text{if } 0.00 < \lambda_{cs} \leq 0.20 \\ l_1 & \text{if } 0.20 < \lambda_{cs} \leq 0.40 \\ l_2 & \text{if } 0.40 < \lambda_{cs} \leq 0.60 \\ l_3 & \text{if } 0.60 < \lambda_{cs} \leq 0.80 \\ l_4 & \text{if } 0.80 < \lambda_{cs} \leq 1 \end{cases} \quad (31)$$

### **Equipment Utilization**

Effective use of equipment resource available for product remanufacture is a key performance measure. This is a measure of the level of throughput of the machines in the remanufacturing plant to their desired theoretical maximum. It is determined by the ratio of the number of units remanufactured to the expected theoretical maximum. The higher the percentage the better the higher the equipment utilization index of a product. We therefore model the equipment utilization in the linguistic term set  $l_i$  using Equation (31), where,  $\lambda_i$ , is obtained using Equation (32)

$$\lambda_i = \lambda_{EU} = \frac{Q_R}{Q_T} \quad (32)$$

Where,  $Q_R$  is the quantity of control drives remanufactured and  $Q_T$  is the theoretical maximum remanufacturable using the available equipment resource. The objective is to realize as much throughput as possible from the process using the available equipment resources.

### 5.5 Environmental Index

In contemporary manufacturing, companies have incorporated environmental and social aspects in their strategic plans to improve their corporate image and competitiveness. Product remanufacture impacts the environment in many ways. Key among these impacts is the amount of waste avoided through remanufacture. In this study, we consider the proportion of cores that are not remanufactured or whose components are not salvaged or sold to recycling plants as a percentage of the number of cores/components received in the plant. This metric considers the effectiveness of core acquisition, scrap material processing and remanufactured products sales strategies. The overall aim is to minimize the environmental impacts while at the same time maximizing profitability [69]. Therefore, the core disposal rate is assessed in the term set  $l_i$  using Equation (31) where,  $\lambda_i$ , is the intermediate variable determined using Equation (33).

$$\lambda_i = \lambda_{cd} = 1 - \frac{Q_{cw}}{Q_{cr}} \quad (33)$$

Where,  $Q_{cw}$  is the quantity of cores and components wasted (not remanufactured, sold or recycled) and,  $Q_{cr}$  is the quantity of cores received. The objective is to reduce wastes as

much as possible and, thus the lower the proportion of cores disposed the better the remanufacturability indicator

## CHAPTER 6: SIMULATION RESULTS AND DISCUSSION

### 6.1 Model Implementation Results

In this section, we apply the fuzzy linguistic evaluation model to product A and B to determine their remanufacturability index. For each of the sub-models we consider each of the attributes according to the domains described earlier for evaluating the remanufacturability index.

Table 9 are the input values for each of the attributes of the model. Some of the assessment values are numerical, some interval and others linguistic.

**Table 9: Attribute Inputs for the Model**

Attribute	Input Type	Product A		Product B	
Inspection & Sorting	Numerical	0.90		0.51	
Cleaning	Numerical	0.34		0.72	
Disassembly	Numerical	0.40		0.71	
Diagnostic Testing	Numerical	0.57		0.50	
Repair and upgrade	Numerical	0.79		0.47	
Reassembly	Numerical	0.56		0.71	
Functional Test	Numerical	0.88		0.58	
Final restoration & Insp	Numerical	0.60		0.54	
Quantity of cores wasted	Linguistic	H		L	

Attribute	Input Type	Product A		Product B	
Product acquisition costs	Interval	0.75	0.89	0.55	0.7
Remanufacturing cost	Interval	0.45	0.64	0.38	0.42
Overheads	Interval	0.6	0.8	0.47	0.6
Component salvage rate	Interval	0.24	0.28	0.26	0.28
Equipment utilization	Interval	0.85	0.90	0.60	0.84

Equations 2-7 are used to fuzzify the input assessments by transforming them into the basic term set described earlier. Table 10 presents the transformed inputs in the basic

linguistic term set (BLTS). For each model, the attribute inputs are aggregated to determine an output, which represents the remanufacturability indicator for the sub-models i.e. TRI, ERI, RUI and EEI.

**Table 10: Transformed Inputs for the Model**

	Product A							Product B						
Attribute	S0	S1	S2	S3	S4	S5	S6	S0	S1	S2	S3	S4	S5	S6
Inspection & Sorting	0	0	0	0.94	0.06	0	0	0	0	0	0	0	0.58	0.42
Cleaning	0	0	0	0.00	0.70	0.30	0	0	0	0.96	0.04	0	0	0
Disassembly	0	0	0	0.00	0.73	0.27	0	0	0	0.61	0.39	0	0	0
Diagnostic Testing	0	0	0.01	0.99	0	0	0	0	0	0	0.60	0.40	0	0
Repair and upgrade	0	0	0.17	0.83	0	0	0	0	0	0	0	0.23	0.77	0
Reassembly	0	0	0	0	0.73	0.27	0	0	0	0	0.62	0.38	0	0
Functional Test	0	0	0	0.52	0.48	0	0	0	0	0	0	0	0.72	0.28
Final restoration & Insp	0	0	0	0.78	0.22	0	0	0	0	0	0.43	0.57	0	0
TRI	0	0	0.02	0.51	0.36	0.11	0	0	0	0.20	0.26	0.20	0.27	0.09
Product Acquisition costs	0	0	0	0	0.5	0.66	0.34	0	0		0.7	0.8	0.2	0
Remanufacturing cost	0	0	0	0.16	0.84	0.66	0.34	0	0	0.72	0.52	0	0	0
Overheads	0	0	0	0.4	0.6	0.8	0	0	0	0.18	0.82	0.6	0	0
ERI	0	0	0	0.19	0.65	0.71	0.23	0	0	0.30	0.68	0.47	0.07	0
Component salvage rate	0	0.57	0.68	0	0	0	0	0	0.42	0.66	0	0	0	0
Equipment utilization	0	0	0	0	0	0.91	0.42	0	0	0	0.39	0.61	0.99	0.01
RUI	0	0.29	0.34	0	0	0.45	0.21	0	0.21	0.33	0.19	0.31	0.50	0.01
Core disposal rate	0	0	0	0	1	0	0	0	1	0	0	0	0	0

These indicators for the four sub-models (TRI, ERI, RUI and EEI) expressed in the BLTS and are still in fuzzy form. Equations (15), (16) and (17) are used to apply the ( $\chi$ ) function obtain a numerical value that supports this output fuzzy set. For example, for product A, the TRI is determined as follows,

$$\omega = \chi(S_T) = \frac{2 \times 0.02 + 3 \times 0.51 + 4 \times 0.36 + 5 \times 0.11}{0.02 + 0.51 + 0.36 + 0.11} = 3.55$$



$$\Delta(\omega) = \{(s_3, 1 - 0.55), (s_4, 0.55)\} = \{(M, 0.45), (H, 0.55)\}$$

$$TRI = k\{(M, 0.45), (H, 0.55)\} = 0.5 * 0.45 + 0.667 * 0.55 = 0.592$$

Similarly, the results for ERI, RUI and EEI and the ultimate RI are obtained. and Table 11 presents a tabulation of these results for the respective indicators.

**Table 11: Defuzzified Model results**

Indicator	Product A			Product B		
	$\omega$	$(s_h, 1 - \gamma), (s_{h+1}, \gamma)$	$y$	$\omega$	$(s_h, 1 - \gamma), (s_{h+1}, \gamma)$	$y$
TRI	3.55	$\{(M, 0.45), (H, 0.55)\}$	0.592	3.78	$\{(M, 0.45), (H, 0.55)\}$	0.630
ERI	4.55	$\{(H, 0.45), (VH, 0.55)\}$	0.758	3.20	$\{(M, 0.80), (H, 0.12)\}$	0.533
RUI	3.48	$\{(M, 0.52), (H, 0.48)\}$	0.580	3.36	$\{(M, 0.64), (H, 0.36)\}$	0.560
EEI	4.00	$\{(H, 1), (VH, 0)\}$	0.667	1.00	$\{(VL, 1), (L, 0)\}$	0.167

Based on the two 2-tuple fuzzy output results, both product A and product B have their technical remanufacturability indicator (TRI) belonging to medium ( $s_3$ ) and high ( $s_4$ ) linguistic labels. However, defuzzification of the outputs indicate that the TRI of Product A is 0.592 while that of B is 0.630. Hence, technically product B is more remanufacturable than Product A.

The ERI indicator for product A is determined to be 0.758, while that of product B is indicated to be 0.533. Hence, from the economic point of view, product A is performing much better than product B. For both products, the resource utilization indicator is about average with product A performing slightly better 0.580 compared to product B at 0.560. The environmental indicator for product B is very low at 0.166 compared to that of product A at 0.667.

To obtain the overall remanufacturability index, the outputs of the sub-models feed into the main (RI) model. Table 12 shows the outputs of the overall RI model of the system.

**Table 12: Overall Remanufacturability Indicator Model**

<i>Attribute</i>	<i>Product A</i>							<i>Product B</i>						
	<i>S0</i>	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>	<i>S0</i>	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>
TRI	0	0	0.02	0.51	0.36	0.11	0	0	0	0.20	0.26	0.20	0.27	0.09
ERI	0	0	0.30	0.68	0.47	0.07	0	0	0	0	0.19	0.65	0.71	0.23
RUI	0	0.21	0.33	0.19	0.31	0.50	0.01	0	0.29	0.34	0	0	0.45	0.21
EEI	0	1	0	0	0	0	0	0	0	0	0	1	0	0
RI	0	0.30	0.16	0.35	0.28	0.17	0.00	0	0.07	0.13	0.11	0.46	0.35	0.13
$RI, \{(s_h, 1 - \gamma), (s_{h+1}, \gamma)\}$	$\{(M, 0.03), (H, 0.97)\}$							$\{(L, 0.07), (M, 0.93)\}$						
RI (Numerical)	0.662							0.488						

Applying Equations (15), (16 and (17 to the aggregated output of the RI model, we obtain two linguistic 2 tuples representations and the respective final defuzzified numerical remanufacturability indicators for product A and B. The results show that product A is more remanufacturable at an index of 0.662 compared to product B at 0.488.

## 6.2 Results Discussion

We indicated earlier that our study considers two product families, A and B because they account for approximately 31% of the total cores received and processed in the plant annually. Secondly, they represent the variability in product profile that the company remanufactures. Particularly, product A, which is manufactured within the USA has been in the market for more than 10 years and has therefore matured in the market. As such, a higher percentage of the units returned for remanufacture are billable and therefore

have less labor restriction, and economically profitable. Product B on the other hand is manufactured by the company's subsidiary plant located in China. The product has been in the market for less than 5 years and is therefore yet to mature in the market. Unlike product A, a higher percentage of product B that are returned for remanufacture are under warranty, rendering them labor restrictive with less profit margins and economically less remanufacturable.

According to the FIS results, product B is technically more remanufacturable than product A. This is especially true given that product B is smaller in size with fewer modules and parts to disassemble and reassemble. Product A on the hand is larger in size with more modules and parts to handle. In addition, the diagnostic tests and functional tests required for the product A not only require high skills levels but is also highly stochastic in terms of the test time required compared to product B. Unlike product A in which most parts are salvaged for reuse if the core is not remanufactured, for product B, units that are not remanufactured are scrapped to recover materials through recycling.

One of the major drivers of remanufacturing is to minimize costs and maximize profits. A cost-effective remanufacturing strategy is therefore important in sustaining the enterprise. The higher the proportion of the core salvaged through remanufacture the higher the economic benefits of remanufacturing a product. Much of the cost saving from remanufacturing are attributed to the fact that the costs associated with initial tooling and development of parts and products are not in a remanufactured unit. Our FIS results indicate that product A is economically far much superior to product B.

Remanufacturing offers a life extension of products, by avoiding use of virgin materials and energy associated with their processing. This is a vital contribution to

environmental protection especially when a high proportion of the product parts are reused. Unlike product A in which most parts are salvaged for reuse if the core is not remanufactured, for product B, units that are not remanufactured are scrapped to recover materials through recycling. In this case, not all the materials in the scrapped unit is recovered. This explains why the environmental indicator for product B is much lower compared to that of product A. Further, unlike remanufacturing, recycling may lead to use of more energy and therefore contribute to some environmental pollution. Thus, a product that has a high proportion of its returns remanufactured is environmentally superior than one that is scrapped for material recovery through recycling.

Various types of performance measures are used to measure business success. Each business segment is unique in its operation and strategic objectives. Whereas, profitability is the bottom line for most business ventures, other indicators such as sustainability and corporate image play an important role in the current market. For business strategists using the remanufacturability index can help discover the rewards of exploring new business opportunities in the after sales market which could offer new solutions to their clients at relatively low cost of ownership.

The role of key performance indicators in the strategic planning process stems from the belief that these indicators provide a measurable and objective standard by which business leaders can track progress and implement change. Businesses can use the remanufacturability index in the strategic planning process to provide benchmark by which they can measure viability of remanufacturing a product. Such an approach would help leaders make more objective and scientific planning decisions, leading to reduced errors. By using a remanufacturability indicator, it is possible to determine what product

returns would yield better returns on investment, what progress the business is making and what changes it needs to implement if positive change does not occur. From the environmental perspective, the index can provide an indicator on how costly disposal processes can be transformed into product loops creating profits through remanufacturing

# CHAPTER 7: WARRANTY COST ALLOCATION OF REMANUFACTURED PRODUCTS

## 7.1 Introduction

From the foregoing study, it was observed that some products have a high number of warranty returns. Key among the concerns of OEM is how to reduce the number of warranty returns. This is more so because warranty returns increase the cost of business and eat into the profit margins of the company. Once a product is remanufactured, proper technical, environmental, and quality data should be provided to convince the consumer of the product's performance. To support this data and claims, warranty allocation is necessary to induce confidence in the consumer that a remanufactured product will perform as good as a new product. Warranty assignment to a remanufactured product therefore plays an important role in enhancing its image and assuring the quality and reliability of the product. According to Pecht [70] "a warranty is a written assurance that the manufacturer of a product will guarantee the quality and reliability of a product in terms of correcting any legitimate problems with the product at no additional cost, for some expressed or implied period of time or use." Warranties are important to both the remanufacturer and the consumer of the remanufactured product. For a consumer, it acts as an insurance against a product's early failures. A consumer cannot tell whether a product will perform as stipulated in the specifications unless he carries a field test which is never the case at the time of purchase. Hence warranty provides a mechanism for a customer to seek redress if a product fails in service within the warranty period. A warranty therefore acts as a statement of the quality of the product for the customer and an

assurance to the customer that should the product fail, it can be repaired or replaced at the manufacturer's cost. Further, when a manufacturer provides better warranty terms than a competitor, there is a tendency for the customers to believe that such a product is more reliable than its competition [71].

From the manufacturer's perspective, warranty acts as a protection against customers claiming replacement on products that fail due to misuse or abuse [72]. Whenever a warranty for a product is provided, it comes with terms and conditions of use. If a customer misuses the product or uses under unfavorable conditions as stipulated in the product guide, then the warranty becomes null and void. The goal to keep their customers amid market competition is one of the key reasons why manufacturers provide warranty for their products [70]. Warranty is essentially an important product feature that manufacturers use to market their products and maintain a positive image as well as long-term relationships with their customer base [71]

Several warranty policies have been used for warranty allocation to second hand products. There are four distinct types that are unique to remanufactured products namely, free repair or replacement warranty (FRW), cost sharing warranty (CSW), rebate warranty (RW), and hybrid warranty (HW) [73].

Under the free replacement warranty policy, the dealer/manufacturer is obliged to repair or replace the product whenever it fails within the warranty period. The FRW can be renewing or nonrenewing. This warranty can be either renewing in which case the policy resets itself after a product is repaired/replaced, or non-renewing in which case the original policy period continues after repair/replacement [71].

Cost sharing warranty entails both the producer and the consumer sharing the cost of repair/replacement as per laid down terms of the warranty. This may include certain parts of the product being covered by the manufacturer while the consumer pays for the rest [73].

The rebate warranty requires that a manufacturer or dealer refunds some proportion of the purchase price to the customer and depending on the age of the product if the product fails within the warranty period. Sometimes dealers give a money back warranty if the product fails to satisfy the requirements within a given period within the warranty duration. In this case the dealer gives a full refund equal to the sale price of the product [73].

A hybrid warranty is a combination of two or more of the foregoing warranty options. The most common hybrid warranty is one in which a product is covered by the free replacement warranty immediately after sale up to a certain period, followed by a rebate warranty for the rest of the warranty coverage period. The second phase may encompass provisions such as reduced prices for replacement parts or whole product replacement [73].

## **7.2 Assessment of life after first end of life**

Products basically have three phases, viz, the setting phase, useful life phase, and wear-out phase. By the time a product is in the market, it is expected to have gone past the setting stage and onto its useful life or second phase of the life cycle. A returned product that is found reusable is thus considered to be in the useful life. The challenge to



product remanufacturers is determination of the remaining life of a product. In this study, we use product return statistics to determine the reliability of the remanufactured product.

Of the distributions reported for modeling reliability, the Weibull distribution is widely used for describing the distribution of times to failure because it is quite flexible in matching a wide variety of failure phenomena [74]. The cumulative density function (CDF) of the two-parameter Weibull distribution is given by Equation (34).

$$F(x) = 1 - \exp \left[ - \left( \frac{t}{\beta} \right)^\alpha \right] \quad (34)$$

Where,  $\beta$  is the scale parameter and  $\alpha$  is the slope or shape parameter. The scale parameter defines the characteristic life of the product and thus the life of the product at which 63.2% of all the units fail. The slope on the other hand defines the mode of failure [71].

When  $\alpha < 1$ , the product is said to be in the setting phase with a decreasing failure rate. At this stage a number of tests are employed to determine the integrity of a component prior to releasing it to the customer. These include burn-in, power cycling, temperature cycling, vibration; highly accelerated stress, life testing and testing at the thermal destruct limits. These are designed to bring the product to the useful life period before it goes into the market. The high potential (HIPOT) test in remanufacturing is one such test that is carried out in the early stage of a remanufactured control drive. When  $\alpha = 1$ , the products face random failures during the useful life of a product. As the product matures, the weaker units fail, the failure rate becomes nearly constant, and devices are said to have entered what is considered the normal life period. This period is also referred to as the “system life” of a product or component and it is during this period that the lowest

failure rate occurs. The useful life period is the most common time frame for making reliability predictions. When  $\alpha > 1$ , the product is in the wear out phase with an increasing failure rate. As components begin to fatigue or wear out, failures occur at increasing rates. Wear out in control drives for instance may be caused by breakdown due to physical, electrical and thermal stress. Figure 29 illustrates the bath-tub curve that describes the three scenarios described by the value of the shape parameter [71].

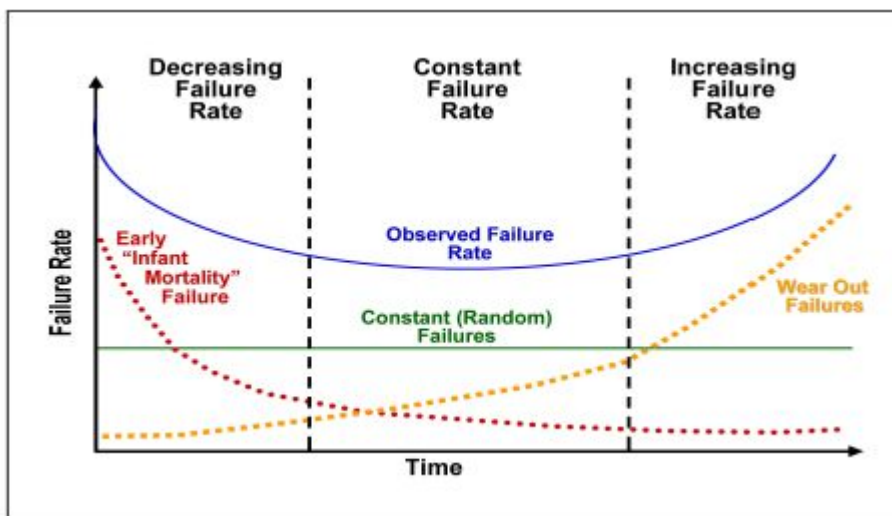


Figure 29: Bathtub curve [71].

The reliability of the product, which is the complement of the CDF is thus given by Equation (35)

$$R(x) = \exp \left[ - \left( \frac{t}{\beta} \right)^\alpha \right] \quad (35)$$

The reliability of an end of life product is a function of the age of the product. Estimation of this age is therefore essential in allocating the warranty cost of a remanufactured product. Different approaches are used in estimating the age of an end

of life product. The most common and simplest is the use of historical data from the maintenance or sales and marketing department. A more advanced and accurate but technology intensive approach is the use of data loggers mounted on the equipment/unit [71].

It is the desire of every manufacturer that all their products perform as expected in the field with 0% failure. However, in practice failures occur and therefore manufacturers set a minimum expected reliability threshold for their products. From Equation (35) the maximum possible time for a product to achieve the required reliability threshold can be determined using Equation (36) and these parameters can be used to estimate the reusability potential of a product.

$$t_p = \beta(-\ln R)^{\frac{1}{\alpha}} \quad (36)$$

The decision to reuse a product is also determined by the age of the product at the end of the first life,  $t_1$ , and the estimated duration of use in the second life  $t_2$ . Therefore the reliability for product reuse is given as  $R(t_1 + t_2)$ . If  $R^*$  is the desired reliability of a product then, if  $R(t_1 + t_2) > R^*$  then the product is reusable without remanufacturing and is expected to perform as good as new, but, if  $R(t_1 + t_2) < R^*$  then the remanufacturing option is more feasible with the product expected to perform at a reliability acceptable just like a new one. Figure 30 illustrates the foregoing scenarios on a reliability curve of a product [71].

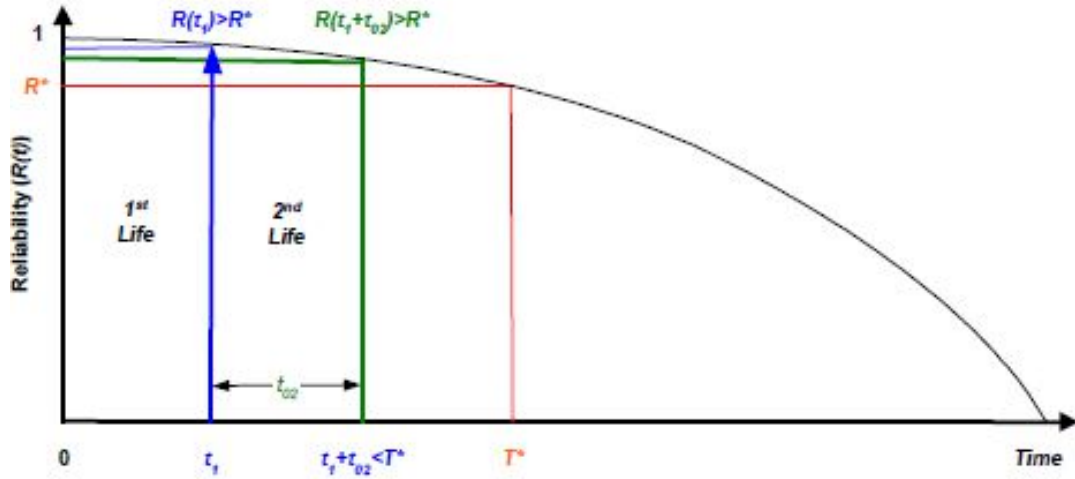


Figure 30: Reliability of products with potential reusability [71].

### 7.3 Warranty cost estimation

The cost of warranty for reuse is a function of the age of the end of life product, the reliability threshold and the length of the warranty period. Considering these factors, warranty costs for remanufactured products are considered for the three most commonly used warranty allocation policies for product reuse. In estimation of the warranty costs ( $C_w$ ) we assume that; customers will claim all failures within the warranty period; all claims made will be genuine; there will be instantaneous replacement of a failed unit by a new or reused one; and the lifetime of the initial and all replacement items are independent and identically distributed [71]. The general expression for the cost of warranty is given by Equation (37)

$$C_w = E[C_w(t_w)] = c_w \times F(t_w) = c_w \times (1 - R(t_w)) \quad (37)$$

Where,  $C_w$  is the producer's total warranty cost reserve per unit,  $E[C_w(t_w)]$  is producer's expected warranty cost,  $t_w$  is the warranty duration,  $c_w$  is warranty cost per failure reserved by manufacturers,  $F(t_w)$  is the cumulative distribution function and  $R(t_w)$  is the reliability function.

The value of the warranty cost per failure reserved by manufacturers,  $c_w$  is depended on the warranty policy allocated for product reuse. Under the free replacement warranty,  $c_w$  is a function of the life cycle cost and the reliability of the reused product. Hence Equation (37) is modified to yield Equation (38) for the average cost of warranty per item remanufactured.

$$C_w = E[C_w(t_w)] = C_{LC} \times \frac{F(t_w)}{R(t_w)} \quad (38)$$

Where,  $C_{LC}$  is the producer's warranty cost per failure,

The life cycle cost is a function of the number of lives a product has undergone. The more the number of lives the higher the life cycle cost. Therefore, the total life cycle cost is higher at the 2<sup>nd</sup> life than in the 1<sup>st</sup> life and hence increases with time from the 1<sup>st</sup> life to the  $i^{\text{th}}$  life. One of the key reasons for product reuse is to make profit. The remanufacturer's profit margin is therefore a function of the market price and the life cycle cost as shown in Equation (39)

$$P_M = \frac{MP_i - C_{LCi}}{C_{LCi}} \quad (39)$$

Where,  $P_M$  is the profit margin,  $MP$  is the market price and the index  $i=1,2,\dots$ , denotes the  $i^{th}$  life of the product. The additional cost of reuse,  $\Delta C_{w2}$  is given by Equation(40)

$$\Delta C_{w2} = C_{w2} - C_{w1} \quad (40)$$

Where,  $C_{w2}$  is the average cost of warranty of a remanufactured product and  $C_{w1}$  the average cost of warranty of the product in its first life. The value of  $C_{w2}$  is determined using Equation (41).

$$C_{w2} = C_{LC} \frac{[F(t_{w2}) - F(t_1)]}{1 - [F(t_{w2}) - F(t_1)]} \quad (41)$$

Under the money back warranty, a customer receives a full refund of the purchase price of the product. Therefore, warranty cost per failure reserved by manufacturers,  $c_w$  is the market price of product. Hence, the producer's total warranty cost reserve per unit,  $C_w$  is estimated using the Equation (42).

$$C_w = E[C_w(t_w)] = MP \times F(t_w) = MP \times (1 - R(t_w)) \quad (42)$$

Where,  $MP$  is the market price of the remanufactured product.

In the case of remanufactured products Equation (42) is modified to take into account the 1<sup>st</sup> life and the cost of warranty for the second life. Hence the remanufacturer's total warranty cost reserve per unit,  $C_w$  is estimated using Equation(43)

$$C_{w2} = E(C_{w2}) = MP \times [F(t_{w2}) - F(t_1)] \quad (43)$$

Under the non-renewing free replacement warranty, the total cost of warranty is estimated by making use of a renewal function that is associated with the cumulative distribution function with the aid of Equation (44) .

$$C_w = E[C_w]) = C_{LC} \times M(t_w) \quad (44)$$

Where,  $M(t_w)$  is a renewal function which is estimated from Equation

$$M(t_w) \approx \frac{t}{\mu} + \frac{\sigma^2}{2\mu^2} - \frac{1}{2} \quad (45)$$

Where,  $\mu$  is the mean of the Weibull distribution, and  $\sigma^2$  is the variance of the Weibull distribution.

$$C_{w2} = E[C_{w2})] = C_{LC} \times [M(t_{w2}) - M(t_1)] \quad (46)$$

#### 7.4 Warranty Allocation for Control Drives

Control drives remanufactured in the plant under study have varying capacities and are used in a variety of applications. The useful life of control drives range from 7 to 15 years depending on the type, capacity and area of application. We therefore take an average of 11 years as the useful life for the control drives under consideration in this study. To determine the cost of warranty of a remanufactured product, we used data from the company. This data was analyzed using the ProModel statistical feature to determine the distribution of the data obtained. Table 13 presents the results from this analysis which shows that the data can best be described by a Weibull distribution.

**Table 13: ProModel Stat Fit output**

distribution	rank	acceptance
Weibull[1., 1.73, 13.2]	100	do not reject
Beta[1., 48., 1.93, 5.84]	74.8	do not reject
Gamma[1., 2.75, 4.17]	1.82	reject
Pearson 6[1., 152, 2.3, 30.6]	0.539	reject
LogLogistic[1., 2.5, 10.2]	0.21	reject
Rayleigh[1., 9.67]	5.42e-002	reject
Erlang[1., 3., 4.17]	4.86e-002	reject
Exponential[1., 11.4]	0.	reject
Pareto[1., 0.432]	0.	reject
Inverse Gaussian[1., 15., 11.4]	0.	reject
Lognormal[1., 2.24, 0.751]	0.	reject
Uniform[1., 48.]	0.	reject
Pearson 5[1., 1.48, 9.61]	0.	reject
Power Function[1., 49., 0.615]	0.	reject
Triangular[0., 48.2, 2.15]	0.	reject
Inverse Weibull[1., 1.08, 0.16]	0.	reject
Chi Squared[1., 10.4]	0.	reject
Johnson SB	no fit	reject

### Chi-Square goodness of fit test of the data for Weibull distribution

The required parameters of the Weibull distribution for the failure times are the minimum value, the shape parameter  $\alpha$ , and the scale parameter  $\beta$ , of the distribution. Therefore, the Weibull pdf function becomes equation (47):

$$f(x) = \frac{\alpha}{\beta} \left( \frac{x - \min}{\beta} \right)^{\alpha-1} \exp \left( - \left( \frac{[x - \min]}{\beta} \right)^{\alpha} \right) \quad (47)$$

And Weibull (min,  $\alpha$ ,  $\beta$ ) = W(1, 1.73, 13.2)

### Chi-Square goodness of fit test of the data for the respective distributions

No. of intervals  $k = (2n)^{1/3} = (2*337)^{1/3} = 8.77 \sim 9$  cells

For a 95% confidence interval  $\alpha = 0.05$

$\chi^2$  Critical =  $\chi^2_{k-1, \alpha/2} = \chi^2_{3, 0.025} = 17.53$

Rejection Criteria: Reject if  $\chi^2 > \chi^2$  critical

The Chi- Square test statistic is given by equation (48)

$$\chi^2 = \frac{(O_i - e_i)^2}{e_i} \quad (48)$$



For the Weibull distribution, the CDF is given by equation (49)

$$F(x) = \begin{cases} 1 - e^{-\left(\frac{x-\min}{\beta-\min}\right)^\alpha} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (49)$$

Thus

$$x_i = \min + (\beta - \min) \times \left(-\ln(1 - F(x_i))\right)^{\frac{1}{\alpha}}$$

$$= 1 + (13.2 - 1) \left(-\ln(1 - F(x_i))\right)^{\frac{1}{1.73}}$$

Therefore;

$X_1 = 4.543$ ,  $X_2 = 6.491$ ,  $X_3 = 8.240$ ,  $X_4 = 9.973$ ,  $X_5 = 11.808$ ,  $X_6 = 13.882$ ,  $X_7 = 16.446$ ,  $X_8 = 20.230$ .

Table 14 shows the chi square test for the Weibull distribution.

**Table 14: Chi-Square Test for Weibull Distribution**

Cell	Interval		Probability	Observed Freq	Expected Freq.	Chi-Sq Stat.
No.	Low	Upper	$P_i$	$O_i$	$e_i = nP_i$	$\chi^2$
1	1	4.543345	0.11	37.44	40	0.1744148
2	4.543345	6.491168	0.11	37.44	27	2.9132872
3	6.491168	8.24008	0.11	37.44	36	0.0557204
4	8.24008	9.973479	0.11	37.44	30	1.4800528
5	9.973479	11.80809	0.11	37.44	32	0.7916255
6	11.80809	13.88159	0.11	37.44	38	0.0082427
7	13.88159	16.44643	0.11	37.44	48	2.9756017
8	16.44643	20.22982	0.11	37.44	45	1.5245631
9	20.22982	48	0.11	37.44	41	0.3376195
		$\Sigma$	1	337	337	10.2611276

Since  $\chi^2 (10.2611276) < \chi^2 \text{ Critical } (17.53)$ , we conclude that the failure data follows a Weibull distribution

A similar approach was taken for product B and the results obtained yielded the following parameters for the Weibull distribution.

$$\text{Weibull}(\min, \alpha, \beta) = W(1, 1.52, 25.14)$$

The reusability potential of a control drive can be evaluated using different threshold values. Table 15 shows the expected time before failure for a given threshold for each of the product streams A and B using the parameters from the Weibull distribution. These results show that the mean time before failure for product A is 10.68 (11 years) while that of product B is 20.19 (20 years).

**Table 15: Product's performance for various reliability thresholds**

R	0.99	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50
T <sub>A</sub>	0.92	2.37	3.59	4.62	5.55	6.42	7.27	8.11	8.95	9.80	10.68
T <sub>B</sub>	1.25	3.64	5.85	7.78	9.58	11.32	13.04	14.77	16.52	18.32	20.19

## **7.5 Assessment of Reliability and Warranty of Used Control Drives**

Two products were considered in our analysis. Using the data from the company the average cost of processing each of the product streams for reuse and the market price of the products were used to determine the cost of warranty of the returns. It was earlier mentioned that for a product to be considered economically feasible for remanufacture, the cost of repair should not exceed 60% of the price of the product. We therefore considered a scenario where the remanufactured product is given a value equal to the price of a new one and a second scenario where the value is equal to 60% of the price of a new one. To determine the average life cycle cost of each of the product streams, the cost of remanufacture a total of 2038 and 4461 units were analyzed for product A and product B respectively. Table 16 shows the market price, and life cycle cost for the two products considering the two scenarios.

**Table 16: Summary of the cost values for product streams A and B**

	Product A			Product B		
	New Units	Reused Units		New Units	Reused Units	
		Scenario 1	Scenario 2		Scenario 1	Scenario 2
Market Price	280	280	168	611	602	361.2
Life Cycle cost	170	92	92	390	212	212

From the data obtained from the company the new control drives are usually sold with a warranty of 3 to 5 years. Remanufactured control drives are sold with a warranty ranging from 1 to 5 years depending on their complexity and terms and conditions of use. To understand the effect of the duration of warranty on the customer perception of the product we look at the failure probability for each of the product streams for different warrant duration scenarios. Using Equation (38) we establish the warranty cost for the respective scenarios. Table 17 shows the CDF,  $F(t)$ , for the different warranty allocation options and the associated cost of warranty for product A and product B.

**Table 17: Control Drive performance within warranty period**

	Warranty Periods for Product A						Warranty Periods for Product B				
	1	2	3	4	5		1	2	3	4	5
$F(t)$	0.007	0.021	0.039	0.060	0.083		0.011	0.037	0.074	0.119	0.170
$R(t)$	0.993	0.979	0.961	0.940	0.917		0.989	0.963	0.926	0.881	0.830
$F(t)/R(t)$	0.008	0.022	0.041	0.064	0.090		0.012	0.039	0.080	0.135	0.205
$C_{w1}$	1.280	3.697	6.910	10.819	15.380		4.518	15.191	31.242	52.705	79.949
Max $\Delta C_{w2}$ for scenario 1					123.39		Max $\Delta C_{w2}$ for scenario 1				258
Max $\Delta C_{w2}$ for scenario 2					37.24		Max $\Delta C_{w2}$ for scenario 2				70

The results show that, for both products  $F(t)$  increases with increase in warranty allocation and therefore the cost of warranty for the products increases with the increase in the number of years of warranty allocation. Even so, within the warranty period of 1 to 5 years the expected number of failures is low for both products. Looking at the two

scenarios presented, the maximum allowable additional cost of warranty for product A under scenario 1 is \$123.39 whereas that of product B is \$258. In both cases, scenario two shows a much lower additional cost of warranty for reuse. This is mainly attributed to the market price of the remanufactured product which is in this case 60% of the market price of a new one.

We further examined the reusability of the products based on the length of the first life. As was indicated earlier, the reliability of a reuse product is a function of the duration of the first life and the expected duration of reuse. This was done by determining the cost of additional warranty of a reused product using Equation (41). For both products A and B, two warranty scenarios are considered and for each scenario, a comparison is made between the three warranty policies. Table 19 on the other hand shows the analysis for reuse under scenario 2 in which case the market price is based on 60% of the price of a new unit. The results indicate that for all combinations of 1st EOL and the duration of reuse of the remanufactured unit, the NRFRW policy is more attractive than the other two policies in which case the additional warranty cost is less than the maximum allowable cost. The free replacement warranty policy is limited to any combination of first EOL and the duration of reuse up to 8 years whereas the money back warranty is only attractive for any combination of the first EOL and the duration of reuse up to 7 years.

Table 18 shows the result of the analysis for reuse of product with a given first life period for various durations of reuse (second life) and the expected cost of additional warranty for product A under scenario 1. The results show that, regardless of the age of the product at the end of its first life within the warranty period of 5 years, product A can still be reused for an additional 10 years without incurring an additional cost of warranty

beyond the maximum allowable value of \$123.39 under any of the three warranty policies. However, of the three warranty policies, the non-renewable free replacement warranty (NRFRW) policy is the cheapest while the money back warranty is the most expensive policy. Table 19 on the other hand shows the analysis for reuse under scenario 2 in which case the market price is based on 60% of the price of a new unit. The results indicate that for all combinations of 1<sup>st</sup> EOL and the duration of reuse of the remanufactured unit, the NRFRW policy is more attractive than the other two policies in which case the additional warranty cost is less than the maximum allowable cost. The free replacement warranty policy is limited to any combination of first EOL and the duration of reuse up to 8 years whereas the money back warranty is only attractive for any combination of the first EOL and the duration of reuse up to 7 years.

**Table 18: Incremental warranty cost of product B reuse under scenario 1**

		Age of used products at first end of life														
		1			2			3			4			5		
		RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW
Duration of reuse in year	1	1.30	1.26	3.84	1.73	1.62	4.94	2.10	1.90	5.77	2.46	2.11	6.43	2.82	2.29	6.95
	2	3.02	2.88	8.78	3.83	3.52	10.71	4.56	4.01	12.20	5.28	4.40	13.38	6.00	4.71	14.33
	3	5.12	4.78	14.55	6.28	5.63	17.14	7.37	6.29	19.16	8.45	6.82	20.76	9.56	7.24	22.03
	4	7.57	6.89	20.98	9.08	7.92	24.10	10.53	8.72	26.53	11.99	9.35	28.46	13.52	9.85	29.97
	5	10.37	9.18	27.93	12.23	10.34	31.47	14.05	11.25	34.23	15.92	11.96	36.40	17.90	12.52	38.10
	6	13.50	11.60	35.31	15.74	12.87	39.17	17.95	13.86	42.18	20.26	14.63	44.53	22.74	15.23	46.35
	7	16.99	14.13	43.01	19.61	15.48	47.12	22.25	16.53	50.31	25.03	17.34	52.78	28.06	17.96	54.66
	8	20.84	16.74	50.95	23.87	18.15	55.24	26.97	19.24	58.55	30.27	20.07	61.09	33.91	20.70	63.00
	9	25.08	19.41	59.08	28.54	20.86	63.49	32.14	21.97	66.87	36.02	22.81	69.43	40.35	23.43	71.30
	10	29.71	22.12	67.33	33.64	23.59	71.81	37.79	24.71	75.20	42.31	25.54	77.73	47.42	26.14	79.55

**Table 19: Incremental warranty cost of product A reuse under scenario 2**

		Age of used products at first end of life														
		1			2			3			4			5		
		RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW
Duration of reuse in year	1	1.30	1.26	2.30	1.73	1.62	2.96	2.10	1.90	3.46	2.46	2.11	3.86	2.82	2.29	4.17
	2	3.02	2.88	5.27	3.83	3.52	6.43	4.56	4.01	7.32	5.28	4.40	8.03	6.00	4.71	8.60
	3	5.12	4.78	8.73	6.28	5.63	10.29	7.37	6.29	11.49	8.45	6.82	12.45	9.56	7.24	13.22
	4	7.57	6.89	12.59	9.08	7.92	14.46	10.53	8.72	15.92	11.99	9.35	17.07	13.52	9.85	17.98
	5	10.37	9.18	16.76	12.23	10.34	18.88	14.05	11.25	20.54	15.92	11.96	21.84	17.90	12.52	22.86
	6	13.50	11.60	21.18	15.74	12.87	23.50	17.95	13.86	25.31	20.26	14.63	26.72	22.74	15.23	27.81
	7	16.99	14.13	25.80	19.61	15.48	28.27	22.25	16.53	30.18	25.03	17.34	31.67	28.06	17.96	32.80
	8	20.84	16.74	30.57	23.87	18.15	33.15	26.97	19.24	35.13	30.27	20.07	36.66	33.91	20.70	37.80
	9	25.08	19.41	35.45	28.54	20.86	38.10	32.14	21.97	40.12	36.02	22.81	41.66	40.35	23.43	42.78
	10	29.71	22.12	40.40	33.64	23.59	43.08	37.79	24.71	45.12	42.31	25.54	46.64	47.42	26.14	47.73

Table 20 and Table 21 shows the result of the analysis for reuse of product B. The result also show that the non-renewable free replacement warranty policy is the most attractive under both scenarios. In scenario 1, for any combination of the age of the product at its first EOL and the duration of reuse, the NRFRW policy yields additional warranty costs less than the maximum allowable value. However, in scenario 2, the NRFRW is only attractive for any combination of the age of the product at the first EOL up to 5 years. Within the 5-year warranty period of product B, at the first EOL the money back warranty policy is only feasible for all combination of reuse up to 2 years under scenario 2. The renewable free replacement policy on the other hand is only feasible for up to 2 years of reuse.

**Table 20: Incremental warranty cost of product B reuse under scenario 1**

		Age of used products at first end of life														
		1			2			3			4			5		
		RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW
Duration of reuse in year	1	5.80	5.52	15.91	8.75	7.78	22.41	11.79	9.52	27.43	15.23	10.83	31.20	19.45	11.75	33.88
	2	14.54	13.30	38.32	20.50	17.29	49.83	26.92	20.34	58.63	34.46	22.58	65.08	44.12	24.09	69.44
	3	26.23	22.81	65.74	35.49	28.12	81.04	45.84	32.10	92.51	58.48	34.92	100.64	75.44	36.71	105.80
	4	41.10	33.64	96.95	54.11	39.87	114.92	69.21	44.44	128.07	88.41	47.53	137.00	115.51	49.33	142.17
	5	59.49	45.39	130.83	76.92	52.21	150.48	97.93	57.05	164.42	125.82	60.16	173.38	167.48	61.73	177.91
	6	81.91	57.73	166.39	104.69	64.83	186.83	133.21	69.67	200.80	172.90	72.56	209.11	236.25	73.72	212.46
	7	109.02	70.35	202.74	138.37	77.45	223.21	176.68	82.07	236.54	232.84	84.54	243.66	329.80	85.14	245.38
	8	141.65	82.97	239.12	179.26	89.85	258.95	230.54	94.06	271.09	310.35	95.97	276.58	462.15	95.88	276.34
	9	180.88	95.37	274.86	229.01	101.83	293.50	297.88	105.48	304.01	412.74	106.71	307.55	660.13	105.87	305.12
	10	228.07	107.35	309.40	289.82	113.26	326.42	383.04	116.23	334.97	551.89	116.70	336.33	982.47	115.04	331.56

**Table 21: Incremental warranty cost of product B reuse under scenario 2**

		Age of used products at first end of life														
		1			2			3			4			5		
		RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW	RFRW	NRFRW	MBW
Duration of reuse in year	1	5.80	5.52	9.55	8.75	7.78	13.45	11.79	9.52	16.46	15.23	10.83	18.72	19.45	11.75	20.33
	2	14.54	13.30	22.99	20.50	17.29	29.90	26.92	20.34	35.18	34.46	22.58	39.05	44.12	24.09	41.66
	3	26.23	22.81	39.45	35.49	28.12	48.62	45.84	32.10	55.51	58.48	34.92	60.39	75.44	36.71	63.48
	4	41.10	33.64	58.17	54.11	39.87	68.95	69.21	44.44	76.84	88.41	47.53	82.20	115.51	49.33	85.30
	5	59.49	45.39	78.50	76.92	52.21	90.29	97.93	57.05	98.65	125.82	60.16	104.03	167.48	61.73	106.75
	6	81.91	57.73	99.83	104.69	64.83	112.10	133.21	69.67	120.48	172.90	72.56	125.47	236.25	73.72	127.47
	7	109.02	70.35	121.65	138.37	77.45	133.93	176.68	82.07	141.92	232.84	84.54	146.20	329.80	85.14	147.23
	8	141.65	82.97	143.47	179.26	89.85	155.37	230.54	94.06	162.65	310.35	95.97	165.95	462.15	95.88	165.81
	9	180.88	95.37	164.91	229.01	101.83	176.10	297.88	105.48	182.41	412.74	106.71	184.53	660.13	105.87	183.07
	10	228.07	107.35	185.64	289.82	113.26	195.85	383.04	116.23	200.98	551.89	116.70	201.80	982.47	115.04	198.94

From the foregoing analysis, it was concluded that for each of the two scenarios considered and under all the three warranty policies the additional cost of warranty increases with the age of the product and the duration of product reuse in the second life. These findings provide a basis upon which a remanufacturer can make decisions on which warranty policy to consider for the product returns based on the age of the product at the first EOL and the remaining useful life of the product.

Key among the drivers of remanufacturing is the economic benefits of being involved in such business. Manufacturers often set a desired profit margin that has to be satisfied before a decision to produce is made. The profit margin determines the maximum allowable additional cost of warranty. To assess the impact of the

remanufacturer's expected economic gain in the remanufacturing business, we considered the impact of varying the profit margin on the additional cost of reuse. Profit margins can range from as low as 5% to as high as 100% depending on the type of product, available technology and product maturity. We therefore considered two additional cases where the desired profit margin is 40% and another with a profit margin of 50%. Table 22 and

Table 23 show the impact of these changes on the maximum allowable additional warranty cost of product reuse.

**Table 22: Maximum Allowable Additional Warranty Cost At 40% Profit Margin for Different Scenarios**

	Warranty Periods for Product A				
	1	2	3	4	5
F(t)	0.01	0.02	0.04	0.06	0.08
R(t)	0.99	0.98	0.96	0.94	0.92
F(t)/R(t)	0.01	0.02	0.04	0.06	0.09
$C_{w1}$	1.27	3.67	6.85	10.73	15.25
Max $\Delta C_{w2}$ for scenario 1					108
Max $\Delta C_{w2}$ for scenario 2					28

	Warranty Periods for Product B				
	1	2	3	4	5
F(t)	0.01	0.04	0.07	0.12	0.17
R(t)	0.99	0.96	0.93	0.88	0.83
F(t)/R(t)	0.01	0.04	0.08	0.14	0.20
$C_{w1}$	4.52	15.19	31.24	52.70	79.95
Max $\Delta C_{w2}$ for scenario 1					224
Max $\Delta C_{w2}$ for scenario 2					50

**Table 23: Maximum Allowable Additional Warranty Cost At 50% Profit Margin for Different Scenarios**

	Warranty Periods for Product A				
	1	2	3	4	5
F(t)	0.01	0.02	0.04	0.06	0.08
R(t)	0.99	0.98	0.96	0.94	0.92
F(t)/R(t)	0.01	0.02	0.04	0.06	0.09
$C_{w1}$	1.27	3.67	6.85	10.73	15.25
Max $\Delta C_{w2}$ for scenario 1					95
Max $\Delta C_{w2}$ for scenario 2					20

	Warranty Periods for Product B				
	1	2	3	4	5
F(t)	0.01	0.04	0.07	0.12	0.17
R(t)	0.99	0.96	0.93	0.88	0.83
F(t)/R(t)	0.01	0.04	0.08	0.14	0.20
$C_{w1}$	4.52	15.19	31.24	52.70	79.95
Max $\Delta C_{w2}$ for scenario 1					195
Max $\Delta C_{w2}$ for scenario 2					32



The results indicate that the maximum allowable additional warranty cost for reuse decreases with increase in the desired profit margin. The additional cost of warranty for reuse is not dependent on the maximum allowable cost of warranty. However, the maximum allowable additional cost of warranty determines the feasibility of product reuse and the manufacturer's decision on the period of warranty allocation for such products. Table 24 and

Table 25 present a pictorial view of the effect of change in the manufacturer's profit margin on additional cost of warranty under each of the warranty policies for product for scenario 1 and 2 respectively. In effect the length of time of product reuse after the first EOL reduces under all warranty policies as the profit margin is increased if the maximum allowable additional warranty cost is not to be exceeded.

**Table 24: Reuse period under different warranty policies for different profit margins of product B under scenario 1**

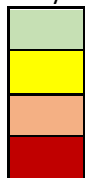
		Age of used products at first end of life																	
		1									2								
		RFRW			NRFRW			MBW			RFRW			NRFRW			MBW		
		30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%
Duration of reuse in year	1																		
	2																		
	3																		
	4																		
	5																		
	6																		
	7																		
	8																		
	9																		
	10																		

Key:	
	Feasible region for all warranty policies
	Non-feasible region under the renewable free replacement warranty (RFRW) policy
	Non-feasible region under the Non-renewable free replacement warranty (NRFRW) policy
	Non-feasible region under the money back warranty (MBW) policy

**Table 25: Reuse period under different warranty policies for different profit margins of product B under scenario 2**

		Age of used products at first end of life																	
		1									2								
		RFRW			NRFRW			MBW			RFRW			NRFRW			MBW		
		30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%
Duration of reuse in year	1																		
	2																		
	3																		
	4																		
	5																		
	6																		
	7																		
	8																		
	9																		
	10																		

Key:



Feasible region for all warranty policies

Non-feasible region under the renewable free replacement warranty (RFRW) policy

Non-feasible region under the Non-renewable free replacement warranty (NRFRW) policy

Non-feasible region under the money back warranty (MBW) policy

## CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

### 8.1 Research Contributions

Unlike conventional product manufacture, remanufacturing is complicated given that end of life (EOL) returns exhibit high variability in terms of the number of returns as well as the condition and quality of the returns. These EOL product characteristics present difficulties that make decision making on the remanufacturability of the returns challenging.

The work presented in this dissertation provides a decision support system for assessing the remanufacturability of the end of life products. The proposed model is based on fuzzy theory which incorporates both quantitative and qualitative attributes of the end of life products. The model consists of four sub-models namely; the technical, economic, resource utilization and the environmental indicators which are combined to form the overall remanufacturability indicator.

The model was implemented using data that was obtained from a local control drive remanufacturing company. Unlike new product manufacture in which the products follow a dedicated process from raw material processing through to the final assembly point with almost constant production time, remanufacturing process times are extremely variable. To understand the variability in process times, and their impact on the throughput of the whole system, we carried out detailed remanufacturing process analysis using ProModel simulation. The simulation identified major bottlenecks in the product remanufacturing process and improvements were suggested to correct the situation. The results from this model were then used in the implementation of the main fuzzy based

model for assessing product remanufacturability. In the model, two product families of control drives were evaluated to determine their remanufacturability indexes.

The following are the major contributions of this study:

1) A new methodology for decision making in product manufacture is presented that is based on fuzzy decision theory. This methodology takes into account both quantitative and qualitative aspects of product remanufacture which are broadly considered under technical, economic, environmental and resources utilization metrics.

2) The other contribution of this work is the ability to use ProModel simulation to identify bottlenecks in the remanufacturing process. The study has shown that simulation in this platform provides an easy way to manipulate the process to achieve improved remanufacturing process performance.

3) Finally, the variability in the age and status of the product returns presents remanufacturers with difficulties in allocating warranty costs for reuse products. This research provides a cost of warranty allocation model based on the age of the end of life product and its remaining useful life.

## **8.2 Future Research Direction**

Some further works can be recommended in some areas as follows:

1) To ensure a comprehensive approach, further research should be carried out to incorporate other aspects of remanufacturing such as reverse logistics, government legislation on product take back as well as development in technology into the fuzzy inference based model for assessing product remanufacturability.

2) There is also need to investigate the effect of the number of lives a product has had on the warranty cost allocation and reliability determination of remanufactured products.

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## APPENDICES

### Appendix I: System Statistics for Entities of Product A and B

Entity	Statistic	Total Exits		Current Quantity in the System		Ave. time in System		Ave Time Waiting		Ave. time in operation		Ave. time blocked	
		A	B	A	B	A	B	A	B	A	B	A	B
Control Drive	Avg	308	251	13	43	193	516	0	0	166.66	222.17	26.81	294.05
	Min	294	243	10	20	190	372	0	0	164.17	215.09	24.87	149.76
	Max	321	262	16	63	201	636	0	0	169.40	238.55	31.12	418.9
	St. Dev.	11	6	2	16	4	106	0	0	1.70	8.50	2.25	106.44
	95% C.I. Low	296	245	10	26	190	405	0	0	164.88	213.25	24.44	182.35
	95% C.I. High	319	258	15	61	197	627	0	0	168.44	231.09	29.18	405.75
Control Board	Avg	106	85	5663	5709	2753	2925	2727	2908	21.78	14.48	4.51	2.7364
	Min	97	73	5630	5639	2407	2666	2383	2651	18.06	12.73	3.83	2.4784
	Max	120	92	5703	5828	3012	3183	2987	3166	24.53	15.92	5.94	3.2015
	St. Dev.	8	7	28	70	238	210	237	210	2.55	1.28	0.75	0.2636
	95% C.I. Low	97	77	5633	5636	2504	2704	2479	2688	19.10	13.13	3.73	2.4598
	95% C.I. High	114	92	5693	5782	3003	3146	2975	3129	24.45	15.82	5.30	3.013
Power Board	Avg	98	87	5664	5680	2841	2870	2818	2852	18.97	14.77	4.05	2.8727
	Min	89	68	5608	5617	2662	2646	2639	2630	13.99	13.50	3.01	2.4626
	Max	120	96	5751	5744	2975	3001	2953	2984	22.57	16.28	4.59	3.0972
	St. Dev.	12	10	59	55	101	131	101	130	2.92	1.17	0.63	0.2508
	95% C.I. Low	86	76	5602	5622	2735	2732	2712	2716	15.90	13.55	3.39	2.6094
	95% C.I. High	110	97	5725	5738	2946	3007	2924	2989	22.03	15.99	4.70	3.1359

Entity	Statistic	Total Exits		Current Quantity in the System		Ave. time in System		Ave Time Waiting		Ave. time in operation		Ave. time blocked	
		A	B	A	B	A	B	A	B	A	B	A	B
Fan	Avg	163	129	5599	5639	2907	2872	2876	2847	25.25	19.63	5.88	5.32
	Min	152	117	5563	5553	2801	2707	2771	2684	24.10	17.52	5.43	4.827
	Max	170	140	5640	5726	3054	3029	3023	3001	26.76	22.97	6.75	5.58
	St. Dev.	7	8	28	58	107	107	106	106	0.94	2.38	0.48	0.30
	95% C.I. Low	155	121	5569	5578	2795	2759	2764	2736	24.26	17.13	5.38	5.00
	95% C.I. High	171	138	5628	5700	3019	2985	2987	2958	26.23	22.13	6.38	5.63
PCB Board	Avg	158	129	5631	5657	2881	2957	2850	2932	24.84	19.14	6.08	5.38
	Min	148	117	5589	5604	2723	2860	2695	2838	21.94	17.11	5.31	5.06
	Max	171	136	5708	5687	3040	3060	3006	3035	26.18	20.51	7.58	5.92
	St. Dev.	9	7	47	33	128	71	127	70	1.58	1.12	0.84	0.30
	95% C.I. Low	148	121	5581	5622	2747	2882	2717	2859	23.19	17.97	5.19	5.06
	95% C.I. High	167	136	5680	5691	3016	3031	2984	3006	26.50	20.32	6.96	5.70
Unrepaired Control Drive	Avg	165	133	0	0	35	299	0	0	24.52	33.31	10.36	265.32
	Min	155	119	0	0	33	153	0	0	24.05	32.69	8.54	120.11
	Max	173	143	1	1	36	432	0	0	24.96	34.22	12.18	398.96
	St. Dev.	8	8	0	0	2	108	0	0	0.34	0.50	1.40	108.31
	95% C.I. Low	157.43	124.37	0	0	33.29	185.11	0	0	24.16	32.79	8.89	151.66
	95% C.I. High	173.23	141.29	0.59	0.59	36.45	412.15	0	0	24.87	33.84	11.82	378.98

## Appendix II: Simulation results for processes for both Product A and B

Process	Statistic	Capacity		Total Entries		Average time per entry		Average Content		% Utilization	
		A	B	A	B	A	B	A	B	A	B
Arrival	Avg	Inf	Inf		428		256.9		19.3		0.0
	Min	Inf	Inf		407		110.6		7.8		0.0
	Max	Inf	Inf		448		393.0		30.6		0.0
	St. Dev.	Inf	Inf		15		109.8		8.8		0.0
	95% C.I. Low	Inf	Inf		412		141.7		10.0		0.0
	95% C.I. High	Inf	Inf		443		372.1		28.6		0.0
Registration	Avg	1	1	485	399	8.3	14.2	0.7	1.0	70.2	98.6
	Min	1	1	474	395	8.1	14.0	0.7	1.0	67.0	97.3
	Max	1	1	505	403	8.8	14.5	0.8	1.0	76.7	99.9
	St. Dev.	0	0	11	3	0.3	0.2	0.0	0.0	3.5	1.0
	95% C.I. Low	1	1	474	396	8.0	14.0	0.7	1.0	66.5	97.5
	95% C.I. High	1	1	497	403	8.6	14.4	0.7	1.0	73.9	99.7
Diagnostic Testing	Avg	1	1	485	398	10.0	14.4	0.8	1.0	84.1	99.6
	Min	1	1	473	394	9.9	14.2	0.8	1.0	82.5	99.1
	Max	1	1	504	402	10.1	14.6	0.9	1.0	87.8	99.9
	St. Dev.	0	0	11	3	0.1	0.1	0.0	0.0	1.9	0.3
	95% C.I. Low	1	1	473	395	9.9	14.3	0.8	1.0	82.2	99.3
	95% C.I. High	1	1	496	402	10.1	14.5	0.9	1.0	86.1	99.9
Repairing	Avg	2	2	395	330	14.5	22.8	1.0	1.3	49.7	65.4
	Min	2	2	366	316	13.9	21.9	0.9	1.2	44.1	60.6
	Max	2	2	424	350	15.0	25.7	1.1	1.6	54.0	78.0
	St. Dev.	0	0	20	12	0.4	1.4	0.1	0.1	3.7	6.3
	95% C.I. Low	2	2	374	318	14.1	21.3	0.9	1.2	45.9	58.8
	95% C.I. High	2	2	415	342	14.9	24.3	1.1	1.4	53.6	72.1

Process	Statistic	Capacity		Total Entries		Average time per entry		Average Content		% Utilization	
		A	B	A	B	A	B	A	B	A	B
Cleaning	Avg	1	1	393	328	8.6	11.5	0.6	0.7	58.5	65.4
	Min	1	1	366	314	8.4	10.9	0.5	0.6	54.3	60.8
	Max	1	1	422	346	8.8	12.8	0.6	0.8	62.7	76.6
	St. Dev.	0	0	19	11	0.1	0.7	0.0	0.1	3.3	5.7
	95% C.I. Low	1	1	373	316	8.4	10.8	0.6	0.6	55.0	59.4
	95% C.I. High	1	1	414	339	8.7	12.2	0.6	0.7	61.9	71.4
Testing	Avg	2	2	393	325	17.4	31.7	1.2	1.8	59.3	89.3
	Min	2	2	365	313	16.7	31.2	1.1	1.7	54.5	85.0
	Max	2	2	422	342	17.8	32.0	1.3	1.9	63.2	94.5
	St. Dev.	0	0	20	10	0.4	0.3	0.1	0.1	2.9	3.0
	95% C.I. Low	2	2	372	314	16.9	31.3	1.1	1.7	56.3	86.1
	95% C.I. High	2	2	414	336	17.9	32.0	1.2	1.8	62.3	92.5
Final Restoration and Inspection	Avg	1	1	315	256	12.0	16.0	0.7	0.7	65.6	70.9
	Min	1	1	302	247	11.9	15.7	0.6	0.7	62.5	68.3
	Max	1	1	330	266	12.1	16.2	0.7	0.7	69.0	74.7
	St. Dev.	0	0	12	6	0.1	0.2	0.0	0.0	2.7	2.2
	95% C.I. Low	1	1	302	249	11.9	15.7	0.6	0.7	62.8	68.6
	95% C.I. High	1	1	328	262	12.1	16.2	0.7	0.7	68.4	73.2
Disassembly	Avg	2	2	166	133	9.5	13.9	0.3	0.3	13.6	16.1
	Min	2	2	155	120	9.1	13.7	0.2	0.3	12.5	14.2
	Max	2	2	174	143	9.8	14.6	0.3	0.3	14.8	17.3
	St. Dev.	0	0	8	8	0.3	0.4	0.0	0.0	0.9	1.1
	95% C.I. Low	2	2	157	125	9.2	13.6	0.3	0.3	12.7	14.9
	95% C.I. High	2	2	174	141	9.8	14.3	0.3	0.3	14.5	17.3
Sorting	Avg		2		531		5.2		0.5		24.0
	Min		2		476		5.1		0.4		21.0
	Max		2		572		5.4		0.5		26.1
	St. Dev.		0		32		0.1		0.0		1.8
	95% C.I. Low		2		497		5.1		0.4		22.0
	95% C.I. High		2		565		5.3		0.5		25.9

### Appendix III: Summaries for Key Variables Statistics for Product A and B

Key Variables	Statistic	Current Value			Key Variables	Statistic	Current Value	
		A	B				A	B
Number of control drives received	Avg	485.8	427.5		Number of New Control Board Used	Avg	121.7	97.3
	Min	474.0	407.0			Min	113.0	87.0
	Max	505.0	448.0			Max	132.0	103.0
	St. Dev.	10.8	15.2			St. Dev.	8.50	6.0
	95% C.I. Low	474.5	411.5			95% C.I. Low	112.75	91.0
	95% C.I. High	497.1	443.5			95% C.I. High	130.59	103.6
Number of Control Drives Disassembled	Avg	165.5	133.0		Number of Fans Reused	Avg	124.3	102.0
	Min	155.0	120.0			Min	114.0	90.0
	Max	174.0	143.0			Max	135.0	110.0
	St. Dev.	7.7	7.7			St. Dev.	9.03	8.2
	95% C.I. Low	157.4	124.9			95% C.I. Low	114.86	93.4
	95% C.I. High	173.6	141.1			95% C.I. High	133.81	110.6
Numb Control Board Reused	Avg	47.6	33.2		Number of PCB Board Reused	Avg	126.2	102.2
	Min	42.0	27.0			Min	123.0	88.0
	Max	53.2	39.0			Max	130.0	112.0
	St. Dev.	7.6	5.8			St. Dev.	2.40	7.9
	95% C.I. Low	41.5	28.6			95% C.I. Low	123.65	93.9
	95% C.I. High	53.7	37.8			95% C.I. High	128.69	110.4
Number of Power Board Reused	Avg	120.7	95.0		Number of New Fans Used	Avg	74.7	63.8
	Min	110.0	87.0			Min	52.0	46.0
	Max	126.0	102.0			Max	104.0	93.0
	St. Dev.	5.8	5.3			St. Dev.	18.69	16.1
	95% C.I. Low	114.6	89.4			95% C.I. Low	55.05	46.9
	95% C.I. High	126.7	100.6			95% C.I. High	94.28	80.8
Number of New Power Board Used	Avg	3.8	0.5		Number New PCB Boards Used	Avg	55.2	46.3
	Min	2.0	0.0			Min	46.0	34.0
	Max	7.0	2.0			Max	63.0	76.0
	St. Dev.	1.9	0.8			St. Dev.	8.04	15.1
	95% C.I. Low	1.8	0.0			95% C.I. Low	46.73	30.5
	95% C.I. High	5.9	1.4			95% C.I. High	63.60	62.2



## Appendix IV: ProModel Simulation Code for Product A

\*\*\*\*\*

```
*          Formatted Listing of Model:          *
* C:\Users\Aminga\OneDrive - University of Wisconsin Milwaukee\My Academics\Re-Manufacturing\Dissertation Working Documents\ProMod files\Product A
Remanufacturing.MOD *
```

\*\*\*\*\*

```
?????:
#
#This model simulates the operation of a remanufacturing plant...
Time Units:      Minutes
Distance Units:   Feet
Initialization Logic:  ACTIVATE BeginAnimation()
```

\*\*\*\*\*

```
*          Locations          *
```

\*\*\*\*\*

Name	Cap	Units	Stats	Rules	Cost
Arrival	INFINITE	1	Time Series	Oldest, ,	
Registration	1	1	Time Series	Oldest, ,	
DiagnosticTesting	1	1	Time Series	Oldest, ,	
RepairingArrivingArea	INFINITE	1	Time Series	Oldest, ,	
Reparing	2	1	Time Series	Oldest, ,	
Cleanning	1	1	Time Series	Oldest, ,	
Testing	2	1	Time Series	Oldest, ,	
Final_Restoration_and_Inspecti	1	1	Time Series	Oldest, ,	
LabelingQ	INFINITE	1	Time Series	Oldest, FIFO,	
FinishProductStorage	INFINITE	1	Time Series	Oldest, ,	
DisassemblyArrivalArea	INFINITE	1	Time Series	Oldest, ,	
Disassembly	2	1	Time Series	Oldest, ,	
Sorting	INFINITE	1	Time Series	Oldest, ,	
Scrap	1	1	Time Series	Oldest, ,	
Cleaning1Q	INFINITE	1	Time Series	Oldest, FIFO,	
Cleaning2Q	INFINITE	1	Time Series	Oldest, FIFO,	
TestingQ	INFINITE	1	Time Series	Oldest, FIFO,	
Cleaning2	1	1	Time Series	Oldest, ,	
UsedPartsArrivals	INFINITE	1	Time Series	Oldest, ,	
UsedPartsStorage	INFINITE	1	Time Series	Oldest, ,	

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		Routing					
Entity	Location	Operation	Blk	Output	Destination	Rule	Move Logic
Control_Drive	Arrival	NumbContDrIn=NumbContDrIn+1					
		1	Control_Drive	Registration	FIRST 1		
Control_Drive	Registration	wait N(5,1.5)	1	Control_Drive	DiagnosticTesting	FIRST 1	
Control_Drive	DiagnosticTesting	wait N(10,2.5)	1	Control_Drive	RepairingArrivingArea	0.650000	1
		Unrepaired_Control_Drive	DisassemblyArrivalArea	0.350000			
Control_Drive	RepairingArrivingArea	1	Control_Drive	Repairing	FIRST 1		
Control_Drive	Repairing	wait N(14,5)					
		Real prob = rand(1)					
		if(prob<0.16) then					
		{					
		if(NumControlBoardInStorage>1) then					
		{					
		JOIN 1 Control_Board					
		dec NumControlBoardInStorage					
		}else{					
		inc NumNewPowerBoardUsed					
		}					
		}else {					
		if(prob<0.3) then					
		{					
		if(NumPowerBoardInStorage>1) then					
		{					
		JOIN 1 Power_Board					
		dec NumPowerBoardInStorage					

```

    }else{
        inc NumNewPowerBoardUsed
    }
}else {
    if(prob<0.56) then
    {
        if(NumFansInStorage>1) then
        {
            JOIN 1 Fan
            dec NumFansInStorage
        }else{
            inc NumNewFansUsed
        }
    }else{
        if(prob<0.76) then
        {
            if(NumPCBBoardInStorage>1) then
            {
                JOIN 1 PCB_Board
                dec NumPCBBoardInStorage
            }else{
                inc NumNewPCBBoardsUsed
            }
        }else{
            if(NumFansInStorage>1 and NumPCBBoardInStorage>1) then
            {
                JOIN 1 Fan
                JOIN 1 PCB_Board
                dec NumFansInStorage
                dec NumPCBBoardInStorage
            }else{
                inc NumNewFansUsed
                inc NumNewPCBBoardsUsed
            }
        }
    }
}
}

1 Control_Drive Cleaning1Q FIRST 1
1 Control_Drive Cleanning FIRST 1
wait N(8,1.8) 1 Control_Drive TestingQ FIRST 1
1 Control_Drive Testing FIRST 1
wait N(16.5,15)
Real prob = rand(1)
if(prob<0.8) then
{

```

Control\_Drive  
Control\_Drive  
Control\_Drive  
Control\_Drive

Cleaning1Q  
Cleanning  
TestingQ  
Testing

```

Route 1
}else {
Route 2
}

1 Control_Drive LabelingQ FIRST 1
2 Control_Drive RepairingArrivingArea FIRST 1
Control_Drive LabelingQ 1 Control_Drive Final_Restoration_and_Inspecti FIRST 1
Control_Drive Final_Restoration_and_Inspect wait N(12,2.5) 1 Control_Drive FinishProductStorage FIRST 1
Control_Drive FinishProductStorage wait N(90,30) 1 Control_Drive EXIT FIRST 1
Unrepaired_Control_Drive DisassemblyArrivalArea NumbContDrDissassembled=NumbContDrDissassembled+1
1 Unrepaired_Control_Drive Disassembly FIRST 1
Unrepaired_Control_Drive Disassembly wait N(9.5,2.5)
SEND 1 Control_Board TO Sorting
SEND 1 Power_Board TO Sorting
SEND 1 Fan TO Sorting
SEND 1 PCB_Board TO Sorting
1 Unrepaired_Control_Drive EXIT FIRST 1
Control_Board UsedPartsArrivals 1 Control_Board Sorting Send 1
Power_Board UsedPartsArrivals 1 Power_Board Sorting Send 1
Control_Board Sorting wait N(5,2.5)

Real prob = rand(1)
if(prob<0.26) then
{
Route 1
}else {
Route 2
inc NumbControlBoardSaved
}

1 Control_Board Scrap FIRST 1
2 Control_Board Cleaning2Q FIRST 1
Control_Board Scrap wait 5 1 Control_Board EXIT FIRST 1
Power_Board Sorting wait N(5,2.5)

Real prob = rand(1)
if(prob<0.26) then
{
Route 1
}else {
Route 2
inc NumbPowerBoardSaved
}

1 Power_Board Scrap FIRST 1
2 Power_Board Cleaning2Q FIRST 1
Power_Board Scrap wait N(4,1) 1 Power_Board EXIT FIRST 1

```

```

Control_Board    Cleaning2Q          1 Control_Board    Cleaning2    FIRST 1
Control_Board    Cleaning2          wait N(8,1.8)
                  inc NumControlBoardInStorage
                  1 Control_Board    UsedPartsStorage    FIRST 1
Power_Board      Cleaning2Q          1 Power_Board      Cleaning2    FIRST 1
Power_Board      Cleaning2          WAIT N(8,1.8)
                  inc NumPowerBoardInStorage
                  1 Power_Board      UsedPartsStorage    FIRST 1
Fan              UsedPartsArrivals    1 Fan              Sorting      Send 1
PCB_Board        UsedPartsArrivals    1 PCB_Board        Sorting      Send 1
Fan              Sorting              wait N(5,2.5)
                  Real prob = rand(1)
                  if(prob<0.76) then
                  {
                    Route 1
                    inc NumbFansSaved
                  }else {
                    Route 2
                  }
                  1 Fan              Cleaning2Q          FIRST 1
                  2 Fan              Scrap                FIRST 1
PCB_Board        Sorting              wait N(5,2.5)
                  Real prob = rand(1)
                  if(prob<0.76) then
                  {
                    Route 1
                    inc NumbPCBBoardSaved
                  }else {
                    Route 2
                  }
                  1 PCB_Board        Cleaning2Q          FIRST 1
                  2 PCB_Board        Scrap                FIRST 1
Fan              Cleaning2Q          1 Fan              Cleaning2    FIRST 1
PCB_Board        Cleaning2Q          1 PCB_Board        Cleaning2    FIRST 1
Fan              Cleaning2          wait N(8,1.8)
                  inc NumFansInStorage
                  1 Fan              UsedPartsStorage    FIRST 1
PCB_Board        Cleaning2          wait N(8,1.8)
                  inc NumPCBBoardInStorage
                  1 PCB_Board        UsedPartsStorage    FIRST 1
Fan              Scrap              wait N(4,1)          1 Fan              EXIT          FIRST 1
PCB_Board        Scrap              wait N(4,1)          1 PCB_Board        EXIT          FIRST 1
Control_Board    UsedPartsStorage    1 Control_Board    Repairing    Join 1
Power_Board      UsedPartsStorage    1 Power_Board      Repairing    Join 1
Fan              UsedPartsStorage    1 Fan              Repairing    Join 1

```



## Appendix V: ProModel Simulation Code for Product B

```
*****
*           Formatted Listing of Model:           *
* C:\Users\Aminga\OneDrive - University of Wisconsin Milwaukee\My Academics\Re-Manufacturing\Dissertation Working Documents\ProMod files\Product B
Remanufacturing.MOD *
*                                           *
*****
```

```
?????:
#
#This model simulates the operation of a remanufacturing plant...
Time Units:      Minutes
Distance Units:  Feet
Initialization Logic:  ACTIVATE BeginAnimation()
```

```
*****
*           Locations           *
*****
```

Name	Cap	Units	Stats	Rules	Cost
Arrival	INFINITE	1	Time Series	Oldest, ,	
Registration	1	1	Time Series	Oldest, ,	
DiagnosticTesting	1	1	Time Series	Oldest, ,	
RepairingArrivingArea	INFINITE	1	Time Series	Oldest, ,	
Repairing	2	1	Time Series	Oldest, ,	
Cleanning	1	1	Time Series	Oldest, ,	
Testing	2	1	Time Series	Oldest, ,	
Final_Restoration_and_Inspecti	1	1	Time Series	Oldest, ,	
LabelingQ	INFINITE	1	Time Series	Oldest, FIFO,	
FinishProductStorage	INFINITE	1	Time Series	Oldest, ,	
DisassemblyArrivalArea	INFINITE	1	Time Series	Oldest, ,	
Disassembly	2	1	Time Series	Oldest, ,	
Sorting	2	1	Time Series	Oldest, ,	
Scrap	1	1	Time Series	Oldest, ,	
Cleaning1Q	INFINITE	1	Time Series	Oldest, FIFO,	
Cleaning2Q	INFINITE	1	Time Series	Oldest, FIFO,	
TestingQ	INFINITE	1	Time Series	Oldest, FIFO,	
Cleaning2	1	1	Time Series	Oldest, ,	
UsedPartsArrivals	INFINITE	1	Time Series	Oldest, ,	

UsedPartsStorage                      INFINITE                      1                      Time Series                      Oldest, ,

\*\*\*\*\*  
\*                      Entities                      \*  
\*\*\*\*\*

Name	Speed (fpm)	Stats	Cost
Control_Board	150	Time Series	
Power_Board	150	Time Series	
Control_Drive	150	Time Series	
Fan	150	Time Series	
PCB_Board	150	Time Series	
Unrepaired_Control_Drive	150	Time Series	

\*\*\*\*\*  
\*                      Processing                      \*  
\*\*\*\*\*

120

		Process		Routing			
Entity	Location	Operation	Blk	Output	Destination	Rule	Move Logic
Control_Drive	Arrival	NumbContDrIn=NumbContDrIn+1	1	Control_Drive	Registration	FIRST 1	
Control_Drive	Registration	wait N(5,1.5)	1	Control_Drive	DiagnosticTesting	FIRST 1	
Control_Drive	DiagnosticTesting	wait N(14.5,2.5)	1	Control_Drive	RepairingArrivingArea	0.650000	1
				Unrepaired_Control_Drive	DisassemblyArrivalArea	0.350000	
Control_Drive	RepairingArrivingArea		1	Control_Drive	Reparing	FIRST 1	
Control_Drive	Reparing	wait N(22,3.5)					

```
Real prob = rand(1)
if(prob<0.26) then
{
  if(NumControlBoardInStorage>1) then
  {
    JOIN 1 Control_Board
    dec NumControlBoardInStorage
  }else{
    inc NumNewControlBoardUsed
  }
}else {
  if(prob<0.3) then
  {
    if(NumPowerBoardInStorage>1) then
```



```

    {
      JOIN 1 Power_Board
      dec NumPowerBoardInStorage
    }else{
      inc NumNewPowerBoardUsed
    }
  }else {
    if(prob<0.56) then
    {
      if(NumFansInStorage>1) then
      {
        JOIN 1 Fan
        dec NumFansInStorage
      }else{
        inc NumNewFansUsed
      }
    }else{
      if(prob<0.76) then
      {
        if(NumPCBBoardInStorage>1) then
        {
          JOIN 1 PCB_Board
          dec NumPCBBoardInStorage
        }else{
          inc NumNewPCBBoardsUsed
        }
      }else{
        if(NumFansInStorage>1 and NumPCBBoardInStorage>1) then
        {
          JOIN 1 Fan
          JOIN 1 PCB_Board
          dec NumFansInStorage
          dec NumPCBBoardInStorage
        }else{
          inc NumNewFansUsed
          inc NumNewPCBBoardsUsed
        }
      }
    }
  }
}

1 Control_Drive Cleaning1Q FIRST 1
1 Control_Drive Cleanning FIRST 1
wait N(10.5,5) 1 Control_Drive TestingQ FIRST 1
1 Control_Drive Testing FIRST 1

```

Control\_Drive  
Control\_Drive  
Control\_Drive

Cleaning1Q  
Cleanning  
TestingQ

```

Control_Drive    Testing    wait N(31.5,9.5)
                    Real prob = rand(1)
                    if(prob<0.8) then
                    {
                        Route 1
                    }else {
                        Route 2
                    }
                    1 Control_Drive    LabelingQ    FIRST 1
                    2 Control_Drive    RepairingArrivingArea    FIRST 1
Control_Drive    LabelingQ    1 Control_Drive    Final_Restoration_and_Inspecti FIRST 1
Control_Drive    Final_Restoration_and_Inspect wait N(16,5) 1 Control_Drive    FinishProductStora ge    FIRST 1
Control_Drive    FinishProductStorage wait N(90,30) 1 Control_Drive    EXIT    FIRST 1
Unrepaired_Control_Drive DisassemblyArrivalArea    NumbContDrDissassembled=NumbContDrDissassembled+1
                    1 Unrepaired_Control_Drive Disassembly    FIRST 1
Unrepaired_Control_Drive Disassembly    wait N(14, 3.5)
                    SEND 1 Control_Board TO Sorting
                    SEND 1 Power_Board TO Sorting
                    SEND 1 Fan TO Sorting
                    SEND 1 PCB_Board TO Sorting
                    1 Unrepaired_Control_Drive EXIT    FIRST 1
Control_Board    UsedPartsArrivals    1 Control_Board    Sorting    Send 1
Power_Board    UsedPartsArrivals    1 Power_Board    Sorting    Send 1
Control_Board    Sorting    wait N(5,2.5)
                    Real prob = rand(1)
                    if(prob<0.26) then
                    {
                        Route 1
                    }else {
                        Route 2
                        inc NumbControlBoardSaved
                    }
                    1 Control_Board    Scrap    FIRST 1
                    2 Control_Board    Cleaning2Q    FIRST 1
Control_Board    Scrap    wait N(4,1) 1 Control_Board    EXIT    FIRST 1
Power_Board    Sorting    wait N(5,2.5)
                    Real prob = rand(1)
                    if(prob<0.26) then
                    {
                        Route 1
                    }else {
                        Route 2
                        inc NumbPowerBoardSaved
                    }

```

```

    }
    1 Power_Board Scrap FIRST 1
    2 Power_Board Cleaning2Q FIRST 1
Power_Board Scrap wait N(4,1) 1 Power_Board EXIT FIRST 1
Control_Board Cleaning2Q 1 Control_Board Cleaning2 FIRST 1
Control_Board Cleaning2 wait N(8,1.8)
inc NumControlBoardInStorage
1 Control_Board UsedPartsStorage FIRST 1
Power_Board Cleaning2Q 1 Power_Board Cleaning2 FIRST 1
Power_Board Cleaning2 WAIT N(8,1.8)
inc NumPowerBoardInStorage
1 Power_Board UsedPartsStorage FIRST 1
Fan UsedPartsArrivals 1 Fan Sorting Send 1
PCB_Board UsedPartsArrivals 1 PCB_Board Sorting Send 1
Fan Fan Sorting wait N(5,2.5)
Real prob = rand(1)
if(prob<0.76) then
{
Route 1
inc NumbFansSaved
}else {
Route 2
}
1 Fan Cleaning2Q FIRST 1
2 Fan Scrap FIRST 1
PCB_Board Sorting wait N(5,2.5)
Real prob = rand(1)
if(prob<0.76) then
{
Route 1
inc NumbPCBBoardSaved
}else {
Route 2
}
1 PCB_Board Cleaning2Q FIRST 1
2 PCB_Board Scrap FIRST 1
Fan Cleaning2Q 1 Fan Cleaning2 FIRST 1
PCB_Board Cleaning2Q 1 PCB_Board Cleaning2 FIRST 1
Fan Fan Cleaning2 wait N(8,1.8)
inc NumFansInStorage
1 Fan UsedPartsStorage FIRST 1
PCB_Board Cleaning2 wait N(8,1.8)
inc NumPCBBoardInStorage
1 PCB_Board UsedPartsStorage FIRST 1
Fan Fan Scrap wait N(4,1) 1 Fan EXIT FIRST 1

```

PCB_Board	Scrap	wait N(4,1)	1	PCB_Board	EXIT	FIRST 1
Control_Board	UsedPartsStorage		1	Control_Board	Repairing	Join 1
Power_Board	UsedPartsStorage		1	Power_Board	Repairing	Join 1
Fan	UsedPartsStorage		1	Fan	Repairing	Join 1
PCB_Board	UsedPartsStorage		1	PCB_Board	Repairing	Join 1
Control_Board	Arrival					

\*\*\*\*\*

\* Arrivals \*

\*\*\*\*\*

Entity	Location	Qty Each	First Time	Occurrences	Frequency	Logic
Control_Drive	Arrival	1	0		INF	W(1,6,15,2)
Control_Board	UsedPartsArrivals	10	0		INF	N(10,2)
Power_Board	UsedPartsArrivals	10	0		INF	N(10,2)
Fan	UsedPartsArrivals	10	0		INF	N(10,2)
PCB_Board	UsedPartsArrivals	10	0		INF	N(10,2)

\*\*\*\*\*

\* Variables (global) \*

\*\*\*\*\*

ID	Type	Initial value	Stats
NumbContDrIn	Integer	0	Time Series
NumbContDrDissassembled	Integer	0	Time Series
NumbControlBoardSaved	Integer	0	Time Series
NumbPowerBoardSaved	Integer	0	Time Series
NumControlBoardInStorage	Integer	0	Time Series
NumPowerBoardInStorage	Integer	0	Time Series
NumNewPowerBoardUsed	Integer	0	Time Series
NumNewControlBoardUsed	Integer	0	Time Series
NumbFansSaved	Integer	0	Time Series
NumbPCBBoardSaved	Integer	0	Time Series
NumFansInStorage	Integer	0	Time Series
NumPCBBoardInStorage	Integer	0	Time Series
NumNewFansUsed	Integer	0	Time Series
NumNewPCBBoardsUsed	Integer	0	Time Series

\*\*\*\*\*

\* Subroutines \*

\*\*\*\*\*

ID	Type	Parameter	Type	Logic
BeginAnimation	None		wait 1	ANIMATE 20

## Curriculum Vitae

**Thomas Omwando**

**Place of Birth:** Nyamira Kenya

**Education:**

BTech., Moi University, Eldoret, Kenya - Oct. 2002  
Major: Mechanical & Production Engineering

MPhil., Moi University, Eldoret, Kenya - Dec. 2006  
Major: Mechanical & Production Engineering

Dissertation Title: A Fuzzy Inference System Approach for Evaluating the Feasibility of Product Remanufacture

**Teaching Experience:**

Lecturer., Masinde Muliro University of Science & Technology - 2007 – July 2011  
Department of Mechanical and Industrial Engineering  
Teaching Assistantship., University of Wisconsin Milwaukee - 2014 – July 2016  
Department of Mechanical and Industrial Engineering

**Conference Publications:**

- Otieno, W., Ross, A., Aydas, O., Omwando, T.O., Labor Capacity Assignment Model for Remanufacturing Environments, International Conference on Remanufacturing Proceedings, Amsterdam, Netherland, 2015.
- Omwando T. A. and Otieno W. “*A Reinforcement Learning Based Optimization of Maintenance of Wind Energy Conversion Systems*” In Proceedings of the ISERC 2013 Conference in San Juan, Puerto Rico, May 18–22, 2013

**University Service:**

Energy Engineer., Industrial Assessment Center @ UWM - May 2013- Dec 2016  
President., Association of Energy Engineers @ UWM – (June 2013 –Dec 2016)  
Vice President., INFORMS - @ UWM Chapter – August 2014 – to Dec 2016)

**Certifications:**

Certified Energy Manager (CEM) – September 2016

**Affiliations/ Membership:**

Association of Energy Engineers (June 2013 –to Present)  
INFORMS - August 2014 – to Present)  
Member – National Society of Black Engineers – Feb 2016 – to Date  
Member - Institution of Industrial Engineer – October 2011 – to Date  
Registered Graduate Engineer - Engineer's Registration Board, Kenya since 2005