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Modular Product Architecture’s Decisions Support For Remanufacturing-Product Service System Synergy

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MODULAR PRODUCT ARCHITECTURE'S DECISIONS SUPPORT FOR REMANUFACTURING-PRODUCT SERVICE SYSTEM SYNERGY

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DISSERTATION

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DEDICATION

To my wife, my dad, and the memory of my mom

ACKNOWLEDGEMENTS

I have learned to exercise caution in appreciating people that have contributed to one's success story because the more people are acknowledged, the more are others that are offended by their exclusion. Therefore I will keep the list short, but with due regard to those that have added values to my life in one way or the other during my doctoral study.

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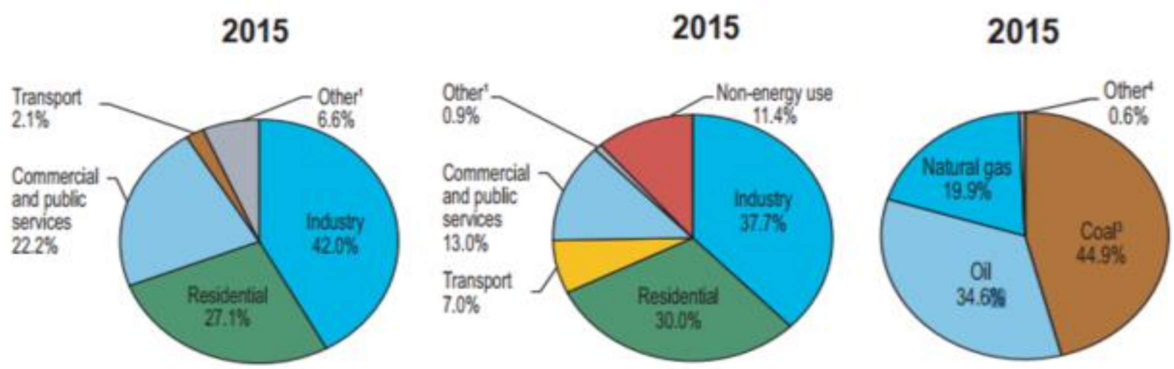
TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Over the years, the manufacturing sector has contributed significantly to improve the quality of life amidst growing human population and increasing demands for better quality product. On the other hand, there are negative consequences that are associated with the manufacturing activities including declining natural resources, large energy consumption, harmful emissions, and disposals of used product in landfills. According to the International Energy Agency (IEA), the manufacturing sector accounts for 42% of electricity (figure 1.1a), 37.7% of natural gas (figure 1.1b), 39.8% of coal, and 8% of oil in global energy consumption, with an equivalent 28% of total global CO_2 release (figure 1.1c) IEA (2017).



(a) (b) (c)

Figure 1.1: Proportion of energy consumption and CO_2 release by manufacturing sector

In order to curtail the negative impacts of the manufacturing activities, governments around the globe are implementing regulations that hold the original equipment manufacturers (OEMs) accountable for the post-consumer phase of their products. Consequently, some product end-of-life (EOL) management strategies have emerged, among which remanufacturing is considered the most viable (Ma & Kremer, 2014). According to the US International Trades

Commission, remanufacturing is recording increasing remarkable strides with the value of remanufactured products rising from $37.3 billion in 2009 to $43 billion by 2011 in the US alone (Commission, 2012). Similarly, remanufacturing prevents the emission of over 28 million tons of CO2 annually (Charter & Gray, 2008). In recognizing the embedded benefits in remanufacturing, the US 114th Congress passed the "Federal Vehicle Repair cost saving acts of 2015" Congress (2015). The sections 3 and 4 of the act specifically advocate increased remanufacturing. Furthermore, international collaboration towards effective remanufacturing was discussed at the 2005 G7 Summit, while the United Nations through its International Resources Panel (IRP) formed a group with global remanufacturing cooperation as the primary focus (Matsumoto et al., 2016). However, as shown in table 1.1, about 80% of manufactured products are currently disposed at their EOL despite the EOL management techniques (Commission, 2012).

Table 1.1: Global Product End-of-life disposal

	Total EOL products		Total recycled			Total disposed		
Year	Units (mill)	Tons (000)	Units (mill)	Tons (000)	Ton (%)	Units (mill)	Tons (000)	Ton (%)
1999	159	1,056	23.6	157	14.9	135.4	899.2	85
2000	161.6	1282	24	190	14.8	137.7	1092	85
2001	193.6	1447.6	28.1	210	14.5	165.5	1237.6	85
2001	225.2	1634	34.6	250	15.3	190.7	1384	85
2003	273.8	1944.7	40.8	290	14.9	232.9	1654.7	85
2004	310.7	2043.5	48.6	320	15.7	262	1723.5	84
2005	342.1	2172.6	54.3	345	15.9	287.8	1827.6	84
2006	342.9	2107.8	61.3	377	17.9	281.5	1730.8	82
2007	372.7	2251.7	68.5	414	18.4	304.2	1837.7	82
2008	412.6	2527.1	72.4	441.2	18	340.1	2088	83
2009	441.5	2674.7	78.2	471.9	18.4	363.2	2205.4	82
2010	470.5	2822.9	84	502.6	18.8	386.3	2322.8	82
2011	499.4	2970.5	89.8	533.3	19.2	409.4	2440.3	82
2012	528.4	3118.7	95.6	564	19.1	432.5	2557.7	82
2013	557.3	3266.3	101.5	595.3	19.9	455.6	2675.1	81
2014	586.3	3414.5	107.3	626	20.3	478.7	2792.5	81
2015	615.2	3562.1	113.1	656.7	20.7	501.8	2909.9	81

Major impediments to remanufacturing include the quality, quantity, recovery time of the used product, and the negative perception of the remanufactured product (Hatcher et al., 2011). Therefore, it is worthwhile to undertake studies to enhance remanufacturing activities in order to harness the considerable gains that are contained therein. Meanwhile, the product service system (PSS) is a business strategy that is predicated on the selling of products' functions rather than the physical product, while the manufacturer retains the product ownership (Annarelli et al., 2016). Due to product sharing philosophy of PSS, fewer products are required to meet the customers' needs, thereby reducing the usage of materials, energy, machinery, equipment, and associated emissions. As a result, PSS is considered a sustainable product offering. An increasing number of OEMs are currently offering their products in PSS (Song & Sakao, 2017). In the same vein, Google trend (https://trends.google.com/trends) shows a gradually increasing interest in PSS since 2012, as depicted in figure 1.2. (Trend captured on February 5, 2018).

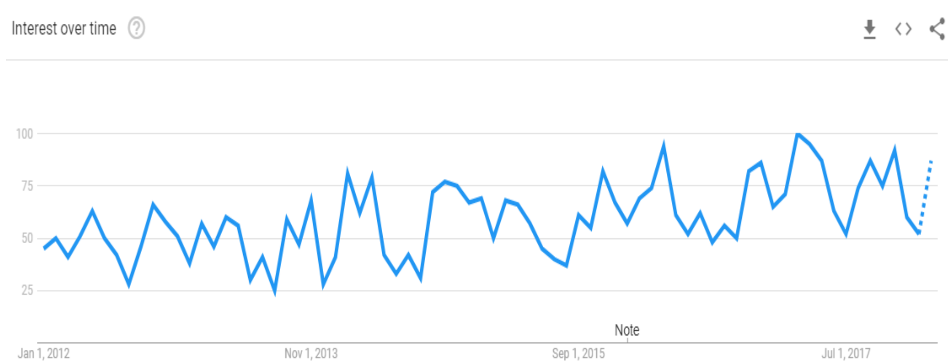


Figure 1.2: Trend in Product service system

With the OEM retaining the product's ownership, the quantity, volume and recovery time of used product can be controlled to a large extent. Similarly, the acceptability of a remanufactured product is substantially heightened because in PSS, only the product's functions are required by the customers. Therefore, the PSS is poised to address the major setbacks of remanufacturing. Consequently, the integration of PSS and remanufacturing as a business enterprise enables the OEM to realize the benefits of PSS and remanufacturing, and translating the remanufacturing hitches into gains simultaneously. The PSS-remanufacturing initiative is conceived as a sustainable product offering.

The PSS-remanufacturing business idea is currently emerging. Theoretical framework linking PSS and remanufacturing has been provided (Sundin and Lindahl, 2008). However, analytical approach in this regard is missing. Similarly, the associated lifecycle variables (e.g. cost) with regard to PSS-remanufacturing business is missing. It is widely reported that product lifecycle is mainly influenced by decisions that are made in the early phase of product development (PD) decisions. Kremer report that about 80% lifecycle. The report that issues no longer rectifiable after the market. Further, modular design is considered as an efficient PD strategy. Our contribution towards the improvement of the PSS-remanufacturing business offering is discussed in three chapters. In general, we develop a unique optimization model that determines the modular product architecture in order to realize an improved PSS-Remanufacturing business. The description framework is shown in figure 1.3.

In chapter 2, the fuzzy system was engaged to quantify the imprecise data that relate to the product's performance in order to develop a unique optimization model based on pairwise comparison of modules. Currently, an individual module is considered on its merit for PD purpose. The study introduces modular pairwise assessment into PD.

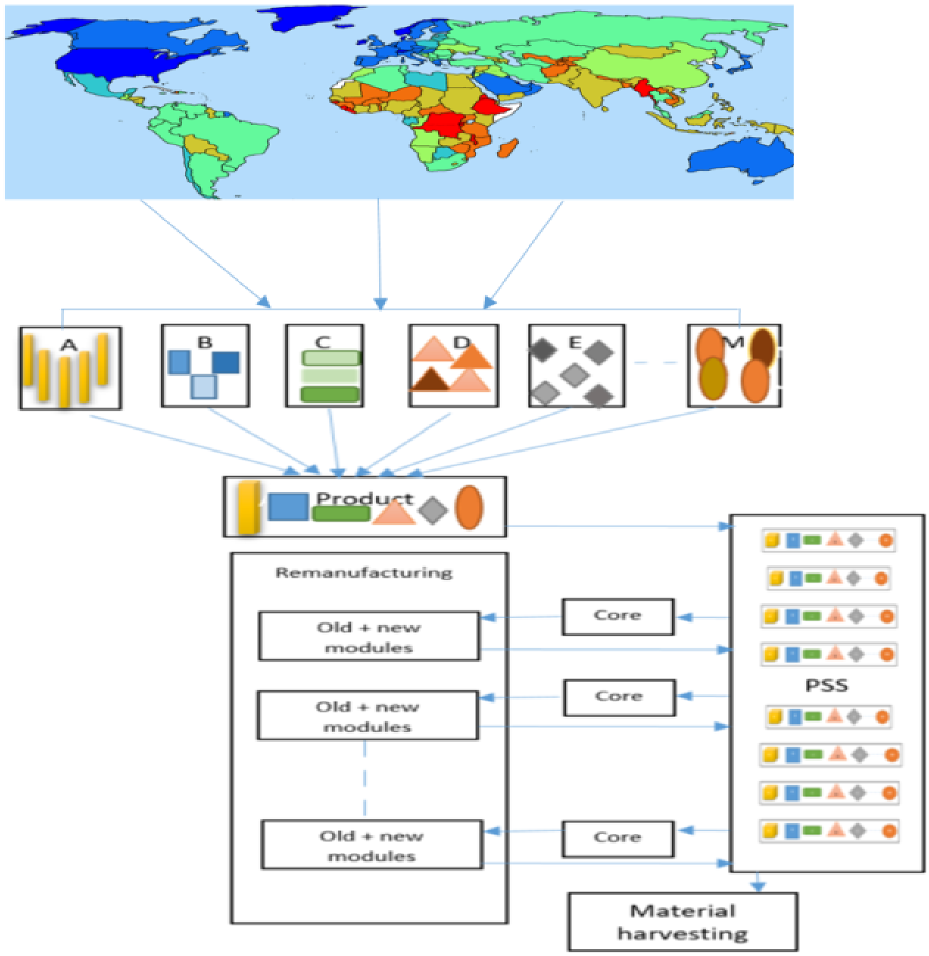


Figure 1.3: Product offering in PSS-Remanufacturing environment

In Chapter 3, the implications of lifecycle cost are considered in the base model that was developed earlier in the early phase of PD. In addition, multi-attribute utility theory (MAUT) was employed to provide a comparative assessment of the optimal product configurations. The sustainability of a PSS-remanufacturing business is the focus of chapter 4. The study performs lifecycle assessment of module variants to determine the ecological impacts of module variants and quantify the environmental sustainability of the modular product architectures. Through MAUT, the degree of sustainability of optimal product configuration was provided. Finally, the conclusions of the study are contained in chapter 5. It reiterates the significance of the study as a modular product architecture decision guide.

CHAPTER 2: MODULAR PRODUCT MODEL DEVELOPMENT

2.1 Introduction

In order to address the sustainability concerns that result from increasing demand for higher quality products as well as population growth, significant efforts have been made with regard to product end-of-life (EOL) management. EOL management strategies include, recycling, reuse, refurbishment, remanufacturing, reconditioning, repurposing, repair, composting, incineration, and disposals in landfill (Ma & Okudan, 2014). Remanufacturing is widely reported to be the most economically and environmentally beneficial among product EOL management strategies (Ma & Okudan, 2014). However, despite the various EOL management strategies, about 80% of manufactured products currently end up as waste (Commission, 2012). Among other challenges, remanufacturing is influenced by uncertainty with regard to the time in which a used product is returned, and also by the quality and quantity of the used product that is returned.

Product service system (PSS) is a business strategy that emphasizes the functions of the product rather than the product itself, while the OEMs retains the ownership of the product. This enables the OEM to have some control over the time, quality and the volume of products that are returned from use. (Meier et al., 2011). Consequently, PSS provides a remedy to some of the challenges of remanufacturing. Govindan et al. (2016) evaluate twenty common barriers to remanufacturing and conclude that low customer acceptance of remanufactured product is a substantial impediment. Meanwhile, PSS remedies this problem as well because customers do not take ownership of the product, and a remanufactured product that provides the functions that the customers desires is well acceptable. In a study on the level of customers' satisfaction with regard to a product that is offered in PSS, Lee et al. (2015) identify measures of customers' values and provide their priority indices. The newness or otherwise of the product is not listed as important among the prioritized eight measures of customers' satisfaction.

As a result, the integration of remanufacturing and PSS is considered to be a potent remedy to the sustainability issues associated with manufacturing. Some theoretical attempts to links remanufacturing and PSS have been reported. The work of Sundin & Lindah (2008) is the earliest that provides such theoretical connection. Due to the potential benefits, the need to conduct further studies on remanufacturing and PSS synergy was emphasized by Hatcher et al. (2011). Nevertheless, analytical-based integration of remanufacturing and PSS at the early phase of product development is still missing.

The aim of this study is to fill this lacuna by providing a mathematical approach to modular product development in order to enhance remanufacturing and PSS. PSS is characterized by heavy product usage, which requires higher product serviceability. Therefore, serviceability must be built into the product at the product development phase. Meanwhile, research has shown that over 70% of product life cycle costs are associated with the product design and development decisions (Nepal et al., 2007). By implication, the integration of both PSS and remanufacturing rests heavily on product development decisions. It has also been shown in the literature that modular architecture significantly enhances product development (Nepal et al., 2008). With modular architecture, complex products are decomposed into simpler units while sustaining product integrity (Nepal et al 2007). Among other benefits, architecture strategy enhances product disassembly, thus improving product serviceability and core cleaning for both PSS and remanufacturing. This paper considers two factors that are essential for both PSS and remanufacturing: serviceability, a major criterion at product use phase, and core cleaning during remanufacturing at the product end-of-use (EOU) phase. These criteria are optimized, and most viable product configurations are obtained from among several product alternatives that are potentially available to the OEM. The outcomes will help product development decision makers to make better informed decisions regarding product modularity at the early stage of product development.

2.2 Literature Review

2.2.1 Overview of remanufacturing

Remanufacturing refers to the process of restoring product at the end-of-life/end-of-use phase into products that are at least as good as the original product (Aksoy & Gupta, 2005). This definition is common to most of the research on remanufacturing. To make this description more encompassing, Ijomah et al. (2007) includes the importance of similar customers' perception of both the remanufactured and new product. Remanufacturing is considered to be the most viable option among product EOL options (Lund & Hauser, 2003). Remanufactured products save landfills, prevent air pollution associated with recycling, mitigate extraction of raw materials, and retain other value added to the materials when the product was initially produced, such as energy and machinery (Gray & Charter, 2007).

Numerous studies have focused on product remanufacturing. Remanufacturing saves about 85% of the energy required to manufacture a new product, the energy equivalent of about 10.744 million barrels of crude (Giutini & Gaudette, 2003). It prevents yearly production of around 28 million tons of CO_2 globally (Gray & Charter, 2007). Remanufacturing also avoids huge manufacturing costs (Lund & Hauser, 2003), creates jobs, and lowers the price of remanufactured products to about 40% to 65% of a similar product when new (Commission, 2012). As a result of the benefits of remanufacturing, several works have studied how it could be improved, while identifying the factors that are required for its success. Among these factors, core cleaning is considered essential. While developing metrics for a generic remanufacturing process, Sundin (2004) reiterates the importance of core cleaning operation. Sundin et al. (2008) study the product properties that are essential so as to improve remanufacturing. The study develops a remanufacturing process matrix called RemPro, which includes cleaning operations as being critical for effective remanufacturing. Gallo et al. (2012) found that in the remanufacturing industries, most processes have fixed sequence of activities. The study concludes that cleaning activities are critical to successful remanufacturing and should be made flexible. While developing remanufacturing decision making framework, Subramoniam et al. (2010) show that core recovery and cleaning strategies are essential in order to realize an enhanced remanufacturing. Another study by Yagar (2012) reinforces the criticality of cleaning processes to successful remanufacturing. The study lists seven major cleaning operations and eight sub-cleaning operations that are used in remanufacturing, and concludes that parts that share similar processes, parts with similar material composition, and parts that attract similar dirt or contamination will enhance cleaning, lower the cost of remanufacturing, and improve the quality of the remanufactured product. However, remanufacturing is inhibited by factors such as unknown quality and quantity of the product's returned core, the uncertain timeframe in which the core is returned, the obsolescence level of returned parts, the acceptability of remanufactured products by customers, and financial benefits to the OEM (Hatcher et al., 2011).

2.2.2 Overview of the product service system

For optimal use of resources and improved sustainability, the product service system (PSS) was designed to offer more of the functions the product is meant to provide rather than offering the product itself (Baines et al., 2007). The earliest work on PSS by Goedkoop et al (1999) defines it as “a system of products, services, networks of ‘players’ and supporting infrastructure that continuously strives to be competitive, satisfy customer needs and have a lower environmental impact than traditional business model.” PSS is generally classified into three types: product-oriented, use-oriented, and result-oriented (Yang et al., 2009). In use-oriented PSS, the manufacturer owns the product, while the usage and functions of the product are offered to the user, usually through shared utilization services (or community products). These product functions are offered rather than selling the product itself. A high level of product usage characterizes use-oriented PSS, thereby underscoring the need to focus more on product serviceability during product development. Use-oriented PSS emphasizes that the product function provides the results that the customer requires (Song & Sakao, 2017).

A fundamental benefit of PSS is that it allows fewer physical products to offer the same or higher level of product functionality, thereby reducing the consumption of natural resources and energy requirements for manufacturing and associated transportation. As a result of the benefits of PSS, an increasing number of manufacturers now look beyond the product end-of-life remedy and are shifting their focus from the traditional product-selling philosophy to selling product functionality. Wijekoon (2011) demonstrates with mixed-integer linear programming that a product offered in PSS is more profitable to the enterprise and has lower environmental effects than a traditional product selling. Thompson et al. (2010) show that the benefits of PSS are higher when the product offered in PSS has a long life. More recent study on PSS highlights the importance of keeping product health monitoring data and user feedbacks during product lifecycle in repositories (Song & Sakao, 2017). These databanks provide valuable inputs that facilitate product development decisions. It is suggested that the PSS-remanufacturing approach will significantly remediate some of the economic and environmental issues associated with the product lifecycle (Hatcher et al., 2011). The environmental and economic advantages of PSS for both OEM and the product user are discussed in previous research. Sundin & Bras (2005) report that tens of thousands of forklifts are offered in PSS in Europe, and increasing volume of these forklifts are returned to remanufacturing facilities, culminating in huge financial savings for BT industries, and at the same time mitigating environmental impact had forklifts been sold into individual ownerships. Ferguson et al. (2009) find that in 2005, Caterpillar earned over $1 billion in sales of remanufactured product, while the product was previously leased. Robin Roy (2000) reports the financial savings by Xerox as a result of incorporating remanufactured parts into its various copiers, while the copiers are offered in PSS. Some industries that are involved in selling the services of their product and also engaged in remanufacturing are discussed in Roy et al. (2009). However, analytical studies on PSS-remanufacturing integration are sparse in the literature. Hatcher et al. (2011) emphasize that more studies are required in order to effectively integrate both PSS and remanufacturing.

2.2.3 Relevance of product modularity to product lifecycle

It is widely reported in the literature that product modularity plays significant roles in the product life cycle: the product design, development, use, and end-of-life management phases. Modular architecture is a concept that aims to decompose a complex product into many simpler units for optimal arrangement of parts (physically and functionally) and optimal user interface with the product (Ma & Okudan, 2014). The importance of modular design with regard to product maintainability or serviceability is detailed in several studies. Nepal et al. (2007) conclude that the cost of product maintainability is reduced as a result of modular architecture. Sundin et al. (2008) note that modular design facilitates product disassembly, and consequently improves product serviceability. Subramoniam et al. (2009) report that 75% of retired products that return to remanufacturing facilities are not designed with remanufacturing in focus, and thereby leading to some operational hitches. The study recommends design simplification such as modular architecture to facilitate remanufacturing. Chebyshev goal programming (CGP) was employed to develop optimal modular product that will enhance product maintainability, as well as other objectives in Nepal et al. (2007) The advantages of modular design for core cleaning are provided in (Yagar, 2012).

2.2.4 Application of fuzzy system in product development

The attributes and performance of a product's parts while the product is in use and during EOL management are uncertain. However, when such uncertainties are classified in linguistic terms, such as bad, fair, good, and very good, fuzzy logic has proven adept at handling such uncertainties by translating the linguistic terms into quantitative values that can be used for mathematical computation. Intense knowledge and experience of a subject matter expert are usually required in other to develop the fuzzy rules. Fuzzy logic has been largely employed in modular product development. While considering modular product design at the early stage, (Ma & Okudan, 2014) apply fuzzy logic to estimate product EOL uncertainties such as parts accessibility and disassembly for remanufacturing. Nepal et al. (2008) apply the trapezoidal membership function of fuzzy logic to capture imprecise data in order to develop optimal modules while considering reliability, maintainability, and cost. In the optimal product architecture developed for medical devices in Aguwa et al. (2010), medical stakeholders' data were obtained and converted into crisp values using the Sugeno fuzzy inference engine. Furthermore, Aguwa et al. (2012) demonstrate the effect of fuzzy rules modification on the optimal number of modules for medical device architecture.

The fuzzy inference system (FIS) consists of four main parts: fuzzifier, if-then rules, inference engine, and defuzzifier. Application of fuzzy inference system in product development research may be found in Büyüközkan & Feyzıoğlu (2004), and also in Famuyiwa et al. (2008). As a simple analogy, the objective to be estimated in numerical values is measured by some inputs (stated in natural language). These inputs are called linguistic variable in fuzzy terminology. Every linguistic variable is measured by some linguistic terms (expressed in levels of intensity, e.g. low, average, high). Every term is associated with a membership function (MF). The MF refers to the extent of membership or belongingness. Generally, development of fuzzy if-then rules and the selection of membership functions (MFs) are based on the experience of the expert, the decision maker, and historical data. Meanwhile, the exceptional efficiency of triangular and trapezoidal MFs in practical applications are discussed in Liou & Wang (1992). These MFs are frequently used in modular product development research. With reference to triangular MF, mathematically, the MF is defined by three parameters; (a, b, c), as expressed in Figure 2.1. The main difference between the Mamdani and Sugeno fuzzy engine is in defuzzification (conversion of fuzzy output into numerical value) process (Gupta, 2015). According to the study, the Sugeno method (with embedded weighted average inference operator as the engine) has the advantage of faster computational time while the Mamdani approach (with product inference operator) has better precision.

$$\text{Triangle}(x: a, b, c) = \begin{cases} 0 & x < a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & x > c \end{cases}$$

Figure 2.1: Triangular Membership function of Fuzzy inference system

Kannan et al. (2015) employ fuzzy triangular membership function to evaluate the materials that different suppliers provide for new product development so as to make green product decisions. In order to develop a model that minimizes modularization cost, Nepal et al. (2005) apply fuzzy triangular membership function to obtain qualitative values from modules' linguistic data.

2.2.5 Knowledge gap addressed

According to the review in the previous sections, past studies reveal that remanufacturing-PSS synergy has been recommended as a business offering with high potential to resolve huge sustainability issues. However, only a few research provide some theoretical link, while a mathematical-based integration, especially during product development phase is still lacking. Meanwhile it is also reported that modular architecture is widely acknowledged as a product development strategy that significantly influences product life cycle management, including product servicing and EOL decisions such as remanufacturing. Consequently, this study attempts to fill the knowledge gap by providing an analytical framework for making informed modular product configuration decision at the early phase of product development in order to enhance the criteria that are crucial to the successful remanufacturing-PSS business offering.

2.3 Methodology

The purpose of this research is to develop an optimization model that will identify the module variants (assessed in pairs) that should be included in product configuration at an early phase of product development, such that the serviceability of the product is enhanced when the product is offered in product service systems, and cleaning of the product core is enhanced when the product is remanufactured at its end of life/end of use. The study applies fuzzy logic to obtain the compatibility indices of a pair of modular variants, with regard to the objectives to be improved. The decision variables are the pairs of module variants that could be grouped into the product. The coefficient of the decision variables in the objective function are the modular pair compatibility indices, which are the outputs from the fuzzy inference system. For each of the two criteria, there are three measures. Every measure has five levels which are expressed in linguistic terms, and every term is associated with a membership function. Fuzzy rules are developed in collaboration with some experts. Using the membership functions of the three measures (or fuzzy inputs), the compatibility index is obtained for every modular pair with respect to each objective. The section is divided into two phases: description and development of the optimization model, and determination of modular pair compatibility indices via a fuzzy inference system.

2.3.1 Model description and assumptions

The study considers an original equipment manufacturer (OEM) that employs a product service system to own and maintain its products while in use by the customers. The OEM will also remanufacture the product at its end of life (EOL) or end of use (EOU). As reported in section 2.2.2, this type of product offering is based on the growing interests in remanufacturing-PSS product offering due to the environmental and economic benefits. The product is modular, with a number of variants for each module that may be provided by different suppliers. The benefits of modular architecture is stated in section 2.2.3. The module variants differ by materials, breakdown rate, service requirements, frequency of service, service resources, cleaning operations, cleaning resources, and so on. This is the real life situation in which product development decision makers are confronted with parts, modules or suppliers' selection problems in order to make product decisions from among several potential product alternatives. The OEM's goal is to determine the module variants to include in the product, such that product serviceability is enhanced when the product is offered in PSS and core cleaning is enhanced when the product is remanufactured at its EOL/EOU. In order to assess the module variants thoroughly so as to determine viable module choices for the new product with regard to an essential criterion, we propose that module variants be evaluated in pairs. If there is odd number of modules, a dummy module is created. Figure 2.2 describes the development of a modular product with M modules, while there are multiple variants n_i available for each module i.

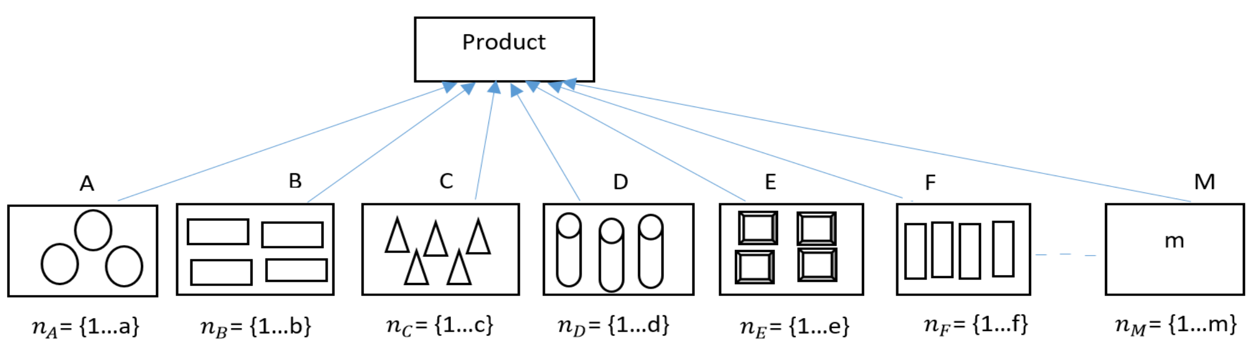


Figure 2.2: Modular product development considering multiple module variants

2.3.2 Optimization model

Consider a modular product with M modules. There are i, j modules in M having k, and l number of variants. Every module must be included in the product, and only one variant of a module is required. A pair of modules i and j is assessed collectively to determine the extent of their compatibility with regard to their serviceability and cleaning. Due the complexity involved when module variants are assessed in pairs and not individually, the problem is structured as a tree for simplification. At the first stage, one module is considered as a base module, while every other module is assessed in pair with the base module. These pairs are referred to as base modular pairs. Every branch β in the tree stems from a base modular pair. A path α in a branch β refers to a set of product configurations that have the same pairs of modules i, j but different variants k, l. From a branch β, the product configurations from all paths $\alpha = 1 \ldots . t$ share similar base modular pair i, j (but not necessarily similar variants k, l). A case study of modular product development is provided. Figure 2.3 depicts the modular pairwise assessment tree for the case study. Table 2.1 contains the notations and their descriptions. The problem is framed as a set of integer programming formulations.

Table 2.1: Notations

Notation	Description
M	*Number of modules that are required for the product*
n_i	*Number of variants for each module i*
n_j	*Number of variants for each module j*
$X_{i_k j_l}$	*If variant k of module i & variant l module j are grouped in the product,* $i \neq j$.
$y = \{0,1\}$	*Binary variable to ensure that every product configuration is unique and no configuration contains more than one variant of a module*
$Z = \{0,1\}$	*Binary variable to linearize non − linear constraints of a main branch*
$\alpha = 1 \dots t$	*Paths in branh* β *that represent same modular pairing in product alternatives but the variants are different.*
$\beta = 1 \dots w$	*The number of branches that represent different modular pairing in product alternatives*
$\gamma = 1 \dots q$	*The number of modular decision variables in a branch*
$I_{i_k j_l}$	*Compatibility index for any objective, if variant k of module i & variant l of module j aregrouped in the product*
$SI_{i_k j_l}$	*Serviceability index if variant k of module i & variant l of module j are grouped in the product*
$KI_{i_k j_l}$	*Cleaning index if variant k of module i & variant l of module j are grouped in the product*

Objective function

The decision variables are the pairs of two module variants that could be grouped or not. The compatibility index of the two modules are obtained from a fuzzy inference system. The objectives are to maximize product serviceability and core cleaning.

$$1.\ \text{Max } S(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} SI_{i_k j_l} X_{i_k j_l} \qquad 1$$

2. $\text{Max } K(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} KI_{i_k j_l} X_{i_k j_l}$ 2

Constraints.

1. A module variant has to pair with not more than 1 variant of another modules.

$$\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \leq 1 \qquad \forall\, i, j \in M, \quad i \neq j$$

2. From any main branch, modular pairs in product alternatives along a path are different from the modular pairs of other paths. Also, the number of product configurations from all paths in a main branch cannot exceed the limit of the branch.

$$\left(\sum_{\gamma=1}^{q} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \right) y_\beta^\alpha \leq \sum_{\alpha=1}^{t} y_\beta^\alpha \qquad \forall\, \beta \qquad 4$$

3. At least one product configuration must be obtained

$$\sum_{\beta=1}^{w} \sum_{\alpha=1}^{t} y_\beta^\alpha \geq 1 \qquad 5$$

4. Two modular variants from different module alternatives can either be grouped or not.

$$X_{i_k j_l} = \begin{cases} 1, & \text{if variant k of module i and variant l of module j are paired} \\ 0, & \text{Otherwise} \end{cases} \qquad 6$$

5. Every product alternative that is selected from any path α is different from any other.

$$y_\beta^\alpha = \begin{cases} 1, & \text{if a product configuration } \alpha \text{ is chosen along path } \beta \\ 0, & \text{Otherwise} \end{cases} \qquad 7$$

6. Linearize the set of quadratic constraints in equation 4

$$Z_\gamma = \left(\sum_{k=1}^{n_i}\sum_{l=1}^{n_j} X_{i_k j_l}\right) y_\beta^\alpha \qquad 8$$

$$Z_\gamma \le \sum_{k=1}^{n_i}\sum_{l=1}^{n_j} X_{i_k j_l} \qquad 9$$

$$Z_\gamma \le y_\beta^\alpha \qquad 10$$

$$Z_\gamma \ge \sum_{k=1}^{n_i}\sum_{l=1}^{n_j} X_{i_k j_l} + y_\beta^\alpha - 1 \qquad 11$$

$$Z_\gamma,\ X_{i_k j_l},\ y_\beta^\alpha \in \{0,1\} \qquad 12$$

7. For every branch β to make product configurations in (4), linearize the non-linear constraints in (4) with Z_γ and add $(9-11)$ to (4)

$$\sum_{\gamma=1}^{q} Z_\gamma \le \sum_{\alpha=1}^{t} y_\beta^\alpha \qquad \forall\,\beta \qquad 13$$

8. For a variant k for module i that is not compatible with variant l of module j, impose a penalty on the compatibility index, 0 for max objective, large number L for min objective.

$$\forall\, I_{i_k j_l} X_{i_k j_l}\ ,\ I_{i_k j_l} = \begin{cases} 0 \text{ for max objective} \\ L \text{ for min objective} \end{cases},\quad i,j \in M, i \ne j, \qquad k,l\ \ni X_{i_k j_l} \quad 14$$

9. For any desirable variant k of module i that must be included in the product, pre-determine a variant l of module j. For max objective, assign a large value L to their compatibility index, and for min objective, assign 0.

$$\forall\, I_{i_k j_l} X_{i_k j_l}\ ,\ I_{i_k j_l} = \begin{cases} L \text{ for max objective} \\ 0 \text{ for min objective} \end{cases},\quad i,j \in M, i \ne j, \qquad k,l \in\ X_{i_k j_l} \qquad 15$$

2.3.3 Evaluation of the modular pair compatibility indices

As stated earlier, trapezoidal and triangular MFs are reported to be efficient for modular product development. The two MFs produce very similar deffuzzified output values. In this study, the triangular MF is employed for more efficiency because it is defined by three parameters while the trapezoidal MF is defined by four parameters. Also, efficient computational time is sacrificed for better precision by selecting the Mamdani inference engine in order to mitigate product development errors. The criteria to be estimated are serviceability and core cleaning. For each criterion, there are 3 measures (or inputs). In FIS terminology, these are the linguistic variables. For every input, there are 5 levels (or linguistic terms), and every term is associated with a membership function. The output is referred to as a modular pair compatibility index. Table 2.2 contains these descriptions.

Table 2.2: Input-output variables from Fuzzy system

Input variables		**Output Variables**		**Criterion of interest**
Linguistic variables	Linguistic terms	Linguistic variables	Linguistic terms	
Frequency of Service Similarity of service Accessibility of modules	Very low Low Medium High Very high	Serviceability index	Very low Low Medium High Very high	Serviceability
Similarity of operations Type of dirt Similarity of modular materials	Very low Low Medium High Very high	Cleaning index	Very low Low Medium High Very high	Core cleaning

As obtained from previous work, serviceability of a pair of modules is measured by the degree of accessibility of the modular pair, the degree of service resources shared by the pair, and degree to which the pair can be serviced together (or frequency of service). Similarly, core cleaning is measured by the degree of similarity of the materials of the pairs, the degree of similarity of the type of dirt associated with the pair, and the extent to which the pair share cleaning resources. The linguistic terms associated with each input variable are as follows: very low, low, medium, high, and very high. For three inputs, each having five levels and one output, there are $\mathbf{5} * 5 * 5 = 125$ rules associated with a criterion. The entire set of fuzzy rules and omitted here to save space. Examples of the rule format are as follows:

IF ("Similarity of materials is low", AND "Similarity of dirt is low" AND "Cleaning resources shared is high") THEN ("Core-cleaning index is medium")

IF ("Frequency of service is medium", AND "Service resources shared are medium" AND "Accessibility is very low") THEN ("Serviceability index is low")

2.4 Case Study

Consider a modular product development scenario. The product consists of six modules, each module having four variants. There are a total of $15 * 16 = 240$ decision variables representing modular pairing. There are 15 main paths, and along each path, $16 * 16 * 16 = 4{,}096$ product configurations could be made. In total, $15 * 4{,}096 = 61{,}440$ product configurations are possible. This analysis is applicable to any product with m modules, and n_i variants available for module m_i. The modeling framework is structured as a tree to enable modules to be assessed in pairs. This framework is depicted in Figure 2.3. The levels of compatibility of modular pairs, measured as serviceability and core cleaning indices are obtained from fuzzy inference system and shown in Tables 2.3 and 2.4 respectively. These indices provide the coefficients of the decision variables in the objective functions of the optimization model. For example, considering the first branch $\beta = 1$ in the tree, there are paths $\alpha = 3$. On every path, $16 * 16 * 16 = 4{,}096$ product alternatives that are possible. All the product configurations on these path have similar modular pairs i, j but different variants k, l. For the branch β, there are $3 * 4{,}096 = 12{,}288$ product alternatives. The products alternatives in this branch all share similar base modular pair i, j but different variant k, l.

For the 5 branches in the tree, there are $12{,}288 * 5 = 61{,}440$ product alternatives that could be made. Accordingly, the formulation for every branch follows similar approach.

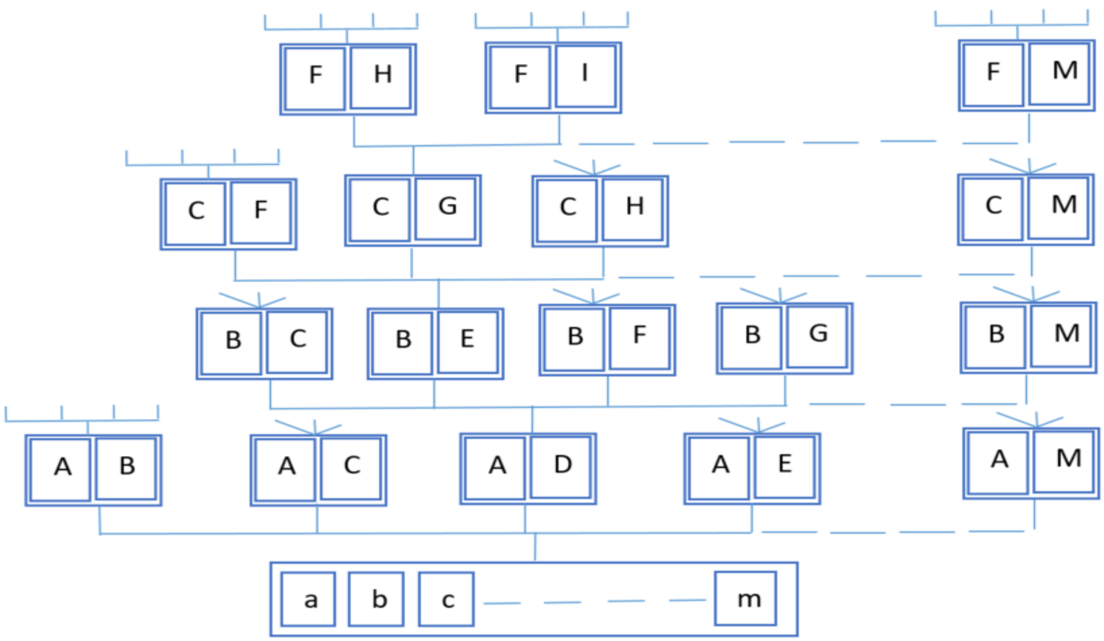


Figure 2.3: Modeling framework for product configuration decisions

For example, according to (4), the constraint formulation for the branch $\beta = 1$ is:

$$\left(\sum_{i=1}^{a}\sum_{j=1}^{b}X_{A_iB_j}+\sum_{k=1}^{c}\sum_{l=1}^{d}X_{C_kD_l}+\sum_{n=1}^{e}\sum_{o=1}^{f}X_{E_nF_o}\right)y_1^{\alpha1}+\left(\sum_{i=1}^{a}\sum_{j=1}^{b}X_{A_iB_j}+\sum_{k=1}^{c}\sum_{n=1}^{e}X_{C_kE_n}+\sum_{l=1}^{d}\sum_{o=1}^{f}X_{D_lF_o}\right)y_1^{\alpha2}$$
$$+\left(\sum_{i=1}^{a}\sum_{j=1}^{b}X_{A_iB_j}+\sum_{k=1}^{c}\sum_{o=1}^{f}X_{C_kF_o}+\sum_{l=1}^{d}\sum_{n=1}^{e}X_{D_lE_n}\right)y_1^{\alpha3}\le\sum_{\alpha=1}^{t}y_1^{\alpha} \qquad 4$$

Similar constraints are written for all branches $\beta = 1 \ldots . w$

Serviceability and core cleaning indices are obtained from a fuzzy inference system according to the procedure described above. These indices are listed in Tables 2.3 and 2.4.

Table 2.3: Modular pair serviceability indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.80	0.75	0.45	0.65	0.55	0.75	0.35	0.65	0.85	0.75	0.55	0.70	0.45	0.90	0.80	0.65	0.75	0.55	0.85	0.70
	A2					0.45	0.35	0.55	0.70	0.65	0.75	0.85	0.75	0.35	0.75	0.45	0.55	0.55	0.65	0.25	0.60	0.75	0.35	0.85	0.75
	A3					0.75	0.90	0.50	0.80	0.65	0.75	0.70	0.70	0.25	0.65	0.55	0.60	0.75	0.35	0.60	0.70	0.65	0.95	0.65	0.85
	A4					0.70	0.75	0.50	0.75	0.60	0.65	0.75	0.70	0.75	0.70	0.65	0.70	0.70	0.80	0.75	0.70	0.65	0.85	0.75	0.70
B	B1	0.80	0.45	0.75	0.70					0.45	0.55	0.80	0.75	0.60	0.55	0.50	0.55	0.60	0.55	0.50	0.75	0.75	0.65	0.50	0.70
	B2	0.75	0.35	0.90	0.75					0.50	0.65	0.60	0.75	0.65	0.45	0.55	0.60	0.35	0.75	0.90	0.70	0.65	0.75	0.80	0.65
	B3	0.45	0.55	0.50	0.50					0.70	0.75	0.40	0.70	0.35	0.70	0.80	0.75	0.75	0.55	0.50	0.60	0.80	0.65	0.60	0.70
	B4	0.65	0.70	0.80	0.75					0.65	0.70	0.75	0.65	0.60	0.35	0.60	0.50	0.65	0.45	0.80	0.60	0.65	0.70	0.70	0.60
C	C1	0.55	0.65	0.65	0.60	0.45	0.50	0.70	0.65					0.45	0.30	0.75	0.65	0.70	0.60	0.45	0.65	0.80	0.75	0.55	0.70
	C2	0.75	0.75	0.75	0.65	0.55	0.65	0.75	0.70					0.25	0.55	0.40	0.50	0.75	0.35	0.80	0.70	0.85	0.85	0.60	0.70
	C3	0.35	0.85	0.70	0.75	0.80	0.60	0.40	0.75					0.70	0.50	0.55	0.65	0.65	0.45	0.40	0.60	0.75	0.70	0.60	0.85
	C4	0.65	0.75	0.70	0.70	0.75	0.75	0.70	0.65					0.65	0.75	0.65	0.70	0.70	0.55	0.35	0.45	0.80	0.70	0.50	0.65
D	D1	0.85	0.35	0.25	0.75	0.60	0.65	0.35	0.60	0.45	0.25	0.70	0.65					0.35	0.50	0.55	0.50	0.85	0.45	0.55	0.60
	D2	0.75	0.75	0.65	0.70	0.55	0.45	0.70	0.35	0.30	0.55	0.50	0.75					0.75	0.65	0.45	0.55	0.75	0.45	0.80	0.70
	D3	0.55	0.45	0.55	0.65	0.50	0.55	0.80	0.60	0.75	0.40	0.55	0.65					0.85	0.65	0.45	0.60	0.65	0.50	0.40	0.65
	D4	0.70	0.55	0.60	0.70	0.55	0.60	0.75	0.50	0.65	0.50	0.65	0.70					0.55	0.60	0.50	0.40	0.70	0.40	0.65	0.50
E	E1	0.45	0.55	0.75	0.70	0.60	0.35	0.75	0.65	0.70	0.75	0.65	0.70	0.35	0.75	0.85	0.55					0.70	0.75	0.65	0.70
	E2	0.90	0.65	0.35	0.80	0.55	0.75	0.55	0.45	0.60	0.35	0.45	0.55	0.50	0.65	0.65	0.60					0.75	0.45	0.70	0.65
	E3	0.80	0.25	0.60	0.75	0.50	0.90	0.50	0.80	0.45	0.80	0.40	0.35	0.55	0.45	0.45	0.50					0.95	0.70	0.50	0.75
	E4	0.65	0.60	0.70	0.70	0.75	0.70	0.60	0.60	0.65	0.70	0.60	0.45	0.50	0.55	0.60	0.40					0.65	0.70	0.60	0.65
F	F1	0.75	0.75	0.65	0.65	0.75	0.65	0.80	0.65	0.700.80	0.85	0.75	0.80	0.85	0.75	0.65	0.70	0.70	0.75	0.95	0.65				
	F2	0.55	0.35	0.95	0.85	0.65	0.75	0.65	0.70	0.75	0.85	0.70	0.70	0.45	0.45	0.50	0.40	0.75	0.45	0.70	0.70				
	F3	0.85	0.85	0.65	0.75	0.50	0.80	0.60	0.70	0.55	0.60	0.60	0.50	0.55	0.80	0.40	0.65	0.65	0.70	0.50	0.60				
	F4	0.70	0.75	0.85	0.70	0.70	0.65	0.70	0.60	0.70	0.70	0.85	0.65	0.60	0.70	0.65	0.50	0.70	0.65	0.75	0.65				

Table 2.4: Modular pair core-cleaning indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.65	0.90	0.55	0.75	0.85	0.55	0.60	0.75	0.75	0.55	0.65	0.60	0.65	0.85	0.70	0.75	0.75	0.90	0.75	0.80
	A2					0.75	0.65	0.85	0.70	0.75	0.75	0.90	0.70	0.75	0.70	0.60	0.65	0.60	0.75	0.45	0.65	0.75	0.85	0.75	0.70
	A3					0.65	0.85	0.70	0.75	0.75	0.55	0.60	0.70	0.45	0.75	0.65	0.70	0.75	0.85	0.65	0.70	0.75	0.85	0.75	0.70
	A4					0.70	0.75	0.70	0.65	0.65	0.65	0.70	0.75	0.65	0.65	0.55	0.45	0.70	0.70	0.60	0.65	0.60	0.75	0.70	0.65
B	B1	0.65	0.75	0.65	0.70					0.85	0.45	0.55	0.75	0.65	0.65	0.70	0.55	0.70	0.65	0.80	0.70	0.65	0.65	0.80	0.75
	B2	0.90	0.65	0.85	0.75					0.60	0.75	0.50	0.65	0.75	0.55	0.85	0.65	0.85	0.45	0.40	0.65	0.55	0.65	0.85	0.65
	B3	0.55	0.85	0.70	0.70					0.65	0.75	0.70	0.70	0.55	0.75	0.70	0.70	0.65	0.85	0.70	0.70	0.80	0.75	0.65	0.70
	B4	0.75	0.70	0.75	0.65					0.70	0.50	0.65	0.60	0.60	0.70	0.80	0.70	0.75	0.60	0.65	0.65	0.70	0.65	0.75	0.65
C	C1	0.85	0.75	0.75	0.65	0.85	0.60	0.65	0.70					0.55	0.80	0.85	0.80	0.80	0.70	0.75	0.70	0.40	0.65	0.75	0.60
	C2	0.55	0.75	0.55	0.65	0.45	0.75	0.75	0.50					0.55	0.35	0.60	0.70	0.65	0.85	0.50	0.90	0.45	0.80	0.70	0.55
	C3	0.60	0.90	0.60	0.70	0.55	0.50	0.70	0.65					0.60	0.70	0.65	0.60	0.45	0.65	0.60	0.50	0.65	0.55	0.70	0.25
	C4	0.75	0.70	0.70	0.75	0.75	0.65	0.70	0.60					0.75	0.60	0.75	0.70	0.70	0.75	0.70	0.65	0.60	0.75	0.55	0.45
D	D1	0.75	0.75	0.45	0.65	0.65	0.75	0.55	0.60	0.55	0.55	0.60	0.75					0.75	0.30	0.65	0.65	0.60	0.75	0.75	0.75
	D2	0.55	0.70	0.75	0.65	0.65	0.55	0.75	0.70	0.80	0.35	0.70	0.60					0.60	0.65	0.55	0.60	0.85	0.80	0.80	0.70
	D3	0.65	0.60	0.65	0.55	0.70	0.85	0.70	0.80	0.85	0.60	0.65	0.75					0.80	0.75	0.75	0.55	0.65	0.60	0.75	0.60
	D4	0.60	0.60	0.70	0.45	0.55	0.65	0.70	0.70	0.80	0.70	0.60	0.70					0.65	0.45	0.55	0.50	0.55	0.65	0.25	0.45
E	E1	0.65	0.60	0.75	0.70	0.70	0.85	0.65	0.75	0.80	0.65	0.45	0.70	0.75	0.60	0.80	0.65					0.55	0.65	0.60	0.60
	E2	0.85	0.75	0.85	0.70	0.65	0.45	0.85	0.60	0.70	0.85	0.65	0.75	0.30	0.65	0.75	0.45					0.80	0.65	0.75	0.70
	E3	0.70	0.45	0.65	0.60	0.80	0.40	0.70	0.65	0.75	0.50	0.60	0.70	0.65	0.55	0.75	0.55					0.80	0.90	0.55	0.55
	E4	0.75	0.65	0.70	0.65	0.70	0.65	0.70	0.65	0.70	0.90	0.50	0.65	0.65	0.60	0.55	0.50					0.75	0.55	0.65	0.60
F	F1	0.75	0.75	0.75	0.60	0.65	0.55	0.80	0.70	0.40	0.45	0.65	0.60	0.60	0.85	0.65	0.55	0.55	0.80	0.80	0.75				
	F2	0.90	0.85	0.85	0.75	0.65	0.65	0.75	0.65	0.65	0.80	0.55	0.75	0.75	0.80	0.60	0.65	0.65	0.65	0.90	0.55				
	F3	0.75	0.75	0.75	0.70	0.80	0.85	0.65	0.75	0.75	0.70	0.70	0.55	0.75	0.80	0.75	0.25	0.60	0.75	0.55	0.65				
	F4	0.80	0.70	0.70	0.65	0.75	0.65	0.70	0.65	0.60	0.55	0.25	0.45	0.75	0.70	0.60	0.45	0.60	0.70	0.55	0.60				

With a pair of different module variants as decision variables, and an index from a fuzzy system as coefficients in the objective function, the optimization problem is coded in Python programming language and the Gurobi solver is called from a python environment for implementation. The product configurations whose modules will enhance serviceability and core cleaning are identified and listed in Table 2.5.

Table 2.5: Optimal product configurations

Criterion	Product Configuration	Product Strength Index (PCI)
Serviceability	A_1D_1, B_1C_3, E_3F_1	2.60
	A_3B_2, C_2F_1, D_3E_1	2.60
	A_3B_2, C_1D_3, E_3F_1	2.60
	A_2C_3, B_3D_3, E_3F_1	2.60
	A_3B_2, C_4D_2, E_3F_1	2.60
	A_2B_2, C_3F_4, D_3E_1	2.60
Core-cleaning	A_1B_2, C_1D_3, E_3F_2	2.65
	A_2C_3, B_2D_3, E_3F_2	2.65
	A_1B_2, C_2E_4, D_2F_1	2.65
	A_1F_2, C_2E_4, B_2D_3	2.65

The result shows that out of 61,440 product configurations, there are ten viable product configurations considering serviceability and core cleaning. Given the fact that industries are no longer looking for one best solution to a problem but a set of viable solutions that permits flexibility of choice, the result of this study provides such desirable solution space. This solution is of significant benefit to the OEMs that offer/intend to offer their product in PSS and also serve as the original equipment remanufacturers (OERs). It helps to guide modular product development decision making, and also helps in a module's supplier selection.

2.5 Conclusion

Although integration of product service systems and remanufacturing has been increasingly recommended, analytical integration of these concepts remains sparse. To fill this lacuna, we identified two criteria that are critical for the success of both product service systems and remanufacturing: product serviceability and core cleaning. Optimization model was developed to determine the module variants that should be included in a product among several available module variants in order to ensure improved product serviceability and core cleaning. Modules are assessed in pairs and the compatibility indices of module pairs are obtained via fuzzy inference system. In order to test the conceptual model, a new product development scenario is provided in which a modular product that consists 6 modules is to be developed, there are four variants available for each module. We provide an analytical approach to bring the essential criteria into the early phase of modular product development. Among 61,440 different product alternatives, the result of the analysis shows that 10 product configurations are most viable for enhanced remanufacturing and PSS. This outcome is particularly important to the OEMs that are already engaged in both PSS and remanufacturing, as well those that contemplate to offer their product in PSS and also serve as the remanufacturer. The result provides informed guidance in making product architecture decisions at the front-end of product development such that the product configuration(s) that will realize effective remanufacturing-PSS business are considered by the PD decision makers. Research on remanufacturing-PSS integration are currently emerging. As much as we know, few studies that relate to this synergy only provide theoretical approach. This study is the first attempt to provide analytical assessment of product configurations at the early phase of modular product development with regard to remanufacturing-PSS integration.

CHAPTER 3: INSTILLING COST IMPLICATIONS INTO MODULAR PRODUCT

3.1 Introduction

A large body of research concurs that manufacturing activities contribute substantially to sustainability issues. In order to curtail the negative impact of manufacturing, there have been increasing global regulatory measures such as Extended Producers Responsibility (EPR) and Waste Electrical and Electronic Equipment (WEEE) which require manufacturers to be responsible for the post-consumer phase of their product (Chen & Chang, 2013; Errington & Childe, 2013). The primary aim is to reduce heavy dependence on virgin resources, conserve energy, reduce pollution, mitigate product disposals, and transform the embedded values in the retired product into operational usefulness. Consequently, some product end-of-life management strategies have evolved, amongst which remanufacturing has been acknowledged as the most viable (Ma & Kremer, 2014).

Remanufacturing refers to the process that returns a used product to like new condition. Details of the remanufacturing process are contained in (Ijomah et al., 2007; Sundin & Bras, 2005). Several manufacturers including Caterpillar, Rank-Xerox, Hewlett Packard, and Océ have reported tremendous savings through product remanufacturing (Errington & Childe, 2013). In 2005 alone, Caterpillar reports a $1 billion revenue from the sales of the remanufactured products (Ferguson et al., 2009). Remanufacturing business was a £5 billion-worth industry in the UK in 2004 (Charter & Gray, 2008). In the US, the value of remanufacturing industry in 2009 was more than $43 billion while employing over 180000 full-time jobs (Commission, 2012). However, remanufacturing is plagued by certain limitations with regard to the used products that are returned at the end-of-life (EOL). These constraints include unknown quality, quantity, and time of core recovery. These bottlenecks have considerably hampered remanufacturing activities. About 80% of manufactured products are disposed at their End-of-life despite all EOL management strategies (Commission, 2012). Consequently, manufacturers are looking for more efficient means of product offering in order to comply with regulations, meet customers' needs, and optimize profitability.

Product service system (PSS) is conceived as a business offering with capacities to remedy most of the challenges in remanufacturing, besides other benefits. PSS is a business philosophy that emphasizes product functionality and not ownership. In order words, the PSS thinking is that the manufacturer is responsible for ownership, maintenance, removal, and replacement of the product while the function of the product is offered to customers. A growing number of original equipment manufacturers (OEMs) are offering their product in PSS. Ferguson et al. (2009) report that $213 billion was traded in leased or PSS business in 2005. As a result of the significant benefits of remanufacturing and product service system, the combination of these concepts as a business offering has been increasingly suggested. In addition, growing number of developed economies are overwhelmed with physical product and more customers are embracing ownerless product usage (Lindahl & Sakao, 2009).

Therefore, PSS-remanufacturing business permits the OEM to meet customers' expectation and sustain operational viability amidst stiff competition that continuously confronts manufacturers. Remanufacturing business is also affected by negative perception of remanufactured product. However, the concerns of the OEMs that customers are not favorably disposed towards remanufactured product in a traditional product selling is allayed due to product ownerless philosophy in PSS. Sundin et al. (2008) report that the effectiveness of both remanufacturing and PSS is largely influenced by the PD. Subramoniam et al. (2009) report that it is extremely difficult to remanufacture a product if such decision is not considered at the PD phase. According to the study, about 75% of used products that are recovered are not designed for remanufacturing thereby leading to operational impediments. Hatcher et al. (2011) state that OEMs that are involved in remanufacturing their product are more enthused to design for remanufacturing. On a similar note, Qu et al. (2016) note that the cost of operations and efficiency of PSS rest heavily on PD decisions. The study concludes that the success of PSS is largely dependent on modular product design. As reported by several researchers, modular design is considered an effective PD strategy (Chung et al., 2011; Nepal et al., 2008). Hatcher et al. (2011) highlight the attempts of researchers to provide some guidelines to incorporate design for remanufacturing into PSS. Sundin & Lindahl (2008) provide the first theoretical approach to combines PSS and remanufacturing. The study was followed by Sundin et al. (2009) which note that improved PSS-remanufacturing model will enhance reverse logistics and boost design for remanufacturing. Other studies on PSS-remanufacturing business are contained in Guidat et al., (2014). These studies conclude that PSS-remanufacturing business requires further research. Meanwhile, analytical models are missing in the research. Mathematical techniques to integrate PSS and remanufacturing at the PD phase are rare in literature. Recently, Fadeyi et al. (2017) develop an optimization model for PSS-remanufacturing integration at the PD phase. The model considered core cleaning and product serviceability as being critical to the success of PSS and remanufacturing. However, the model did not take the importance of product lifecycle costs into account. Chiu & Okudan (2014) and Nepal et al. (2008) report that over 70% of product lifecycle cost is determined by the PD decisions. Since cost consideration during PD is vital to the product lifecycle performance, it is expedient to bring product lifecycle costs into account at the PD phase in order to realize an efficient PSS-Remanufacturing enterprise. Additionally, transportation cost becomes more significant in PSS because the OEM is responsible for the product performance during the use phase, and also for reverse logistics. Furthermore, the optimization model in Fadeyi et al. (2017) stops at the identification of the optimal product architecture. The analyses of the multiple optimal product configurations to determine the relative benefits of the configurations are missing.

The objective of this study is to determine the product configurations that minimize design, (re)manufacturing, and transportation costs while maximizing product serviceability and cleaning by implementing the PSS-remanufacturing optimization model. Furthermore, the study performs sensitivity analysis to provide comparative advantages of the optimal product configurations. The primary goal of the study is to provide product architecture decision guide to the OEM that is involved in PSS-Remanufacturing business as well as the potential OEMs in this regard.

3.2 Literature review

3.2.1 Influence of modular architecture on remanufacturing

Modular design plays a significant role in the success of remanufacturing process. Modular design permits aggregation of parts to form a complex product without compromising the product integrity (Nepal et al., 2007). Also, modular design simplifies assembly and disassembly of parts of a product (Ma & Kremer, 2014). Researchers agree that product disassembly plays a crucial role in product remanufacturing. Hatcher et al. (2013) identify the processes that are involved in remanufacturing to include disassembly, inspection, cleaning, reprocessing and reassembly and emphasize that other processes are largely influenced by the degree of product disassembly. Vyas & Rickli (2016) further reiterate the criticality of disassembly to remanufacturing business and develop methods to extract disassembly data to determine disassembly feasibility in order to enhance remanufacturing. Behdad (2013) investigates the economic benefits of disassembly process of the used product. The study determines that partial disassembly or disassembly at the modular level is an efficient strategy if the OEM disassembles its own product and the product usage data is known. The effectiveness of partial disassembly depends on the availability of product data such as resilience, durability, failure rate, among others. Mutha & Pokharel (2009) develop network design for reverse logistics and remanufacturing in which modules from recovered products are assigned into remanufacturing facilities without complete disassembly. Partial disassembly at the modular level is a viable strategy in the PSS-remanufacturing enterprise because the OEM is able to monitor the products' health, obtain product lifecycle data, and save significant resources that are associated with complete product disassembly during remanufacturing process. Among the remanufacturing processes, the importance of core cleaning has been emphasized by previous studies (Subramoniam et al., 2010; Sundin & Lindahl, 2008).

3.2.2 Effectiveness of modular design for product service system

As conceptualized by Goedkoop et al. (1999), PSS refers to a system of tangible products and intangible services designed and combined so that they are jointly capable of fulfilling final customer needs. At the conception of PSS, product refers to "a tangible commodity to be sold" and service as "an activity with an economic value and is performed on a commercial basis". Currently, PSS is attracting huge research interest due to its sustainability benefits. Most of the available research on PSS are overly concentrated on the service aspect, with little reference to the tangible product. Sundin et al. (2008) emphasize that despite the huge attention given to the service aspect of PSS, the design of the physical product will remain the prime driver of PSS success. Sundin et al. (2009) take product design processes into consideration in designing an efficient PSS offering. Qu et al. (2016) analyze product structure with case studies and recommend product modularity to manufacturers as the effective configuration that enhances PSS efficiency and lowers cost of operations. Yang et al (2009) note that while the static product data remains constant throughout the product lifecycle, it is important to capture product dynamic data such as reliability, servicing, preventive maintenance, market performance. Modular design significantly enables such data collection. In addition, customers' requirements are constantly changing and modification of few modules are sometimes necessary to meet these change. Song & Sakao (2017) report that modular designs enable PSS to cope effectively with the changing customer demands. Thus, modular design enables PSS business to be more competitive than in traditional product selling.

3.2.3 Importance of cost in PSS-remanufacturing business

Researchers report that about 70% of product lifecycle cost is determined by product development decisions (Chiu & Okudan, 2014; Nepal et al., 2008). Therefore, it is important to take product lifecycle costs into product architecture decision during at early phase of PD in order to facilitate PSS-remanufacturing offering. Teunter et al. (2008) studied product remanufacturing alongside the traditional manufacturing process and conclude that manufacturing and remanufacturing of the same product are linearly related. By implication, when the manufacturing cost of product A is higher than product B, there is a higher remanufacturing cost of product A. Therefore, remanufacturing cost may be assumed as a certain proportion of the manufacturing cost. Furthermore, transportation cost becomes more critical in PSS because the OEM is responsible for the product lifecycle. Transportation cost is usually estimated in remanufacturing and product supply chain. Mutha & Pokharel (2009) estimate transportation cost with expected distance covered and as a percentage of overhead cost.

Gavidel & Rickli (2015) extensively discussed the importance of core sorting based on the quality level in remanufacturing facilities and remarked that high cost could be a major concern in remanufacturing. However, the quality of the core, hence the cost, are controllable to a larger extent in an OEM-managed PSS. The resulting benefit of lower cost of remanufacturing translates to a win-win scenario for both the OEM and the customer-lesser operating cost to the OEM, lower cost of the remanufactured product to the customer. On another note, the age of used product is often used to assess its worth for remanufacturing purposes. Ferguson et al. (2009) and other researchers have used the age of used product to assess its worth. Although the age of a product plays an important role on its quality level and hence its cost, however, product usage is another important factor in the evaluation of the worthiness of core with regard to quality and cost. Gavidel & Rickli (2017) find that the usage level of the used product is more relevant in determining the worth of core than age. Unlike in product selling, PSS provides an effective avenue to the OEM (as the product owner) to effectively monitor the usage level of product. This permits the effective evaluation of the cost of the remanufactured product. Consequently, the cost of a remanufactured product could be appropriately determined, to the benefits of the OEM and the customers.

3.2.4 Multi-objective optimization in product development

Multi-objective optimization has been widely employed in the research involved in modular product development. For the development of mathematical models at the product development stage, it is important to quantify the uncertain data that relate to the performance of the product lifecycle. The fuzzy system has been largely employed to capture such imprecise and uncertain product data. Uncertainty refers to the gap between the amount of information that is required to perform the task at hand and the amount of information that is already possessed (Büyüközkan & Feyzıoğlu, 2004). Fuzzy system is capable of converting uncertainties into quantitative terms for computational purposes when the imprecise data are categorized in linguistic terms such as low, medium, and high. Büyüközkan & Feyzıoğlu (2004) apply fuzzy analytic hierarchy process to determine the product structure that optimizes firms' management, profitability and utilization of resources. Aguwa et al (2012) obtain the vagueness in stakeholders' data via fuzzy engine and applied Archimedean Goal Programming (GP) to develop an optimal product configuration for medical devices. (Nepal et al., 2008) obtain uncertain data in product decomposition through fuzzy logic and applied Chebyshev GP to develop product architecture that enhances manufacturability and reduces cost. Previously, (Nepal et al., 2005; Nepal et al., 2007) had developed Archimedean GP model for product modularization, having obtained the indices of the objectives through fuzzy engine. Most of the research in PD apply either triangular or trapezoidal membership function of fuzzy system.

Meanwhile, the multi-criteria optimization methods described above provide a single optimal solution as the product architecture. However, manufacturers are looking beyond a single solution approach towards other method that offers a set of solutions so that comparative analyses could be performed to enable efficient decision making. Currently, such a method are rare in product development literature. Multi-Attributes Utility theory (MAUT) is a decision making concept that provides analytical procedures which permit multiple alternatives to be compared. According to Chelst & Canbolat (2011), one of the fundamental and difficult challenges that confront decision makers is how to make trade-off among alternatives, but MAUT provides such decision platform. The theory permits weight and probability values to be assigned to measures through which the attributes or objectives are assessed. The analysis result assigns a utility value that ranges from 0 to 1 to each objective for comparison. More importantly, the comparative assessment of all objectives can be performed through sensitivity analysis. The application of MAUT through Logical Decisions software package, is contained in Chelst & Canbolat (2011).

3.2.5 The missing gap addressed

As stated in the previous sections, PSS-remanufacturing enterprise could be significantly improved by modular architecture. Also, it is emphasized that product lifecycle costs should be taken into account at the PD phase because PD decisions determine over 70% of the product lifecycle costs. Currently, an analytical solution to determine the modular architecture that minimizes costs in a PSS-remanufacturing enterprise is missing. The objective of this study is to incorporate design, manufacturing, and transportation cost data into product architecture optimization model at the PD phase. Being major drivers of successful PSS and remanufacturing, serviceability and core cleaning data are incorporated into the model development. Furthermore, this research performs sensitivity analyses that provide comparative benefits of the optimal product architectures. Accordingly, the research bridges a knowledge chasm by providing data-driven guidance for making product architecture decision at the early phase of PD in order to enhance PSS-remanufacturing business at reduced costs. In addition, the study presents an analytical technique to determine the relative importance of the optimal product architectures in order to enhance decision making.

3.3 Methodology

The research describes a PSS-Remanufacturing scenario in which the OEM is responsible for the product ownership. This implies that the OEM is accountable for servicing, upgrading, replacement, and product retrieval. Furthermore, the OEM will remanufacture its product at the end-of-use. The goal of the OEM is to determine the appropriate modular product configuration(s) given that several module variants are available from suppliers. The aim of this research is to determine these product configuration(s) so as to minimize cost, maximize product serviceability and cleaning, in other to realize an efficient PSS-Remanufacturing enterprise.

3.3.1 Problem description

The model considers the development of a modular product architecture to be offered in a PSS-remanufacturing scenario. The product consists of m modules. There are different module sets i & j. There are k variants available for module set i and l variants for module j from which $\mathrm{k}-\mathrm{l}$ pair will be clustered into the product framework until there are m modules in the product. If the product requires odd number of modules, a dummy module will be created for modelling purpose. This description fits a typical product development environment where parts are available to the OEM through multiple suppliers and the OEM is required to make supplier selection decision. Generally, modules are assessed on their individual merits during product development. This study proposes assessment by modular pairing so that the modules can be relatively assessed such that modules that jointly optimize PSS-remanufacturing objectives are included in the product architecture. This modular PD scenario is described in figure 3.1. The model is developed with the $\mathrm{i}-\mathrm{j}$ module pairs as the decision variables. At the first level, one module set is arbitrarily chosen as the base module while every module variant from other module sets is evaluated in pair with the variants of the base module. A pair with the base module is referred to as base modular pair. This combination makes the problem complex. The modeling framework is structured as a tree for tractability and modeling, and depicted in figure 3.1. A base modular pair starts a main branch β. Every path α in a main branch β represents product configurations with the same $i-j$ modules but different $k-l$ variants. The problem is formulated as a binary integer programing (BIP) problem. Binary variables y_{β}^{α} are introduced at the nodes along path α in a main branch β to distinguish the every product configuration, thereby leading to non-linear problem. In order not to call the optimality of the solution into question, the non-linear constraints are linearized.

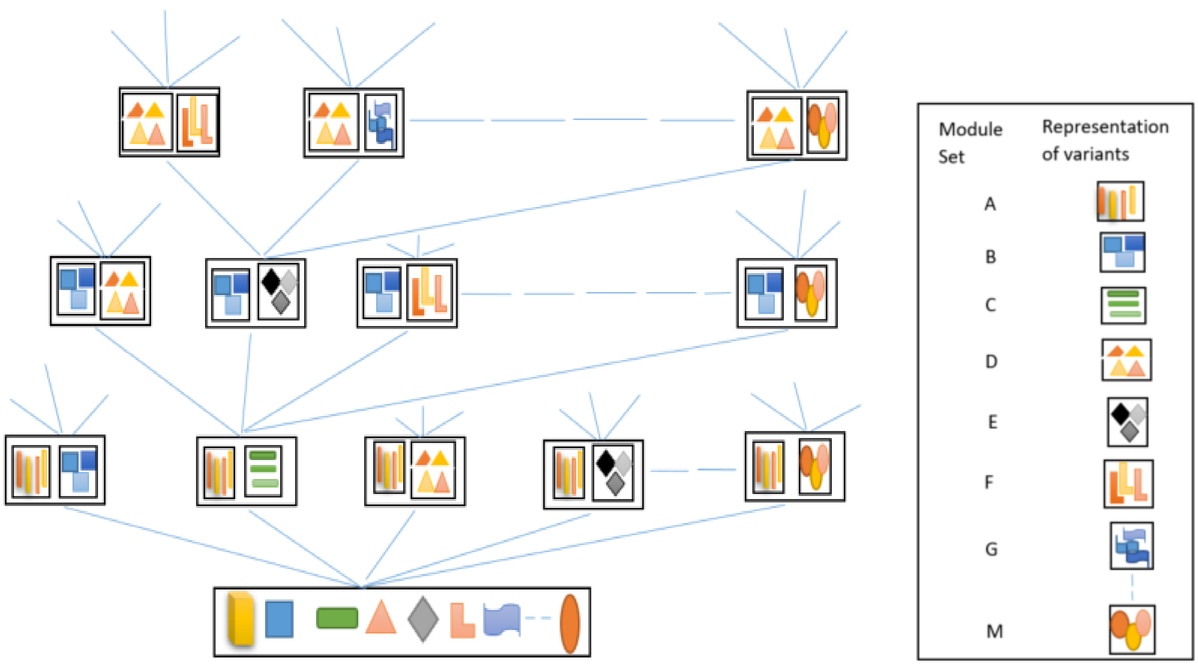


Figure 3.1: Development of modular architecture for PSS-Remanufacturing enterprise

The notations below is used for the model development

Indices and parameters

M PD environment containing module sets. A module set contains different variants

m Number of modules to cluster into the product

i, j Sets of modules available for m

n The number of module variants in module set i or set j

k Variant of module set i ; $k \in i$

l Variant of module set j ; $l \in j$

β Branch in the tree

w Number of branches β.

t Number of paths in a tree branch β

α Path in a branch of the tree

γ Node along path α in a branch β representing modular pairs of same i & j.

q Number of nodes of on path α

y Indicator variable to distinguish each configuration of on a path α in a branch β

λ Number of Indicator variables at node γ

Z Binary variable to linearize nonlinear constraints

$X_{i_k j_l}$ Decision variable; a pair of variant k of set i and variant l of set j

$I_{i_k j_l}$ Compatibility index of a pair of variant k of set i and variant l of set j

SI Serviceability index

KI Core-cleaning index

CI Cost index

3.3.2 Mathematical model

Objective function

The decision variable is a pair of variant k from module i and variant l from module set j which are either jointly included in the product or not. Cost index is the sum of the relevant cost data for a pair of modules. Serviceability and core cleaning indices are obtained as module pair compatibility indices from fuzzy engine.

1. $$\text{Min } C(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} \sum_{k,l} CI_{i_k j_l} X_{i_k j_l} \qquad (1)$$

2. $$\text{Max } S(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} SI_{i_k j_l} X_{i_k j_l} \qquad (2)$$

3. $$\text{Max } K(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} KI_{i_k j_l} X_{i_k j_l} \qquad (3)$$

Constraints.

4. A variant k from module set i cannot be paired with more than 1 variant of module set j

$$\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \leq 1 \qquad \forall\, i, j \in M, \quad i \neq j \qquad (4)$$

5. Along a path α in a branch β, $k - l$ variants from module sets i & j are paired to form unique product configurations. In addition, the total configurations that can be produced from all paths in branch β cannot exceed the total configurations on .

$$\sum_{\gamma=1}^{q} \left(\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \right) y_{\beta}^{\alpha} \leq \sum_{\alpha=1}^{t} y_{\beta}^{\alpha} \qquad \forall\, \beta \qquad (5$$

6. A variant k from module set i and a variant l from module set j can either be paired or not.

$$X_{i_k j_l} = \begin{cases} 1 \\ 0 \end{cases} \qquad (6)$$

7. From a path α in a branch β, every product configuration is unique. In order words every configuration has at least one $k - l$ module pair that is different from others.

$$y_{\beta}^{\alpha} = \begin{cases} 1 & \text{if a configuration is chosen from } \alpha \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

8. Linearize the sets of non-linear constraints in (5)

$$Z_{\gamma} = \left(\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \right) y_{\beta}^{\alpha} \tag{8}$$

$$Z_{\gamma} \leq \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \tag{9}$$

$$Z_{\gamma} \leq y_{\beta}^{\alpha} \qquad \forall y \tag{10}$$

$$Z_{\gamma} \geq \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} + \sum_{\lambda=1}^{n_y} y_{\beta}^{\alpha} - n_y \qquad \forall \beta \tag{11}$$

$$Z_{\gamma},\ X_{i_k j_l},\ y_{\beta}^{\alpha} \in \{0,1\} \tag{12}$$

9. For every branch β to make product configurations in (5), linearize the non-linear constraints in (5) with Z_{γ} and add $(9-12)$ to (5)

$$\sum_{\gamma=1}^{q} Z_{\gamma} \leq \sum_{\alpha=1}^{t} y_{\beta}^{\alpha} \qquad \forall \beta \tag{13}$$

10. At least one product architecture must be developed

$$\sum_{\beta=1}^{w} \sum_{\alpha=1}^{t} y_{\beta}^{\alpha} \geq 1 \tag{14}$$

11. If variant k module i is not compatible with variant l of module j, penalize their compatibility index, 0 for max objective, large number L for min objective. The same approach is followed if variant k cannot be remanufactured.

$$I_{i_k j_l} = \begin{cases} 0 \text{ for max objective} \\ L \text{ for min objective} \end{cases}, \quad i, j \in M, i \neq j, \qquad k, l \ni X_{i_k j_l} \tag{15}$$

12. If module variant k of module i that must be included in the product, pair k with a pre-determined variant l of module j. For max objective, assign a large value L to their compatibility index, and for min objective, assign 0.

$$I_{i_k j_l} = \begin{cases} L \text{ for max objective} \\ 0 \text{ for min objective} \end{cases}, \quad i, j \in M, i \neq j, \qquad k, l \in X_{i_k j_l} \tag{16}$$

3.3.3 Estimation of cost and compatibility of module pairs

As stated earlier, researchers employ proxy measures for the transportation cost. Accordingly, this study uses the weight of the module variant as a proxy of the transportation cost. The model is developed with a modular pair as the decision variable, therefore costs are obtained for module variants in pairs. Product serviceability plays a significant role in PSS. It determines the extent to which product could be retained in operational effectiveness. Serviceability of modular pair was measured by the degree of accessibility, the service resources shared by the module pair, and the service requirements of the pair (frequency of service). Similarly, core cleaning operation plays an effective role in remanufacturing. Core cleaning objective is measured by the similarity of materials of the module pair, the similarity of the type of dirt that is related to the module pair, and degree of cleaning resources that are shared by the pair. There are five levels associated with every measure. These measures are: Very low, low, medium, high, and very high. Each level is associated with triangular membership function of the fuzzy engine. As stated previously, the triangular MF is grossly employed in product development studies to quantify the vagueness in the product lifecycle. The study adopts the assumptions of the previous researchers that triangular MF is appropriate for modular architecture development. A detailed description of how to obtain compatibility indices using triangular membership function is contained in contained in (Fadeyi et al., 2017).

3.3.4 Application of multi-criteria technique

Multi-attribute utility theory (MAUT) is a powerful tool in decision analysis due to its prowess in joint assessments of multiple alternatives. Besides its ability to assess conflicting objecting, another important aspect of the utility function is that it enables comparative evaluation of alternatives with different metrics and units. Such capacity is built into the Logical Decisions software. The study employs this software for the assessment of the multiple product configurations.

3.4 Model implementation with a case study.

The cost data of a subassembly was provided by an auto industry in Michigan, United States. There are six modules in the subassembly. Four variants are available for every module. For identification purpose, the modules sets are labeled A, B, C, D, E, and F. The variants of the module set A are referenced as $\mathrm{A}: \mathrm{A}_1, \mathrm{A}_2, \mathrm{A}_3, \mathrm{A}_4$. Other module variants are recognized accordingly.

With regard to the product development strategy in figure 2.1 in which module variants are clustered in pairs. At the first level, there are 5 decision nodes, because there are 6 module sets. The five nodes are the base modular pairs that begin five main branches. At this level, two candidate modules have been determined, remaining four modules to cluster into the product. At the second level, every node leads to three decision nodes (since four modules are remaining). Therefore, there are a total of 15 nodes at level 2. At this level, four modules have been included in the product, leaving out 2 more modules. At level 3, every node at level 2 leads to one node (a pair on modules is required). Therefore, there are 15 nodes at level three. In total, there are three paths in every branch, giving a total of 15 paths in the tree. Along every path, there are three decision nodes from which 3 modules pairs are required. Four variants are available for every module, so there are $4 * 4 = 16$ module variant pairs (decision variables) at every node. Therefore, there are $16 * 16 * 16 = 4096$ product configurations along a path. In this PD environment, a total of $15 * 4096 = 61,440$ product configurations are potentially available. The design and manufacturing cost data that are provided by the OEM are contained in Tables 3.1 and 3.2. The cost data are presented for a pair of modules. The weights (as estimates of the transportation cost) of the module variants are presented in table 3.3. Similarly, a value represents the weights of a module pair. These values are the cost indices (CI) in the optimization model.

Table 3.1: Design cost modular pair indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					6.29	5.69	5.15	4.66	5.87	5.31	4.81	4.35	4.95	4.48	4.06	3.68	9.2	8.31	7.51	6.78	3.66	3.32	3.01	2.74
	A2					6.26	5.66	5.12	4.63	5.84	5.28	4.78	4.32	4.92	4.45	4.03	3.65	9.17	8.28	7.48	6.75	3.63	3.29	2.98	2.71
	A3					6.24	5.64	5.10	4.61	5.82	5.26	4.76	4.30	4.90	4.43	4.01	3.63	9.15	8.26	7.46	6.73	3.61	3.27	2.96	2.69
	A4					6.22	5.62	5.08	4.59	5.80	5.24	4.74	4.28	4.88	4.41	3.99	3.61	9.13	8.24	7.44	6.71	3.59	3.25	2.94	2.67
B	B1	6.29	6.26	6.24	6.22					11.62	11.06	10.56	10.1	10.7	10.23	9.81	9.43	14.95	14.06	13.26	12.53	9.41	9.07	8.76	8.49
	B2	5.69	5.66	5.64	5.62					11.02	10.46	9.96	9.50	10.1	9.63	9.21	8.83	14.35	13.46	12.66	11.93	8.81	8.47	8.16	7.89
	B3	5.15	5.12	5.10	5.08					10.48	9.92	9.42	8.96	9.56	9.09	8.67	8.29	13.81	12.92	12.12	11.39	8.27	7.93	7.62	7.35
	B4	4.66	4.63	4.61	4.59					9.99	9.43	8.93	8.47	9.07	8.60	8.18	7.80	13.32	12.43	11.63	10.9	7.78	7.44	7.13	6.86
C	C1	5.87	5.84	5.82	5.80	11.62	11.02	10.48	9.99					10.28	9.81	9.39	9.01	14.53	13.64	12.84	12.11	8.99	8.65	8.34	8.07
	C2	5.31	5.28	5.26	5.24	11.06	10.46	9.92	9.43					9.72	9.25	8.83	8.45	13.97	13.08	12.28	11.55	8.43	8.09	7.78	7.51
	C3	4.81	4.78	4.76	4.74	10.56	9.96	9.42	8.93					9.22	8.75	8.33	7.95	13.47	12.58	11.78	11.05	7.93	7.59	7.28	7.01
	C4	4.35	4.32	4.30	4.28	10.1	9.50	8.96	8.47					8.76	8.29	7.87	7.49	13.01	12.12	11.32	10.59	7.47	7.13	6.82	6.55
D	D1	4.95	4.92	4.90	4.88	10.7	10.1	9.56	9.07	10.28	9.72	9.22	8.76					13.61	12.65	11.92	11.19	8.07	7.73	7.42	7.15
	D2	4.48	4.45	4.43	4.41	10.23	9.63	9.09	8.60	9.81	9.25	8.75	8.29					13.14	12.25	11.45	10.72	7.60	7.26	6.95	6.68
	D3	4.06	4.03	4.01	3.99	9.81	9.21	8.67	8.18	9.39	8.83	8.33	7.87					12.72	11.83	11.03	10.3	7.18	6.84	6.53	6.26
	D4	3.68	3.65	3.63	3.61	9.43	8.83	8.29	7.80	9.01	8.45	7.95	7.49					12.34	11.45	10.65	9.92	6.80	6.46	6.15	5.88
E	E1	9.2	9.17	9.15	9.13	14.95	14.35	13.81	13.32	14.53	13.97	13.47	13.01	13.61	13.14	12.72	12.34					12.32	11.98	11.67	11.4
	E2	8.31	8.28	8.26	8.24	14.06	13.46	12.92	12.43	13.64	13.08	12.58	12.12	12.65	12.25	11.83	11.45					11.43	11.09	10.78	10.51
	E3	7.51	7.48	7.46	7.44	13.26	12.66	12.12	11.63	12.84	12.28	11.78	11.32	11.92	11.45	11.03	10.65					10.63	10.29	9.98	9.71
	E4	6.78	6.75	6.73	6.71	12.53	11.93	11.39	10.9	12.11	11.55	11.05	10.59	11.19	10.72	10.3	9.92					9.90	9.56	9.25	8.98
F	F1	3.66	3.63	3.61	3.59	9.41	8.81	8.27	7.78	8.99	8.43	7.93	7.47	8.07	7.60	7.18	6.80	12.32	11.43	10.63	9.90				
	F2	3.32	3.29	3.27	3.25	9.07	8.47	7.93	7.44	8.65	8.09	7.59	7.13	7.73	7.26	6.84	6.46	11.98	11.09	10.29	9.56				
	F3	3.01	2.98	2.96	2.94	8.76	8.16	7.62	7.13	8.34	7.78	7.28	6.82	7.42	6.95	6.53	6.15	11.67	10.78	9.98	9.25				
	F4	2.74	2.71	2.69	2.67	8.49	7.89	7.35	6.86	8.07	7.51	7.01	6.55	7.15	6.68	6.26	5.88	11.4	10.51	9.71	8.98				

Table 3.2: Manufacturing cost modular pair indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					2.91	2.55	2.19	1.98	3.12	2.70	2.27	2.03	3.55	3.12	2.56	2.27	2.78	2.48	2.13	1.93	3.82	3.32	2.66	2.34
	A2					2.70	2.34	1.98	1.77	2.91	2.49	2.06	1.82	3.34	2.91	2.35	2.06	2.57	2.27	1.92	1.72	3.61	3.11	2.45	2.13
	A3					2.30	1.94	1.58	1.37	2.51	2.09	1.66	1.42	2.94	2.51	1.95	1.66	2.17	1.87	1.52	1.32	3.21	2.71	2.05	1.73
	A4					2.19	1.83	1.47	1.26	2.40	1.98	1.55	1.31	2.83	2.40	1.84	1.55	2.06	1.76	1.41	1.55	3.10	2.60	1.94	1.62
B	B1	2.91	2.70	2.30	2.19					3.67	3.25	2.82	2.58	4.10	3.67	3.11	2.82	3.33	3.03	2.68	2.48	4.37	3.87	3.21	2.89
	B2	2.55	2.34	1.94	1.83					3.31	2.89	2.46	2.22	3.74	3.31	2.75	2.46	2.97	2.67	2.32	2.12	4.01	3.51	2.85	2.53
	B3	2.19	1.98	1.58	1.47					2.95	2.53	2.10	1.86	3.38	2.95	2.39	2.10	2.61	2.31	1.96	1.76	3.65	3.15	2.49	2.17
	B4	1.98	1.77	1.37	1.26					2.74	2.32	1.89	1.65	3.17	2.74	2.18	1.89	2.40	2.10	1.75	1.55	3.44	2.94	2.28	1.96
C	C1	3.12	2.91	2.51	2.40	3.67	3.31	2.95	2.74					4.31	3.88	3.32	3.03	3.54	3.24	2.89	2.69	4.58	4.08	3.42	3.10
	C2	2.70	2.49	2.09	1.98	3.25	2.89	2.53	2.32					3.89	3.46	2.90	2.61	3.12	2.82	2.47	2.27	4.16	3.66	3.0	2.68
	C3	2.27	2.06	1.66	1.55	2.82	2.46	2.10	1.89					3.46	3.03	2.47	2.18	2.69	2.39	2.04	1.84	3.73	3.23	2.57	2.25
	C4	2.03	1.82	1.42	1.31	2.58	2.22	1.86	1.65					3.22	2.79	2.23	1.94	2.45	2.15	1.80	1.60	3.49	2.99	2.33	2.01
D	D1	3.55	3.34	2.94	2.83	4.10	3.74	3.38	3.17	4.31	3.89	3.22	3.22					3.97	3.67	3.32	3.12	5.01	4.51	3.85	3.53
	D2	3.12	2.91	2.51	2.40	3.67	3.31	2.95	2.74	3.88	3.46	2.79	2.79					3.54	3.24	2.89	2.69	4.58	4.08	3.42	3.10
	D3	2.56	2.35	1.95	1.84	3.11	2.75	2.39	2.18	3.32	2.90	2.23	2.23					2.98	2.68	2.33	2.13	4.02	3.52	2.86	2.54
	D4	2.27	2.06	1.66	1.55	2.82	2.46	2.10	1.89	3.03	2.61	1.94	1.94					2.69	2.39	2.04	1.84	3.73	3.23	2.57	2.25
E	E1	2.78	2.57	2.17	2.06	3.33	2.97	2.61	2.40	3.54	3.12	2.45	2.45	3.97	3.54	2.98	2.69					4.24	3.74	3.08	2.76
	E2	2.48	2.27	1.87	1.76	3.03	2.67	2.31	2.10	3.24	2.82	2.15	2.15	3.67	3.24	2.68	2.39					3.94	3.44	2.78	2.46
	E3	2.13	1.92	1.52	1.41	2.68	2.32	1.96	1.75	2.89	2.47	1.80	1.80	3.32	2.89	2.33	2.04					3.59	3.09	2.43	2.11
	E4	1.93	1.72	1.32	1.55	2.48	2.12	1.76	1.55	2.69	2.27	1.60	1.60	3.12	2.69	2.13	1.84					3.39	2.89	2.23	1.91
F	F1	3.82	3.61	3.21	3.10	4.37	4.01	3.65	3.44	4.58	4.16	3.49	3.49	5.01	4.58	4.02	3.73	4.24	3.94	3.59	3.39				
	F2	3.32	3.11	2.71	2.60	3.87	3.51	3.15	2.94	4.08	3.66	2.99	2.99	4.51	4.08	3.52	3.23	3.74	3.44	3.09	2.89				
	F3	2.66	2.45	2.05	1.94	3.21	2.85	2.49	2.28	3.42	3.0	2.33	2.33	3.85	3.42	2.86	2.57	3.08	2.78	2.43	2.23				
	F4	2.34	2.13	1.73	1.62	2.89	2.53	2.17	1.96	3.10	2.68	2.01	2.01	3.53	3.10	2.54	2.25	2.76	2.46	2.11	1.91				

Table 3.3: Estimation of Transportation cost indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					6.0	5.25	6.65	5.65	8.60	9.75	8.0	11.0	5.95	7.45	5.35	6.75	10.25	8.75	11.0	8.0	7.75	6.25	8.75	7.25
	A2					5.0	4.25	5.65	4.65	7.6	8.75	7.0	10.0	4.95	6.45	4.35	5.75	9.25	7.75	10.0	7.0	6.75	5.25	7.75	6.25
	A3					6.75	6.0	7.40	6.40	9.35	10.5	8.75	11.75	6.70	8.20	6.10	7.50	11.0	9.50	11.75	8.75	8.50	7.0	9.5	8.0
	A4					5.45	4.70	6.10	5.10	8.05	9.20	7.45	10.45	5.40	6.90	4.80	6.20	9.70	8.20	10.45	7.45	7.20	5.70	8.20	6.70
B	B1	6.0	5.0	6.75	5.45					7.6	8.75	7.0	10.0	4.95	6.45	4.35	5.75	9.25	7.75	10.0	7.0	6.75	5.25	7.75	6.25
	B2	5.25	4.25	6.0	4.70					6.85	8.0	6.25	9.25	4.20	5.70	3.60	5.0	8.50	7.0	9.25	6.25	6.0	4.50	7.0	5.50
	B3	6.65	5.65	7.40	6.10					8.25	9.40	7.65	10.65	5.60	7.10	5.0	6.40	9.90	8.40	10.65	7.65	7.40	5.90	8.40	6.90
	B4	5.65	4.65	6.40	5.10					7.25	8.40	6.65	9.65	4.60	6.10	4.0	5.40	8.90	7.40	9.65	6.65	6.40	4.90	7.40	5.90
C	C1	8.60	7.6	9.35	8.05	7.60	6.85	8.25	7.25					7.55	9.05	6.95	8.35	11.85	10.35	12.60	9.60	9.35	7.85	10.35	8.85
	C2	9.75	8.75	10.5	9.20	8.75	8.0	9.40	8.40					8.70	10.20	8.10	9.50	13.0	11.50	13.75	10.75	10.5	9.0	11.5	10.0
	C3	8.0	7.0	8.75	7.45	7.0	6.25	7.65	6.65					6.95	8.45	6.35	7.75	11.25	9.75	12.0	9.0	8.75	7.25	9.75	8.25
	C4	11.0	10.0	11.75	10.45	10.0	9.25	10.65	9.65					9.95	11.45	9.35	10.75	14.25	12.75	15.0	12.0	11.75	10.25	12.75	11.25
D	D1	5.95	4.95	6.70	5.40	4.95	4.20	5.60	4.60	7.55	8.70	6.95	9.95					9.20	7.70	9.95	6.95	6.70	5.20	7.70	6.20
	D2	7.45	6.45	8.20	6.90	6.45	5.70	7.10	6.10	9.05	10.2	8.45	11.45					10.7	9.20	11.45	8.45	8.20	6.70	9.20	7.70
	D3	5.35	4.35	6.10	4.80	4.35	3.60	5.0	4.0	6.95	8.10	6.35	9.35					8.60	7.10	9.35	6.35	6.10	4.60	7.10	5.60
	D4	6.75	5.75	7.50	6.20	5.75	5.0	6.40	5.40	8.35	9.50	7.75	10.75					10.0	8.50	10.75	7.75	7.50	6.0	8.50	7.0
E	E1	10.25	9.25	11.0	9.70	9.25	8.50	9.90	8.90	11.85	13.0	11.25	14.25	9.20	10.7	8.60	10.0					11.0	9.50	12.0	10.5
	E2	8.75	7.75	9.50	8.20	7.75	7.0	8.40	7.40	10.35	11.5	9.75	12.75	7.70	9.20	7.10	8.50					9.50	8.0	10.5	9.0
	E3	11.0	10.0	11.75	10.45	10.0	9.25	10.65	9.65	12.60	13.75	12.0	15.0	9.95	11.45	9.35	10.75					11.75	10.25	12.75	11.25
	E4	8.0	7.0	8.75	7.45	7.0	6.25	7.65	6.65	9.60	10.75	9.0	12.0	6.95	8.45	6.35	7.75					8.75	7.25	9.75	8.25
F	F1	7.75	6.75	8.50	7.20	6.75	6.0	7.40	6.40	9.35	10.5	8.75	11.75	6.70	8.20	6.10	7.50	11.0	9.50	11,75	8.75				
	F2	6.25	5.25	7.0	5.70	5.25	4.50	5.90	4.90	7.85	9.0	7.25	10.25	5.20	6.70	4.60	6.0	9.50	8.0	10.25	7.25				
	F3	8.75	7.75	9.50	8.20	7.75	7.0	8.40	7.40	10.35	11.5	9.75	12.75	7.70	9.20	7.10	8.50	12.0	10.5	12.75	9.75				
	F4	7.25	6.25	8.0	6.70	6.25	5.50	6.90	5.90	8.85	10.0	8.25	11.25	6.20	7.70	5.60	7.0	10.5	9.0	11.25	9.75				

Furthermore, the degree of compatibility of the modular pairs with respect to product serviceability and core cleaning is obtained through the fuzzy system. The data are contained in Tables 2.3 & 2.4 respectively. The optimization model is implemented in Gurobi-python interface. The optimal architectures for the objectives are contained in table 3.4.

Table 2.3: Modular pair serviceability indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.80	0.75	0.45	0.65	0.55	0.75	0.35	0.65	0.85	0.75	0.55	0.70	0.45	0.90	0.80	0.65	0.75	0.55	0.85	0.70
	A2					0.45	0.35	0.55	0.70	0.65	0.75	0.85	0.75	0.35	0.75	0.45	0.55	0.55	0.65	0.25	0.60	0.75	0.35	0.85	0.75
	A3					0.75	0.90	0.50	0.80	0.65	0.75	0.70	0.70	0.25	0.65	0.55	0.60	0.75	0.35	0.60	0.70	0.65	0.95	0.65	0.85
	A4					0.70	0.75	0.50	0.75	0.60	0.65	0.75	0.70	0.75	0.70	0.65	0.70	0.70	0.80	0.75	0.70	0.65	0.85	0.75	0.70
B	B1	0.80	0.45	0.75	0.70					0.45	0.55	0.80	0.75	0.60	0.55	0.50	0.55	0.60	0.55	0.50	0.75	0.75	0.65	0.50	0.70
	B2	0.75	0.35	0.90	0.75					0.50	0.65	0.60	0.75	0.65	0.45	0.55	0.60	0.35	0.75	0.90	0.70	0.65	0.75	0.80	0.65
	B3	0.45	0.55	0.50	0.50					0.70	0.75	0.40	0.70	0.35	0.70	0.80	0.75	0.75	0.55	0.50	0.60	0.80	0.65	0.60	0.70
	B4	0.65	0.70	0.80	0.75					0.65	0.70	0.75	0.65	0.60	0.35	0.60	0.50	0.65	0.45	0.80	0.60	0.65	0.70	0.70	0.60
C	C1	0.55	0.65	0.65	0.60	0.45	0.50	0.70	0.65					0.45	0.30	0.75	0.65	0.70	0.60	0.45	0.65	0.80	0.75	0.55	0.70
	C2	0.75	0.75	0.75	0.65	0.55	0.65	0.75	0.70					0.25	0.55	0.40	0.50	0.75	0.35	0.80	0.70	0.85	0.85	0.60	0.70
	C3	0.35	0.85	0.70	0.75	0.80	0.60	0.40	0.75					0.70	0.50	0.55	0.65	0.65	0.45	0.40	0.60	0.75	0.70	0.60	0.85
	C4	0.65	0.75	0.70	0.70	0.75	0.75	0.70	0.65					0.65	0.75	0.65	0.70	0.70	0.55	0.35	0.45	0.80	0.70	0.50	0.65
D	D1	0.85	0.35	0.25	0.75	0.60	0.65	0.35	0.60	0.45	0.25	0.70	0.65					0.35	0.50	0.55	0.50	0.85	0.45	0.55	0.60
	D2	0.75	0.75	0.65	0.70	0.55	0.45	0.70	0.35	0.30	0.55	0.50	0.75					0.75	0.65	0.45	0.55	0.75	0.45	0.80	0.70
	D3	0.55	0.45	0.55	0.65	0.50	0.55	0.80	0.60	0.75	0.40	0.55	0.65					0.85	0.65	0.45	0.60	0.65	0.50	0.40	0.65
	D4	0.70	0.55	0.60	0.70	0.55	0.60	0.75	0.50	0.65	0.50	0.65	0.70					0.55	0.60	0.50	0.40	0.70	0.40	0.65	0.50
E	E1	0.45	0.55	0.75	0.70	0.60	0.35	0.75	0.65	0.70	0.75	0.65	0.70	0.35	0.75	0.85	0.55					0.70	0.75	0.65	0.70
	E2	0.90	0.65	0.35	0.80	0.55	0.75	0.55	0.45	0.60	0.35	0.45	0.55	0.50	0.65	0.65	0.60					0.75	0.45	0.70	0.65
	E3	0.80	0.25	0.60	0.75	0.50	0.90	0.50	0.80	0.45	0.80	0.40	0.35	0.55	0.45	0.45	0.50					0.95	0.70	0.50	0.75
	E4	0.65	0.60	0.70	0.70	0.75	0.70	0.60	0.60	0.65	0.70	0.60	0.45	0.50	0.55	0.60	0.40					0.65	0.70	0.60	0.65
F	F1	0.75	0.75	0.65	0.65	0.75	0.65	0.80	0.65	0.700.80	0.85	0.75	0.80	0.85	0.75	0.65	0.70	0.70	0.75	0.95	0.65				
	F2	0.55	0.35	0.95	0.85	0.65	0.75	0.65	0.70	0.75	0.85	0.70	0.70	0.45	0.45	0.50	0.40	0.75	0.45	0.70	0.70				
	F3	0.85	0.85	0.65	0.75	0.50	0.80	0.60	0.70	0.55	0.60	0.60	0.50	0.55	0.80	0.40	0.65	0.65	0.70	0.50	0.60				
	F4	0.70	0.75	0.85	0.70	0.70	0.65	0.70	0.60	0.70	0.70	0.85	0.65	0.60	0.70	0.65	0.50	0.70	0.65	0.75	0.65				

Table 2.4: Modular pair core-cleaning indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.65	0.90	0.55	0.75	0.85	0.55	0.60	0.75	0.75	0.55	0.65	0.60	0.65	0.85	0.70	0.75	0.75	0.90	0.75	0.80
	A2					0.75	0.65	0.85	0.70	0.75	0.75	0.90	0.70	0.75	0.70	0.60	0.65	0.60	0.75	0.45	0.65	0.75	0.85	0.75	0.70
	A3					0.65	0.85	0.70	0.75	0.75	0.55	0.60	0.70	0.45	0.75	0.65	0.70	0.75	0.85	0.65	0.70	0.75	0.85	0.75	0.70
	A4					0.70	0.75	0.70	0.65	0.65	0.65	0.70	0.75	0.65	0.65	0.55	0.45	0.70	0.70	0.60	0.65	0.60	0.75	0.70	0.65
B	B1	0.65	0.75	0.65	0.70					0.85	0.45	0.55	0.75	0.65	0.65	0.70	0.55	0.70	0.65	0.80	0.70	0.65	0.65	0.80	0.75
	B2	0.90	0.65	0.85	0.75					0.60	0.75	0.50	0.65	0.75	0.55	0.85	0.65	0.85	0.45	0.40	0.65	0.55	0.65	0.85	0.65
	B3	0.55	0.85	0.70	0.70					0.65	0.75	0.70	0.70	0.55	0.75	0.70	0.70	0.65	0.85	0.70	0.70	0.80	0.75	0.65	0.70
	B4	0.75	0.70	0.75	0.65					0.70	0.50	0.65	0.60	0.60	0.70	0.80	0.70	0.75	0.60	0.65	0.65	0.70	0.65	0.75	0.65
C	C1	0.85	0.75	0.75	0.65	0.85	0.60	0.65	0.70					0.55	0.80	0.85	0.80	0.80	0.70	0.75	0.70	0.40	0.65	0.75	0.60
	C2	0.55	0.75	0.55	0.65	0.45	0.75	0.75	0.50					0.55	0.35	0.60	0.70	0.65	0.85	0.50	0.90	0.45	0.80	0.70	0.55
	C3	0.60	0.90	0.60	0.70	0.55	0.50	0.70	0.65					0.60	0.70	0.65	0.60	0.45	0.65	0.60	0.50	0.65	0.55	0.70	0.25
	C4	0.75	0.70	0.70	0.75	0.75	0.65	0.70	0.60					0.75	0.60	0.75	0.70	0.70	0.75	0.70	0.65	0.60	0.75	0.55	0.45
D	D1	0.75	0.75	0.45	0.65	0.65	0.75	0.55	0.60	0.55	0.55	0.60	0.75					0.75	0.30	0.65	0.65	0.60	0.75	0.75	0.75
	D2	0.55	0.70	0.75	0.65	0.65	0.55	0.75	0.70	0.80	0.35	0.70	0.60					0.60	0.65	0.55	0.60	0.85	0.80	0.80	0.70
	D3	0.65	0.60	0.65	0.55	0.70	0.85	0.70	0.80	0.85	0.60	0.65	0.75					0.80	0.75	0.75	0.55	0.65	0.60	0.75	0.60
	D4	0.60	0.60	0.70	0.45	0.55	0.65	0.70	0.70	0.80	0.70	0.60	0.70					0.65	0.45	0.55	0.50	0.55	0.65	0.25	0.45
E	E1	0.65	0.60	0.75	0.70	0.70	0.85	0.65	0.75	0.80	0.65	0.45	0.70	0.75	0.60	0.80	0.65					0.55	0.65	0.60	0.60
	E2	0.85	0.75	0.85	0.70	0.65	0.45	0.85	0.60	0.70	0.85	0.65	0.75	0.30	0.65	0.75	0.45					0.80	0.65	0.75	0.70
	E3	0.70	0.45	0.65	0.60	0.80	0.40	0.70	0.65	0.75	0.50	0.60	0.70	0.65	0.55	0.75	0.55					0.80	0.90	0.55	0.55
	E4	0.75	0.65	0.70	0.65	0.70	0.65	0.70	0.65	0.70	0.90	0.50	0.65	0.65	0.60	0.55	0.50					0.75	0.55	0.65	0.60
F	F1	0.75	0.75	0.75	0.60	0.65	0.55	0.80	0.70	0.40	0.45	0.65	0.60	0.60	0.85	0.65	0.55	0.55	0.80	0.80	0.75				
	F2	0.90	0.85	0.85	0.75	0.65	0.65	0.75	0.65	0.65	0.80	0.55	0.75	0.75	0.80	0.60	0.65	0.65	0.65	0.90	0.55				
	F3	0.75	0.75	0.75	0.70	0.80	0.85	0.65	0.75	0.75	0.70	0.70	0.55	0.75	0.80	0.75	0.25	0.60	0.75	0.55	0.65				
	F4	0.80	0.70	0.70	0.65	0.75	0.65	0.70	0.65	0.60	0.55	0.25	0.45	0.75	0.70	0.60	0.45	0.60	0.70	0.55	0.60				

Table 3.4: Product architectures for decision making

Objective	Product Architecture	Product Strength & Cost Indices
Manufacturing Cost	A_4B_4, C_4E_4, D_4F_4	\$5.11
Design Cost	A_4F_4, B_4D_4, C_4E_4	\$21.06
Transportation Cost (Weight as estimate)	A_2B_2, C_3F_2, D_3E_4	17.80 lbs.
Serviceability	A_1D_1, B_1C_3, E_3F_1	2.60
	A_3B_2, C_2F_1, D_3E_1	2.60
	A_3B_2, C_1D_3, E_3F_1	2.60
	A_2C_3, B_3D_3, E_3F_1	2.60
	A_3B_2, C_4D_2, E_3F_1	2.60
	A_3B_2, C_3F_4, D_3E_1	2.60
Core-cleaning	A_1B_2, C_1D_3, E_3F_2	2.65
	A_2C_3, B_2D_3, E_3F_2	2.65
	A_1B_2, C_2E_4, D_2F_1	2.65
	A_1F_2, C_2E_4, B_2D_3	2.65

It is important to provide further analyses to determine the comparative benefits of the optimal configurations. We employ multi-attribute utility theory (MAUT) as provided by Logical Decisions for Window. For these analyses, the study obtains the objective values the optimal configurations with regard to all objectives as required by MAUT. These values are listed in table 3.5 as the strength indices of the product configurations.

Table 3.5: Strength indices of optimal architectures

	Product Architecture	DCI	MCI	TCI	SI	KI
1	A_4B_4, C_4E_4, D_4F_4	21.06	**5.10**	24.10	1.7	1.75
2	A_4F_4, B_4D_4, C_4E_4	**21.06**	5.10	24.10	1.65	2.0
3	A_2B_1, C_4D_3, E_3F_2	24.42	8.02	**17.80**	1.80	2.40
4	A_1D_1, B_1C_3, E_3F_1	26.13	9.96	24.70	**2.60**	2.10
5	A_3B_2, C_2F_1, D_3E_1	21.75	9.08	25.10	**2.60**	2.10
6	A_3B_2, C_1D_3, E_3F_1	25.65	8.84	24.70	**2.60**	2.50
7	A_2C_3, B_3D_3, E_3F_1	24.07	8.03	23.75	**2.60**	2.40
8	A_3B_2, C_4D_2, E_3F_1	24.56	8.31	29.20	**2.60**	2.25
9	A_3B_2, C_3F_4, D_3E_1	25.39	7.56	22.85	**2.60**	1.90
10	A_1B_2, C_1D_3, E_3F_2	25.36	8.96	22.45	2.20	**2.65**
11	A_2C_3, B_2D_3, E_3F_2	24.27	7.90	20.85	2.10	**2.65**
12	A_1B_2, C_2E_4, D_2F_1	24.84	9.40	24.20	2.20	**2.65**
13	A_1F_2, C_2E_4, B_2D_3	24.08	8.35	22.0	1.80	**2.65**

From the analysis result, figure 3.2 shows the utility ranking of the product configuration indicating that product architecture 2 has the highest utility value. With other optimization methods that produce a single optimal solution such as GP, this architecture corresponds to the optimal solution. The strength of this product architecture lies on its potential for design and manufacturing cost reduction. The sensitivity analysis in figure 3.3 provides clearer comparative advantages of the configurations. The first six architectures on the utility ranking scale are involved in the analysis. The first vertical line depicts the overall utility value, with the product architecture 2 topmost ranked, while architecture 7 ranks least. However, this solution is not robust. As the graph moves towards serviceability criterion, architecture 7 ranks topmost while architecture 2 ranks least. Similarly, as the graph approaches core-cleaning criterion, architecture 11 that is ranked fourth on the utility scale becomes the most viable product architecture, implying higher remanufacturing value. Another observation shows that product architecture 3 is ranked highest in transportation cost reduction.

Figure 3.2: Assessment of product architecture alternatives

Notice that architecture 2 and 1 are exactly the same. They contain the same module variants that are clustered into the product in a different pairing. They have the same values of cost indices, but slightly different values of serviceability and core cleaning. This is due to the marginal error of deffuzzification process of the fuzzy system. However, the difference did not alter any decision since they are closely ranked on the two objectives.

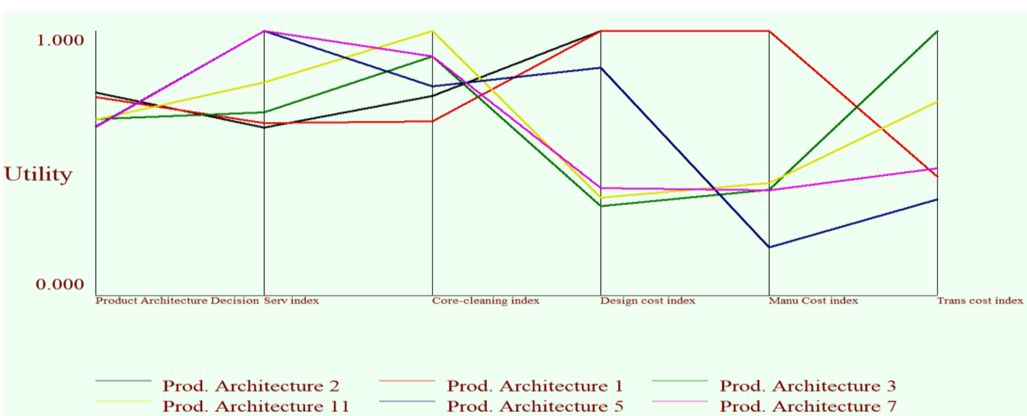


Figure 3.3: Sensitivity of product alternatives to model objectives

In decision making, an OEM may decide on either architecture 2 due to the savings in design and manufacturing costs. The OEM will then need to seek further improvement on other objectives. Similarly, architecture 7 could be the preferred option for the OEM considering that it ranks highest in serviceability and ranks second in core cleaning. However, this option ranks very low in costs reduction. With this option, the OEM will have to find alternative means to reduce cost. These may include considering local module supply or redesigning the (re)manufacturing facilities. Furthermore, architecture 11 has the highest remanufacture value and ranks second in terms of transportation cost reduction. The OEM may also make this the choice architecture if it has the capability to remedy the weaker areas. These analyses provide informed platform to guide the OEM in product architecture decision making.

3.5 Conclusion

PSS-Remanufacturing business is a promising enterprise that is attracting the focus of a growing number of OEMs. The success of these business rest heavily on PD decision while these decisions account for over 70% of product lifecycle cost. Transportation cost is especially essential in PSS because the OEM is responsible for product's ownership throughout its lifecycle. Having determined the critical importance of cost in the product lifecycle, the study obtains real-life design and manufacturing cost data from a notable OEM and uses the weight of module variant as a proxy for the transportation cost. Similarly, product serviceability and core cleaning are identified to be essential to the success of PSS-Remanufacturing business. The study obtains the compatibility indices of module pairs with regard to serviceability and core-cleaning through fuzzy system. Similarly, the cost data are also considered for the module pairs at the PD phase.

The study improves on an optimization model that was developed previously by incorporating costs considerations into the early phase of product development. The model was tested with the case study involving the development of a 6-module product (subassembly). There are 4 variants available for every module. The implementation of the optimization model in Gurobi-python interface produces 13 optimal product configurations. These product configurations minimize transportation, design and (re)manufacturing costs while maximizing product serviceability and cleaning processes in other to enhance PSS-remanufacturing enterprise. Furthermore, the study applies MAUT technique through logical decisions for windows (LDW) to provide sensitivity analyses of the product configurations. The results indicate that some product configurations that a ranked low in overall utility have some comparative benefits. These analyses reveal that the OEM may prefer a configuration that is strong on desirable objectives and pursues improvement on the objectives on which it is deficient. The study provides an analytic approach to guide product architecture decision at the early phase of PD so as to enhance PSS-remanufacturing business. Furthermore, it offers broader decision horizon to the product architecture decision managers through the sensitivity analyses. This research offers a unique contribution to the PSS-remanufacturing research domain.

CHAPTER 4: INCORPORATING SUSTAINABILITY INTO MODULAR DESIGN

4.1 Introduction

Due to the substantial benefits that are embedded in remanufacturing and PSS, the integration of these concepts as a business offering has been recommended (Hatcher et al., 2011). Currently, the PSS-remanufacturing business is increasingly gaining the attention of both the industry and the research communities. The business initiative is intended to take the advantages of remanufacturing and remedy its limitation concurrently, and also realize other benefits of PSS. Among the product EOL management strategies, remanufacturing is adjudged the most viable in terms of economic and environmental gains (Butzer et al., 2014). However, the remanufacturing business is significantly impeded by certain factors. These include the quality level, the volume, the recovery time of cores (used product), as well as negative perception of the remanufactured product. PSS is a business offering in which the OEM is responsible for product's ownership while the product is offered to customers for use (Song, 2017).

The PSS-remanufacturing business permits the OEM to monitor the product usage and remedies the problems that are identified with remanufacturing to a large extent. Thus, PSS-remanufacturing business is considered a more sustainable product offering. Researchers maintain that PD decisions significantly influence remanufacturing (Sundin et al., 2009), and PSS (Qu et al., 2016). In addition, researchers claim that product modularity is an efficient PD strategy (Kremer & Gupta, 2013). Furthermore, the fundamental assumption is that PSS enhances sustainability because fewer products (than in the traditional product offering) are required to meet the customers' needs, since the PSS is predicated on product sharing among multiple users.

However, the assumption is flawed if the production of the modules has a substantive negative impact on the environment. For example, lesser environmental impact is associated with the use phase of a lead-acid battery, however, its production yields significantly high lead contamination (Tian et al., 2017). Therefore a PSS-remanufacturing business may not realize the acclaimed sustainable benefits unless sustainability consideration is given to the production of the parts that constitute the product. Therefore, it is essential to consider the environmental impacts that are associated with the modules in order to develop a modular product that could be deemed environmentally friendly. One suitable means of instilling environmental considerations into the modular product at the PD phase is to perform the lifecycle impact assessment of the modules that constitute the product. LCA offers an appropriate method to perform such environmental assessment.

In addition, Kremer et al. (2016) conclude that sustainable product development should consider other aspects of sustainability of the product lifecycle other than environmental impacts. The PSS-remanufacturing model in Fadeyi et al. (2017) determines the product architectures that optimize core-cleaning and serviceability. Enhanced core-cleaning increases the quality of remanufacturing, implying cost savings (Gavidel & Rickli, 2017). Charter & Gray (2008) report that remanufactured products cost about 40% to 65% less than a similar new product. Similarly, an improved product serviceability increases the efficiency of the PSS by ensuring higher product availability (Sundin et al., 2009), and lowers the costs associated with product failures (Qu et al., 2016). Consequently, the PD optimization model that Fadeyi et al. (2017) develop for PSS-remanufacturing business has embedded cost-saving implication.

In order to develop the environmentally benignant modular product, this study performs the LCA of the module variants to determine the product architecture with minimal environmental impact. Similarly, the study improves the previous optimization model in Fadeyi et al. (2017) and determine the architectures that enhance the core cleaning and product serviceability. Having obtained the optimal product configurations with regard to core cleaning, product serviceability, and environmental impact, a multi-criteria decision technique is employed to determine the sustainability measures of the product configurations.

4.2 Literature review

4.2.1 Design of PSS-Remanufacturing business model

A growing number of OEMs are getting involved in the PSS-remanufacturing business (Guidat et al., 2014). The concept depicts a scenario in which the OEM takes the responsibility of product ownership while offering the product functions to the customer for payment, while the OEMs remanufacture the product at the end of use (EOU). Remanufacturing refers to the process that restores used products to useful life (Östlin et al., 2009). Remanufacturing saves energy equivalent to over 10.74 million barrel of crude oil and mitigates extraction of virgin resources (Giutini & Gaudette, 2003), prevents annual production of over 28 million tons of CO_2 globally and lower landfills (Charter & Gray, 2008). Therefore, improved remanufacturing enables significant cost savings and environmental preservation. Core cleaning is an essential process that enhances the quality of remanufacturing (Subramoniam et al., 2008). Gavidel & Rickli (2017) discuss the importance of core quality for efficient remanufacturing. However, remanufacturing is significantly impeded by the quality and quantity of the core as well as the timing of core recovery (Gavidel & Rickli, 2015).

The PSS is a business method that is premised on the offering of product functions rather than product ownership, thereby satisfying customers' needs with fewer products (Annarelli et al., 2016). As a result, the PSS is characterized by higher product usage than in traditional business offering. In order to meet the needs of multiple users, product serviceability becomes an essential criterion in PSS (Song & Sakao, 2017; Sundin et al., 2009). Since the product ownership lies with the OEM, the PSS enables the OEM to have some control over the quantity, recovery time, and quality level of used product. Consequently, the remanufacturing facilities can be designed efficiently, thereby making PSS-remanufacturing business a more sustainable venture. The earliest studies to incorporate PSS and remanufacturing are contained in Sundin & Lindahl (2008) and Sundin et al. (2009). These studies basically provide theoretical framework. A thorough review by Hatcher et al. (2011) highlight the enormous potential befits that are embedded in this business idea. Sundin et al. (2008) and Qu et al. (2016) corroborate other researchers that the performance of both PSS and remanufacturing are significantly influenced by PD decision.

It is important to estimate the imprecise data that pertain to the product during its lifecycle so as to develop an efficient optimization model at the early phase of PD. Fuzzy system has been widely used in PD to obtain such vague data. Nepal et al. (2008) apply fuzzy system to obtain vague data in product decomposition and developed an optimization model to identify optimal product architecture than improves manufacturability. Fadeyi et al. (2017) apply fuzzy system to estimate the compatibility level of module pair with regard to core cleaning and product serviceability in order to develop PD optimization model. Some application of fuzzy system in product development are contained in Aguwa et al. (2012) and Nepal et al. (2007).

Furthermore, PD often involves satisfying multiple and conflicting objectives. Multi-attribute utility theory (MAUT) has been widely applied in PD research. MAUT is an analytical decision making technique for analyzing multiple alternatives. MAUT converts different units of multiple options to utility values that rank between 0 and 1. The generic unit-less scale enables alternatives to be comparatively assessed. Salari & Bhuiyan (2018) employ MAUT to handle the trade-offs in a new product development model. Chelst & Canbolat (2011) describe the application of MAUT within the environment of Logical Decisions' package.

4.2.2 Influence of modular design on product lifecycle

A large volume of research agrees that PD decisions significantly influence all the phases of the product life lifecycle and that product modularity is an effective PD strategy. It is largely reported that modular design impacts all phases of the product lifecycle. At the PD phase, product modularity simplifies product architecting and enhance assembly processes (Yan & Feng, 2014). Nepal et al. (2005) demonstrate that modular design enhances manufacturing agility with a development of a fuzzy-based modular product that enables the OEM to sustain market share. Also, it is shown that modular design enhances the use phase of the product. Nepal et al. (2007) develop a modular product that improves product serviceability at a reduced cost. Aguwa et al. (2010) develop a modular architecture to improve the functional performance of a medical device in order to boost the quality of patient care. PSS is characterized by high product usage, hence product serviceability is critical to the performance of a product in the functional sale (Sundin & Lindahl, 2008). Furthermore, modular design substantially improves disassembly, product recovery, ease of reuse, to enhance product EOL management such as remanufacturing. Sundin & Lindahl (2008) report that enhanced product disassembly as a result of modular architecture facilitates core cleaning for remanufacturing purpose. Core cleaning is an essential criterion in remanufacturing processes. Qu et al. (2016) affirm that modular design is an efficient PD approach for both PSS and remanufacturing. Therefore, an efficient PSS-remanufacturing business could be realized through product modularity. The proponents of PSS-remanufacturing opine that it is a sustainable business strategy.

However, the environmental impact due to modular design has not been well addressed. Meanwhile, Kremer et al. (2016) report that the influence of product architecture on sustainability measure (e.g. carbon footprint) has not been addressed. The study calls for further studies to investigate the impact of modular architecture on environmental sustainability. Previously, Chung et al. (2011) obtain data that pertain to product assembly (for manufacturing), product use, and product disassembly (for EOL options) to develop a modular design that enhances product lifecycle. However, the study ignores the environmental impacts that are associated with the production of the modules from raw materials. In another study, Li et al. (2008) provide a modular design by considering impacts that are associated with the material composition of the parts of the product, as well as the product usage and end-of-life phase. However, only the environmental impact that relates to the materials (such as toxicity) was considered in the architectural design, leaving out other important factors that are connected with the conversion processes of the materials (e.g. energy and transportation). In a nutshell, the environmental impacts which are factored into the modular design in these studies are under quantified. In order to determine the environmental impact of the modular product, it is necessary to consider all the processes that are involved in the production of the modules including the materials, the energy inputs, and the associated transportation.

A comprehensive Impact assessment such as in lifecycle assessment (LCA) provides more encompassing environmental impact assessment. The LCA permits the environmental impact assessment of the available parts (or module variants) which enables the modular architecture that minimizes environmental impacts to be developed at the early stage of PD.

4.2.3 Design for sustainable product development

It is acknowledged in the PD research domain that product development plays a fundamental role in the environmental impacts of a product during its life cycle. Hallstedt (2017) and (Ijomah et al. (2007) emphasize that PD is the strongest determinant of the environmental impact of a product through its lifecycle. PD researchers note that PD flaws are extremely difficult to remedy. According to Ardente & Mathieux (2014) and Luttropp & Lagerstedt (2006), products have significant sustainability impact all through their lifecycle but very little could be done when the product has hit the market. Therefore, it is important to incorporate environmental considerations into the early stage of PD. To address this challenge, design for environment (DfE) was recently added to the design for X (DfX) concepts. Substantial studies have been done to incorporate lifecycle issues into the early phase of PD through DfX concepts. Few examples include design for remanufacturing, design for disassembly, design for cost, etc. Arnette et al. (2014) report that there are over 75 different DfX concepts in literature and provide a comprehensive review on 14. For tractability purposes, Jawahir et al. (2007) and later Arnette et al. (2014) attempt to condense the DfX concepts into one framework towards design for sustainability (DfS) . However, a wide gap still exists among the DfX concepts as a clear-cut integration is completely missing Kremer et al. (2016). In many instances, studies in PD that relate to only environmental implications have been loosely labeled green design, ecological design, environmental design, lifecycle design, or sustainable design. For example, in the research to integrate sustainability into early PD, Devanathan et al. (2010) considered only the environmental impacts. Consequently, Kremer et al. (2016) conclude that a design for sustainability must include other aspects of sustainability (such as cost) with the environmental consequences. Referring to the model in Fadeyi et al. (2017), core cleaning and product serviceability are considered. The cost saving that relates to improved core cleaning and product serviceability was discussed earlier. Therefore the integration of the environmental considerations with the core cleaning and product serviceability optimization enables a more sustainable modular product architecture to be determined.

4.2.4 Measurement of product lifecycle environmental impacts

The product lifecycle is generally subdivided into four phases, namely, raw material extraction, production, use, and End-of-life (Witik et al., 2013). Some methodologies that are based on impact categories have been used to measure the impact of product lifecycle on the environment. Carbon footprint has been grossly employed to evaluate the environmental impacts of products and as the basis for decision making. Recently, Rezaee et al. (2017) employ the carbon price that is associated with the carbon footprint to design a sustainable product supply chain network. However, carbon footprint is focused on a single environmental impact category-the CO_2 emission. Every phase of a product lifecycle is characterized with consumption of resources and emission release, which ultimately result into some classification of environment impacts such as climate change, ozone depletion, acidification, eutrophication, toxicological stress on human health and ecosystem, and depletion of resources (Witik et al., 2013). The impact categories are integrated to develop the Lifecycle assessment (LCA) methodology.

Currently, LCA is the most widely applied procedure to estimate the environmental impacts that are related to goods and services (Chaabane, Ramudhin, & Paquet, 2012; Haapala et al., 2013). Recently, some researchers attempt to critique the LCA with an argument that quantifying the sustainability or unsustainability of materials, products, and processes in numerical terms is defective and suggest qualitative methods of assessment. Schöggl etal. (2017) propose a qualitative method for sustainability evaluation and suggest that 'dialogs' among relevant PD departments through a tool called "Checklist for Sustainable Product Development (CSPD)" should inform sustainable product design. Also, Hallstedt (2017) develops a qualitative-based sustainability criteria index (SCI) that is obtained through brainstorming among relevant groups for PD. However, a fundamental flaw of a sustainable product design methodology that lacks quantifiable variables is that the comparison among multiple product alternatives is difficult. Despite its limitation, LCA is a globally accepted standardized method and the most widely applied approach in research (Witik et al., 2013). Recently, Schöggl et al. (2017) employ LCA in the development of a computer-aided sustainable product. Similarly, Hallstedt & Isaksson (2017) apply LCA for materials assessment in order to realize a sustainable product development scenario.

Environmental impact categories as identified previously are integrated differently to build a lifecycle impact assessment (LCIA) method. Some of the notable LCIA methodologies that are employed in LCA include eco-indicator 99, Recipe Endpoint, and CML. There are popular LCA packages (e.g. OpenLCA, SimaPro and GaBi) that either contain inbuilt LCIA methods or permit such to be imported. Eco-indicator 99 LCIA method is particularly important for product development. According to Goedkoop & Spriensma (2000), “the use of Eco-indicators has just one purpose, namely making products more environmentally sound”. Detailed description of the eco-indicator 99 is contained in Goedkoop & Spriensma (2000). As described in ISO (2006), the procedure for a LCA involves four basic stages: goal and scope definition; inventory analysis; lifecycle impact assessment; and interpretation. Other stages of the procedure are meant for decision purposes. Detailed discussion on LCA could be find in Danilecki et al. (2017).

4.2.5 The missing gap addressed

As discussed previously, for a PSS-Reman business to be considered sustainable, it is essential to consider the environmental impacts that relate to the production of the parts (modules) that constitute the product that is offered in PSS. Furthermore, a sustainable business scenario should integrate other aspects of sustainability with the environmental consequences. A sustainable PSS-Reman product offering of this description is missing. In order to fill this gap, this research employs LCA to determine the environmental indicators of the module variants in order to develop an environmentally sustainable modular product. In addition, the study highlights the cost benefits that relate to improved core-cleaning and product serviceability and modified an optimization model to determine the modular architectures that enhance core cleaning and product serviceability. The optimal product architecture with regard to core cleaning, product serviceability, and environmental impact are jointly evaluated by a multi-criteria decision-making technique in order to determine the appropriate modular architectures that ensure sustainable PSS-Reman business offering.

4.3 Methodology

This study is premised on a PSS-Reman Business setting. The OEM offers the product to the customer through functional sales. It is the responsibility of the OEM that the product is available for customer's use. The product is retrieved at the end-of-use (EOU) for Reman. The overall goal of the OEM is to install a sustainable PSS-Reman business through a modular product. Several module variants are available to the OEM through multiple suppliers. This section is divided into two parts. The first part relates to the determination of product architectures that enhance core-cleaning and product serviceability through an optimization model. The second section discusses the environmental impact assessment of the module variants in order to determine the modular architecture with minimal environmental impact.

4.3.1 Framework for development of modular architecture

The OEM needs to develop a modular product for the PSS-Reman business. The product consists of m modules. There are module sets i & j in m. Different variants k of module i and l variants of module j are available from multiple suppliers. The $\mathrm{k}-\mathrm{l}$ module pair compatibility is evaluated using fuzzy system with respect to core-cleaning and product serviceability. The product is developed by clustering into it the $\mathrm{k}-\mathrm{l}$ pairs that optimize the required objectives. In the situation where m is not even, a dummy module set is created in order to ensure complete module pairing. Pairwise assessment of modules permits thorough evaluations with respect to the desired objectives. The problem becomes complex as the number of m increases. The model is structured as a tree for efficient modeling and formulated as a binary integer programing (BIP) problem. The modeling framework is provided in prior study (Fadeyi et al., 2017). In the optimization model, the $\mathrm{k}-\mathrm{l}$ module pair is the decision variable. The resulting non-linear optimization model is linearized to guarantee optimality of solution. The $\mathrm{k}-\mathrm{l}$ module pair compatibility is evaluated using fuzzy system with respect to core-cleaning and product serviceability. The output from the fuzzy system provides the compatibility index of the $\mathrm{k}-\mathrm{l}$ module pair with regard to the criterion of interest. The notations in the model are descried below.

Notations and descriptions

M	Sample space of available module
m	Number of modules in the product drawn from M ; $m \in M$
i, j	Sets of modules available in ; $i, j \in m$, $i \neq j$
k	Variant of module set i ; $k \in i$
l	Variant of module set j ; $l \in j$
n	The number of items in a set
β	Branch in the tree
w	Number of branches β.
t	Number of paths in a tree branch β
α	Path in a branch of the tree
γ	Node along path α in a branch β representing modular pairs of same i & j.
q	Number of nodes on path α
y	Indicator variable to distinguish each configuration of on a path α in a branch β
λ	Number of Indicator variables at node γ
Z	Binary variable to linearize nonlinear constraints
$X_{i_k j_l}$	Decision variable representing $k - l$ module pair; $k \in i$, $l \in j$
$I_{i_k j_l}$	Compatibility index of $k - l$ pair; $k \in i$, $l \in j$
SI	Serviceability index
KI	Core-cleaning index

4.3.1.1 Development of optimization model

Objective functions

From module sets $i \,\&\, j$, $k - l$ pair is either jointly clustered into the product or not. Modular pair compatibility index is estimated by fuzzy system with regard to product serviceability and core cleaning.

1. $$\text{Max } S(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} SI_{i_k j_l} X_{i_k j_l} \qquad (1)$$

2. $$\text{Max } K(X) = \sum_{i,j=1}^{m} \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} KI_{i_k j_l} X_{i_k j_l} \qquad (2)$$

Constraints.

3. A variant k from module set i can be jointly clustered with at most a variant l of module set j

$$\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \leq 1 \qquad \forall\, i, j \in M, \quad i \neq j \qquad (3)$$

4. From module sets $i \,\&\, j$, $k - l$ pairs along a path α are jointly clustered to produce a unique modular product architecture. Also, in a branch β, the number of product configurations that can be produced is no more than the total available configurations in the branch

$$\sum_{\gamma=1}^{q} \left(\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \right) y_\beta^\alpha \leq \sum_{\alpha=1}^{t} y_\beta^\alpha \qquad \forall\, \beta \qquad (4)$$

5. The $k - l$ pair from module sets $i \,\&\, j$ can either be jointly clustered or not.

$$X_{i_k j_l} = \begin{cases} 1 \\ 0 \end{cases} \qquad (5)$$

6. Distinguish every product configuration along path α in branch β.

$$y_\beta^\alpha = \begin{cases} 1 & \text{if a configuration is chosen from } \alpha \\ 0 & \text{otherwise} \end{cases} \qquad (6)$$

7. Linearize the of non-linear constraints in (4)

$$Z_\gamma = \left(\sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \right) y_\beta^\alpha \qquad (7)$$

$$Z_\gamma \leq \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} \qquad (8)$$

$$Z_\gamma \leq y_\beta^\alpha \qquad \forall y \qquad (9)$$

$$Z_\gamma \geq \sum_{k=1}^{n_i} \sum_{l=1}^{n_j} X_{i_k j_l} + \sum_{\lambda=1}^{n_y} y_\beta^\alpha - n_y \qquad \forall \beta \qquad (10)$$

$$Z_\gamma, \quad X_{i_k j_l}, \quad y_\beta^\alpha \in \{0,1\} \qquad (11$$

8. For every branch β to make product configurations in (4), linearize the non-linear constraints in (4) with Z_γ and add $(8-11)$ to (4)

$$\sum_{\gamma=1}^{q} Z_\gamma \leq \sum_{\alpha=1}^{t} y_\beta^\alpha \qquad \forall \beta \qquad (12)$$

9. At least one product configuration should be developed

$$\sum_{\beta=1}^{w} \sum_{\alpha=1}^{t} y_\beta^\alpha \geq 1 \qquad (13)$$

10. For a variant k that cannot be remanufactured, the compatibility index of the $\mathrm{k}-\mathrm{l}$ pair should be penalized, 0 for max objective, large number L for min objective. Use same approach for module variants that are incompatible.

$$I_{i_k j_l} = \begin{cases} 0 \text{ for max objective} \\ L \text{ for min objective} \end{cases}, \quad i,j \in M, i \neq j, \qquad k,l \ni X_{i_k j_l} \qquad (14)$$

11. For a variant k that is desirable in the product, pair k with a pre-determined variant l of module j. For max objective, assign a large value L to their compatibility index, and 0 for min objective

$$I_{i_k j_l} = \begin{cases} L \text{ for max objective} \\ 0 \text{ for min objective} \end{cases}, \quad i,j \in M, i \neq j, \qquad k,l \in X_{i_k j_l} \qquad (15)$$

4.3.1.2 Estimation of modular pair indices

The compatibility of the $\mathrm{k}-\mathrm{l}$ modular pair with respect to product serviceability and core-cleaning are estimated through Fuzzy system (Fadeyi et al., 2017). The compatibility of a modular pair with respect to product serviceability was measured by the degree of accessibility of the module pairs, the services resources that are jointly shared and their degree of relationship in service requirement (service frequency). The fussy system converts these inputs to an index that is a measure of serviceability of the pair. On a similar note, the compatibility of a core-cleaning of $\mathrm{k}-\mathrm{l}$ modular pair is measured by the similarity of materials composition of the pair, the similarity in the dirt relating to the pair, and the level of cleaning resources that are jointly shared by the two modules. Similar, the fuzzy system converts these input into module pair core-cleaning index.

4.3.2 Modular product design for minimal environmental impact

This section describes the development of modular configuration(s) to ensure environmental sustainability. In a scenario related to section 3.1, there are m modules in the product. There are k variants available from different suppliers for every module i in m. The goal of the OEM is to perform LCA of all k variants of module set i in order to determine the variant with the minimal environmental impact.

4.3.2.1 Estimation of ecological indicators of module variants

The evaluation of the environmental impact of the module variants is performed according to the procedure for LCA as described in ISO (2006). Three out of four procedures that are mentioned in section 2.4 are discussed here. The interpretation is included in section 4.2.

A. Goal and scope definition: The functional unit is a module variant. The scope includes the extraction of the materials, the production of the module variant, the transportations involved in producing the variant, and the transportation involved in product distribution. The retirement of the product is not considered.

B. Inventory analysis:

1. The material compositions of the functional unit (module variant). For example, the module variant that consists mainly of stainless steel and it is made in Texas, USA. From the OpenLCA database, select “steel, billets, at plant-US” and “chromium, 25.5% in chromite, 11.6 in crude ore, in ground”.
2. The weight of the module: Energy consumption is dependent of the weight of the material. The total embodied energy of the functional unit (weight * embodied energy/kg) included in the product system of the LCA. The kilogram (kg) is commonly used in the LCA assessment

3. The energy required for producing the part from raw materials. The dominant energy where the part was produced is imported from the LCA database. For example, a module variant that consists of stainless steel and is produced in Texas US, import “Electricity at Grid, Texas US, 2000-US” from the OpenLCA database. Energy unit, MJ/kg is commonly used.
4. Production-based transportation: Huge amount of environmental impact is attributed to transportation in manufacturing. An estimate of the transportation distance (based on the supplier’s location) that are associated with the production of a module variant is made. For example, a module variant that is produced in Alaska, United States and shipped to an OEM in Detroit, United States, import “Transport, Ocean freighter, residual fuel oil powered-US” from the OpenLCA database.
5. Product distribution based transportation: The study is focused on a product that is offered in PSS, therefore an assumption of a market geographical location is made. A generic transportation distance is assumed to assess all the module variants because the irrespective of the location of the product, all the modules that are clustered therein. For example, a product that is manufactured in the United States and the United States as the target market, an average distance of 5000 miles (8050km) is assumed. In the LCA, import “transport, combination truck, average fuel mix-US“. The LCA provides the ecological impact that is due to the transportation energy.

Howarth et al. (2014) and Abbes et al. (2014) provide the embodied energy of a unit (kg) of metals and composites. Some of these are contained in table 4.1. The Embodied energy of a part is the energy consumed in all the processes to make the part, from the extraction of the raw materials, through transportation, manufacture, installation, disassembly, and decomposition (Dixit et al., 2010). The average values of the embodied energy of the materials are used for the LCIA in the OpenLCA.

Table 4.1: Energy contents of materials

Metals and Composite Materials	Embodied energy (MJ/kg)
Aluminum alloy	196-257
Stainless steel	110-210
Steel	30-60
Cast Iron	60-260
Carbon fiber	183-286

C. Method of Lifecycle impact assessment: A significant benefit of the eco-indicator 99 is that it contains an inbuilt mechanism that converts several environmental impact values into a single indicator for each of the three classification- Human health, Ecosystem quality, and resources (fossil fuels). This single indicator is significantly useful for evaluating multiple module variants which enable the development of environmentally sustainable modular product architecture. The built-in effects in ecological class (ecosystem quality) include ecotoxicity which relates to biological, chemical and physical pressures on the ecosystem; acidification which relates to the potential impact of CO2 release; eutrophication that refers to the release of harmful substances that affect plant growth, and land use. The Ecosystem quality impact assessment category of the eco-indicator 99 is considered appropriate for the measure of the environmental impact of module variants in this study. This LCIA is accessed in the OpenLCA 14.

4.3.2.2 Impact assessment of module variants in OpenLCA

To provide a brief description of the application of the OpenLCA. In the OpenLCA, a 'process' is created for every module set. The 'flows' or parameters such as weight, energy, and transportation that are associated with module variants are included in the 'process' to create the 'product system'. Then, a 'project', is created and the 'product system' is imported for each variant of the particular module into the 'project'. The "Eco-indicator 99 (H)" is chosen as the lifecycle impact assessment (LCIA) method and "Ecosystem-total" as the impact category. Several environmental impact results are generated which may be explored for more elaborate PD. For the modular product development purpose, a summarized result that yields a single value as the overall estimate of the environmental impacts is considered appropriate. As an example, the analysis result of a module set that consists 4 variants is depicted in figure 4.1. The indicator of each variant shows its estimated impact on the ecosystem with a larger number indicating higher environmental impact. F1 with 173.95 $\mathrm{PDF} * \mathrm{m}^2 * \mathrm{yr}$ (potentially disappeared fraction $* \mathrm{m}^2 * \mathrm{yr}$) is the module variant of choice for a sustainable modular product development.

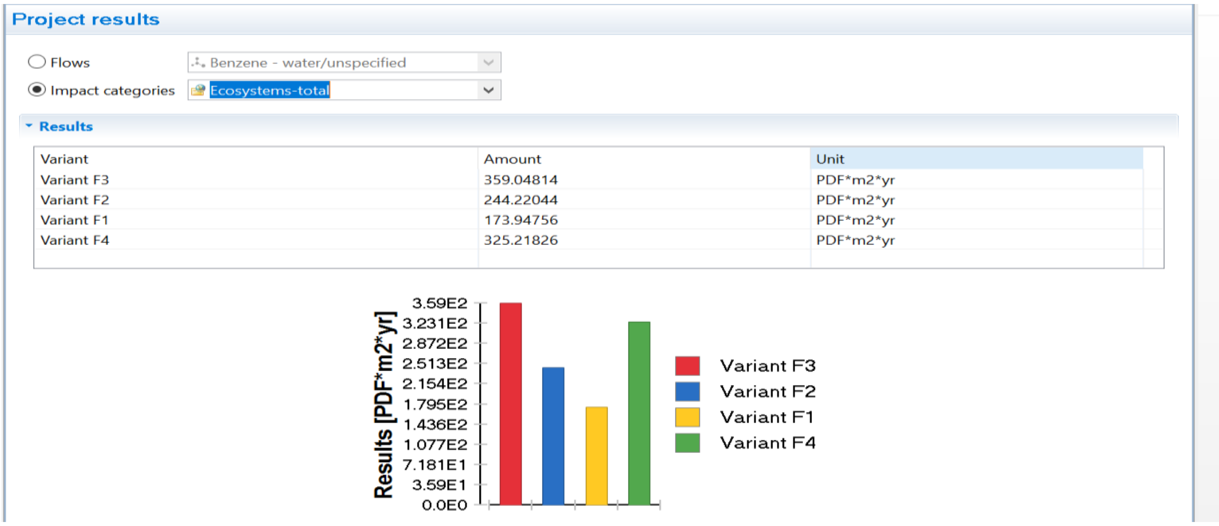


Figure 4.1: Eco-indicators of variants of a functional unit using ecosystem LCIA.

4.4 Case study

An auto industry in Michigan, United States provides a data that relate to the modules of a subassembly that consists six modules. During the PD process, there are four available variants for each module. For the ease of identification, the modules are referred to A, B, C, D, E, and F. The variants of module set A are referred to as A_1, A_2, A_3, A_4. Other module sets are categorized on a similar vein. From this scenario, there are a total of 61440 potential product configurations.

4.4.1 Modular design for enhanced core cleaning and serviceability

The $k-l$ modular pair compatibility with regard to product serviceability and core-cleaning are provided by the fuzzy system. The results are depicted in Tables 2.3 and 2.4.

Table 2.3: Modular pair serviceability indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.80	0.75	0.45	0.65	0.55	0.75	0.35	0.65	0.85	0.75	0.55	0.70	0.45	0.90	0.80	0.65	0.75	0.55	0.85	0.70
	A2					0.45	0.35	0.55	0.70	0.65	0.75	0.85	0.75	0.35	0.75	0.45	0.55	0.55	0.65	0.25	0.60	0.75	0.35	0.85	0.75
	A3					0.75	0.90	0.50	0.80	0.65	0.75	0.70	0.70	0.25	0.65	0.55	0.60	0.75	0.35	0.60	0.70	0.65	0.95	0.65	0.85
	A4					0.70	0.75	0.50	0.75	0.60	0.65	0.75	0.70	0.75	0.70	0.65	0.70	0.70	0.80	0.75	0.70	0.65	0.85	0.75	0.70
B	B1	0.80	0.45	0.75	0.70					0.45	0.55	0.80	0.75	0.60	0.55	0.50	0.55	0.60	0.55	0.50	0.75	0.75	0.65	0.50	0.70
	B2	0.75	0.35	0.90	0.75					0.50	0.65	0.60	0.75	0.65	0.45	0.55	0.60	0.35	0.75	0.90	0.70	0.65	0.75	0.80	0.65
	B3	0.45	0.55	0.50	0.50					0.70	0.75	0.40	0.70	0.35	0.70	0.80	0.75	0.75	0.55	0.50	0.60	0.80	0.65	0.60	0.70
	B4	0.65	0.70	0.80	0.75					0.65	0.70	0.75	0.65	0.60	0.35	0.60	0.50	0.65	0.45	0.80	0.60	0.65	0.70	0.70	0.60
C	C1	0.55	0.65	0.65	0.60	0.45	0.50	0.70	0.65					0.45	0.30	0.75	0.65	0.70	0.60	0.45	0.65	0.80	0.75	0.55	0.70
	C2	0.75	0.75	0.75	0.65	0.55	0.65	0.75	0.70					0.25	0.55	0.40	0.50	0.75	0.35	0.80	0.70	0.85	0.85	0.60	0.70
	C3	0.35	0.85	0.70	0.75	0.80	0.60	0.40	0.75					0.70	0.50	0.55	0.65	0.65	0.45	0.40	0.60	0.75	0.70	0.60	0.85
	C4	0.65	0.75	0.70	0.70	0.75	0.75	0.70	0.65					0.65	0.75	0.65	0.70	0.70	0.55	0.35	0.45	0.80	0.70	0.50	0.65
D	D1	0.85	0.35	0.25	0.75	0.60	0.65	0.35	0.60	0.45	0.25	0.70	0.65					0.35	0.50	0.55	0.50	0.85	0.45	0.55	0.60
	D2	0.75	0.75	0.65	0.70	0.55	0.45	0.70	0.35	0.30	0.55	0.50	0.75					0.75	0.65	0.45	0.55	0.75	0.45	0.80	0.70
	D3	0.55	0.45	0.55	0.65	0.50	0.55	0.80	0.60	0.75	0.40	0.55	0.65					0.85	0.65	0.45	0.60	0.65	0.50	0.40	0.65
	D4	0.70	0.55	0.60	0.70	0.55	0.60	0.75	0.50	0.65	0.50	0.65	0.70					0.55	0.60	0.50	0.40	0.70	0.40	0.65	0.50
E	E1	0.45	0.55	0.75	0.70	0.60	0.35	0.75	0.65	0.70	0.75	0.65	0.70	0.35	0.75	0.85	0.55					0.70	0.75	0.65	0.70
	E2	0.90	0.65	0.35	0.80	0.55	0.75	0.55	0.45	0.60	0.35	0.45	0.55	0.50	0.65	0.65	0.60					0.75	0.45	0.70	0.65
	E3	0.80	0.25	0.60	0.75	0.50	0.90	0.50	0.80	0.45	0.80	0.40	0.35	0.55	0.45	0.45	0.50					0.95	0.70	0.50	0.75
	E4	0.65	0.60	0.70	0.70	0.75	0.70	0.60	0.60	0.65	0.70	0.60	0.45	0.50	0.55	0.60	0.40					0.65	0.70	0.60	0.65
F	F1	0.75	0.75	0.65	0.65	0.75	0.65	0.80	0.65	0.700. 80	0.85	0.75	0.80	0.85	0.75	0.65	0.70	0.70	0.75	0.95	0.65				
	F2	0.55	0.35	0.95	0.85	0.65	0.75	0.65	0.70	0.75	0.85	0.70	0.70	0.45	0.45	0.50	0.40	0.75	0.45	0.70	0.70				
	F3	0.85	0.85	0.65	0.75	0.50	0.80	0.60	0.70	0.55	0.60	0.60	0.50	0.55	0.80	0.40	0.65	0.65	0.70	0.50	0.60				
	F4	0.70	0.75	0.85	0.70	0.70	0.65	0.70	0.60	0.70	0.70	0.85	0.65	0.60	0.70	0.65	0.50	0.70	0.65	0.75	0.65				

Table 2.4: Modular pair core-cleaning indices

		A				B				C				D				E				F			
		A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4	D1	D2	D3	D4	E1	E2	E3	E4	F1	F2	F3	F4
A	A1					0.65	0.90	0.55	0.75	0.85	0.55	0.60	0.75	0.75	0.55	0.65	0.60	0.65	0.85	0.70	0.75	0.75	0.90	0.75	0.80
	A2					0.75	0.65	0.85	0.70	0.75	0.75	0.90	0.70	0.75	0.70	0.60	0.65	0.60	0.75	0.45	0.65	0.75	0.85	0.75	0.70
	A3					0.65	0.85	0.70	0.75	0.75	0.55	0.60	0.70	0.45	0.75	0.65	0.70	0.75	0.85	0.65	0.70	0.75	0.85	0.75	0.70
	A4					0.70	0.75	0.70	0.65	0.65	0.65	0.70	0.75	0.65	0.65	0.55	0.45	0.70	0.70	0.60	0.65	0.60	0.75	0.70	0.65
B	B1	0.65	0.75	0.65	0.70					0.85	0.45	0.55	0.75	0.65	0.65	0.70	0.55	0.70	0.65	0.80	0.70	0.65	0.65	0.80	0.75
	B2	0.90	0.65	0.85	0.75					0.60	0.75	0.50	0.65	0.75	0.55	0.85	0.65	0.85	0.45	0.40	0.65	0.55	0.65	0.85	0.65
	B3	0.55	0.85	0.70	0.70					0.65	0.75	0.70	0.70	0.55	0.75	0.70	0.70	0.65	0.85	0.70	0.70	0.80	0.75	0.65	0.70
	B4	0.75	0.70	0.75	0.65					0.70	0.50	0.65	0.60	0.60	0.70	0.80	0.70	0.75	0.60	0.65	0.65	0.70	0.65	0.75	0.65
C	C1	0.85	0.75	0.75	0.65	0.85	0.60	0.65	0.70					0.55	0.80	0.85	0.80	0.80	0.70	0.75	0.70	0.40	0.65	0.75	0.60
	C2	0.55	0.75	0.55	0.65	0.45	0.75	0.75	0.50					0.55	0.35	0.60	0.70	0.65	0.85	0.50	0.90	0.45	0.80	0.70	0.55
	C3	0.60	0.90	0.60	0.70	0.55	0.50	0.70	0.65					0.60	0.70	0.65	0.60	0.45	0.65	0.60	0.50	0.65	0.55	0.70	0.25
	C4	0.75	0.70	0.70	0.75	0.75	0.65	0.70	0.60					0.75	0.60	0.75	0.70	0.70	0.75	0.70	0.65	0.60	0.75	0.55	0.45
D	D1	0.75	0.75	0.45	0.65	0.65	0.75	0.55	0.60	0.55	0.55	0.60	0.75					0.75	0.30	0.65	0.65	0.60	0.75	0.75	0.75
	D2	0.55	0.70	0.75	0.65	0.65	0.55	0.75	0.70	0.80	0.35	0.70	0.60					0.60	0.65	0.55	0.60	0.85	0.80	0.80	0.70
	D3	0.65	0.60	0.65	0.55	0.70	0.85	0.70	0.80	0.85	0.60	0.65	0.75					0.80	0.75	0.75	0.55	0.65	0.60	0.75	0.60
	D4	0.60	0.60	0.70	0.45	0.55	0.65	0.70	0.70	0.80	0.70	0.60	0.70					0.65	0.45	0.55	0.50	0.55	0.65	0.25	0.45
E	E1	0.65	0.60	0.75	0.70	0.70	0.85	0.65	0.75	0.80	0.65	0.45	0.70	0.75	0.60	0.80	0.65					0.55	0.65	0.60	0.60
	E2	0.85	0.75	0.85	0.70	0.65	0.45	0.85	0.60	0.70	0.85	0.65	0.75	0.30	0.65	0.75	0.45					0.80	0.65	0.75	0.70
	E3	0.70	0.45	0.65	0.60	0.80	0.40	0.70	0.65	0.75	0.50	0.60	0.70	0.65	0.55	0.75	0.55					0.80	0.90	0.55	0.55
	E4	0.75	0.65	0.70	0.65	0.70	0.65	0.70	0.65	0.70	0.90	0.50	0.65	0.65	0.60	0.55	0.50					0.75	0.55	0.65	0.60
F	F1	0.75	0.75	0.75	0.60	0.65	0.55	0.80	0.70	0.40	0.45	0.65	0.60	0.60	0.85	0.65	0.55	0.55	0.80	0.80	0.75				
	F2	0.90	0.85	0.85	0.75	0.65	0.65	0.75	0.65	0.65	0.80	0.55	0.75	0.75	0.80	0.60	0.65	0.65	0.65	0.90	0.55				
	F3	0.75	0.75	0.75	0.70	0.80	0.85	0.65	0.75	0.75	0.70	0.70	0.55	0.75	0.80	0.75	0.25	0.60	0.75	0.55	0.65				
	F4	0.80	0.70	0.70	0.65	0.75	0.65	0.70	0.65	0.60	0.55	0.25	0.45	0.75	0.70	0.60	0.45	0.60	0.70	0.55	0.60				

The mathematical model was implemented in Gurobi-python interface. The optimal product architectures are depicted in Table 2.5.

Table 2.5: Optimal product configuration

Criterion	Product Configuration	Product Strength Index (PCI)
Serviceability	A_1D_1, B_1C_3, E_3F_1	2.60
	A_3B_2, C_2F_1, D_3E_1	2.60
	A_3B_2, C_1D_3, E_3F_1	2.60
	A_2C_3, B_3D_3, E_3F_1	2.60
	A_3B_2, C_4D_2, E_3F_1	2.60
	A_3B_2, C_3F_4, D_3E_1	2.60
Core-cleaning	A_1B_2, C_1D_3, E_3F_2	2.65
	A_2C_3, B_2D_3, E_3F_2	2.65
	A_1B_2, C_2E_4, D_2F_1	2.65
	A_1F_2, C_2E_4, B_2D_3	2.65

4.4.2 Determination of eco-friendly modular architecture

The primary materials of the module variants and their weights are provided, as well as the suppliers' locations. These are contained in table 5. The embodied energy is the product of the average embodied energy/kg and the weight (kg) of the module variant. The embodied energies of materials are contained in Table 4.1. "Trans1" is the estimated distance from the source of the module variant to the manufacturing facilities of the OEM. As described in section 4.3.2.1, the most likely means of transportation (in km) is imported from the OpenLCA database into the "Product System" for every variant. Similarly, the type of the dominant energy at the module supplier's location is imported into every "Product system". It is assumed that the product is offered for use within the United States. A transportation distance (Trans2) of 5000 miles (8050 km) is assumed for product distribution within the United States. This value applies to all the module variants because they are contained in the product. A generic transportation flow “transport, combination truck, average fuel mix-US “is assigned to all the module variants.

Table 4.2: Parameters of module variants for LCA

Module	Variant	Weight (kg)	Embodied Energy (MJ)	Trans1 (km)	Trans2 (km)
A Steel	1	3.5	157.5	90000	8050
	2	2.5	112.5	120000	8050
	3	4.25	191.25	75000	8050
	4	2.95	132.75	55000	8050
B Aluminum Alloy	1	2.5	566.25	16845	8050
	2	1.75	396.38	21200	8050
	3	3.15	713.48	23500	8050
	4	2.15	486.96	15500	8050
C Stainless Steel	1	5.1	816	19960	8050
	2	6.25	1000	25500	8050
	3	4.5	720	17650	8050
	4	7.5	1200	19500	8050
D Aluminum Alloy	1	2.45	554.93	19960	8050
	2	3.95	894.68	25500	8050
	3	1.85	419.03	17650	8050
	4	3.25	736.13	19500	8050
E Cast Iron	1	6.75	1080	26650	8050
	2	5.25	840	25750	8050
	3	7.50	1200	23750	8050
	4	4.5	720	15350	8050
F Steel plate	1	4.25	191.25	4025	8050
	2	2.75	123.75	15750	8050
	3	5.25	236.25	10750	8050
	4	3.75	168.75	15350	8050

Following the description in section 4.3.2.2, the “Eco-indicator 99 (H) is chosen as the Lifecycle impact assessment (LCIA) method and “Ecosystem-total” as the impact category. A “project” is created for every module. Four “product systems” and created within the “project, and the parameters of each variant are included in its “product system”. Every “product system” relates to a module variant. The summary of the LCA results containing the ecological indicators (EI) is contained in Table 6.

Table 4.3: Eco-indicators of module variants using Ecosystem LCIA

Variants	Modules					
	A	B	C	D	E	F
1	1010.21	717.92	816.0	553.70	1080.0	**173.95**
2	1028.11	**521.44**	1000.0	992.70	840.0	244.22
3	**933.27**	956.55	**720.0**	**418.10**	1200.0	359.05
4	1174.64	610.24	1200.0	734.50	**720.0**	325.21

From the LCA result, the module variants that should be clustered into the product to realize minimal environmental impacts include: $\mathrm{A}_3, \mathrm{B}_2, \mathrm{C}_3, \mathrm{D}_3, \mathrm{E}_4, \mathrm{F}_1$

4.4.3 Multi-criteria decision analysis and results

Having obtained the optimal modular configurations with regard to core cleaning, product serviceability, and environmental sustainability, it is essential to evaluate the relative sustainability of the architectures. The overall indices of the optimal configurations are obtained as contained in Table 7. MAUT is applied through Logical Decision for Windows (LDW).

Table 4.4: Indices of optimal product configurations

	Product Architecture	EI	SI	KI
1	A_3B_2, C_3D_3, E_4F_1	3486.74	1.7	1.75
2	A_1D_1, B_1C_3, E_3F_1	4375.78	**2.60**	2.10
3	A_3B_2, C_2F_1, D_3E_1	4126.76	**2.60**	2.10
4	A_3B_2, C_1D_3, E_3F_1	4062.76	**2.60**	2.50
5	A_2C_3, B_3D_3, E_3F_1	4496.71	**2.60**	2.40
6	A_3B_2, C_4D_2, E_3F_1	5021.36	**2.60**	2.25
7	A_3B_2, C_3F_4, D_3E_1	3998.02	**2.60**	1.90
8	A_1B_2, C_1D_3, E_3F_2	4209.97	2.20	**2.65**
9	A_2C_3, B_2D_3, E_3F_2	4131.87	2.10	**2.65**
10	A_1B_2, C_2E_4, D_2F_1	4418.3	2.20	**2.65**
11	A_1F_2, C_2E_4, B_2D_3	3913.97	1.80	**2.65**

The sustainability ranking of the product configurations is depicted in Figure 4.2. Product alternative 4 is ranked 1st in overall utility (sustainability score).

Figure 4.2: Evaluation of the product alternatives on a common scale

It could be seen that although product alternative 1 is the most environmentally sustainable architecture, however, it has the lowest sustainability score. As much as the OEM is enthused to curtain the harm of its business activities on the environment, its economic viability through enhanced core cleaning and product serviceability cannot be sacrificed. Therefore, product alternative 1 is not a suitable architecture for the OEM. Figure 4.3 provides the utility values of all product alternatives with regards to environmental impact assessment.

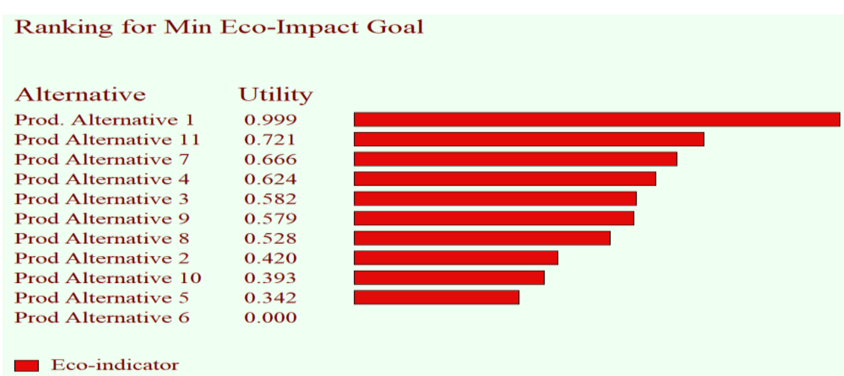


Figure 4.3: Environmental impact measure of product alternatives

From the analyses, alternatives 4 and 8 that are top ranked in overall sustainability are ranked 4th and 7th with regard to environmental impact. Similarly, alternative 11 has a low environmental impact but it is poorly ranked in overall utility, implying inefficient core-cleaning and serviceability. Alternative 6 is not an option whatsoever in relation to environmental sustainability. Another observation shows that alternative 5 that ranks high in overall sustainability ranks low in environmental sustainability. The OEM with a commitment to environmental preservation should not consider this architecture. Product configurations 4, 3, 9, and 8 have fairly low environmental impacts and are ranked among the first 5 on the overall utility scale. Further assessment of these alternatives is shown figure 4.4.

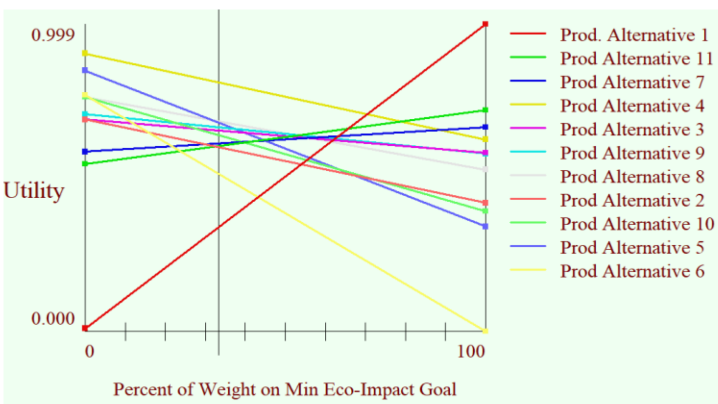


Figure 4.4: Sensitivity of product configurations to Eco-indicator

At about more than 50% weight assigned to eco-impact, all the alternatives appear to be sensitive, with the exception of alternatives 1 & 6. The second vertical line represents environmental impact measure. The line is positioned at 33.33% of the X-axis because the three measures are equally weighted. Alternative 4 appears to be a robust solution relative to environmental impact until a weight above 70% is assigned to eco-impact (less than 30% for both core-cleaning and serviceability objectives) before it is displaced by 3 product alternatives.

Product alternative 1 can only be the ideal candidate when a weight of more than 70% is assigned to environmental impact measure. As mentioned earlier, this is not a realistic business decision for the OEM. Again alternative 4 ranks higher than configurations 3, 9 and 8. However, figure 4.5 shows that alternatives 8 and 9 are the architectures with optimal core-cleaning, thereby improving remanufacturing.

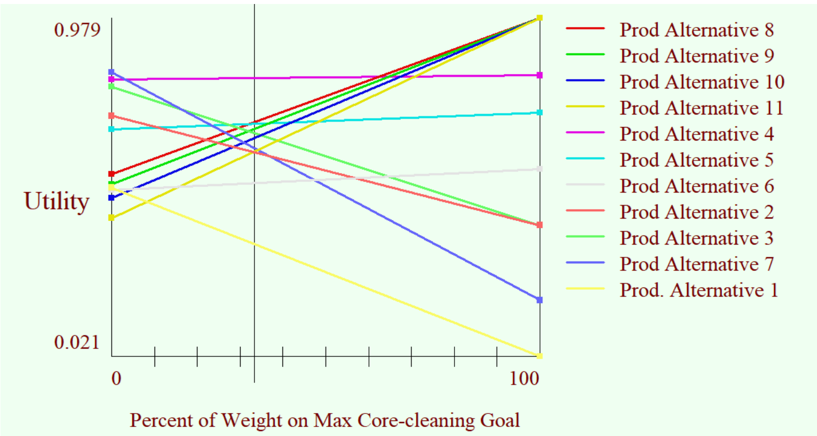


Figure 4.5: Sensitivity of product configurations to core-cleaning objective

Therefore, in order make sustainable product architecture decisions among alternatives 4, 8, and 9, it behooves the OEM to reach some compromise between its commitment to environmental sustainability and business growth. With these analyses, the OEM is better equipped to realize a more sustainable PSS-Remanufacturing business.

4.5 Conclusion

The PSS-Remanufacturing business idea is conceived to be a sustainable venture. However, this claim could be faulty unless adequate consideration is given to the environmental implications that are involved in the production of the parts (modules) through which the product is built. In addition, a sustainable design needs to integrate the environmental consequences with the other aspect of sustainability. With the relevant data of a 6-module product, the study applies LCA to obtain the ecological indicators of the module variants and determines the modular architecture with minimal environmental impacts. Furthermore, the study obtains the optimal product configurations that enhance core cleaning and product serviceability through an optimization model. In addition, MAUT was applied to assess the overall sustainability of the product configurations. The results show that the configuration with the least environmental impact is not a desirable architecture because of its low performance with regard to remanufacturing and product servicing. Further trade-off analyses reveal that three configurations are relatively more viable in relation to environmental impact, core-cleaning, and product serviceability. The study provides analytical insight to the OEM in order to make informed decisions on product architectures that enable a sustainable PSS-Remanufacturing business.

Although, equal global weights are assigned to the objectives for proof of concept, several sensitivity analyses could be provided by adjusting the weights of the objectives as desired by the OEM for practical application. Therefore, it is essential to collaborate with the OEM so that the actual preference of the objectives are appropriately apportioned as their weights. Consequently, the real life scenarios are reflected by the resulting sensitivity analyses.

Finally, the OEM could engage the robustness of a product configuration as a tool to satisfy regulatory measures, bolster its public image, and gain competitive advantage. For example, product configuration 4 is a robust solution when any weight between 0 and 70% is assigned to eco-impact, and other weights of other objectives remain unaltered. Given that this is choice product architecture, the OEM may claim that its business is 70% environmentally sustainable.

CHAPTER 5: CONCLUSION AND FUTURE STUDIES

5.1 Conclusion

This study offers considerable contributions to the emerging PSS-remanufacturing business enterprise. Specifically, a research lacuna is filled by providing an analytical integration of PSS and remanufacturing at the early phase of PD with the development of a unique optimization model for identifying viable modular product architecture. In addition, pairwise assessment of modules is introduced into modular PD. This PD approach permits a thorough evaluation of modules with respect to all the criteria that are essential for product lifecycle optimal performance. Furthermore, the cost implications of the product lifecycle are considered at the PD phase to ensure the economic viability of the PSS-Remanufacturing product offering. Also, the study employs LCA to estimate the ecological effects of module variants and quantifies the environmental consequences of modular architecture in order to realize a sustainable business venture. In addition, the research provides comparative assessments of optimal product configurations so as to guide modular product architectures' decisions. Finally, the study highlights the importance of robust solutions in emphasizing the commitment of the OEM to sustainability.

5.2 Future studies

With the increasing growth in PSS-Remanufacturing business, the competitiveness among the manufacturers in the similar business sphere is expected to rise. Therefore, it becomes expedient to factors other variables such as the voice of customers into product architecture decision making. Future research in this regard enables the realization of competitive advantages. In addition, the remanufacturing thinking is that product's parts are reusable a number of cycles. However, customers' requirements are increasingly changing, thereby increasing product's obsolescence. It is needful to consider a family of product scenario in which recovered cores are reusable in another product version. This is a worthwhile extension of this research. Furthermore, an exhaustive LCA of a product over the four phase of its lifecycle is a complex task. At the PD phase, this research considers only the dominant materials in the module variants. A comprehensive LCA will require every material input, no matter how little, to be included in the LCA. An extension of this research is to perform a more detailed LCA for an improved evaluation of environmental impact of PD. In addition, this research assumes equal weight for ecological impacts as other measures of sustainability. In reality, a manufacturer defines its specific obligation to environmental sustainability, different from others. Through more collaborative research with the OEM, the firm's level of commitment to the environment would be appropriately integrated into PD decisions.

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ABSTRACT

MODULAR PRODUCT ARCHITECTURE'S DECISIONS SUPPORT FOR REMANUFACTURING-PRODUCT SERVICE SYSTEM SYNERGY

by

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Remanufacturing is identified as the most viable product end-of-life (EOL) management strategy. However, about 80% of manufactured products currently end up as wastes. Besides other benefits, the product service system (PSS) could curtail the main bottlenecks to remanufacturing namely quantity, quality, recovery time of used product, and negative perception of remanufactured products. Therefore, the integration of PSS and remanufacturing has been increasingly recommended as an enhanced product offering. However, an integration that is informed by mathematical analysis is missing. Meanwhile, the variables that bolster the performance of PSS and remanufacturing are substantially influenced by product development (PD) decisions. Among the PD strategies, modular architecture is a technique that significantly enhances product lifecycle management. Consequently, modular design is a suitable PD approach for an enhanced PSS-remanufacturing enterprise. Furthermore, it is argued that the PSS-remanufacturing initiative is poised to be a sustainable venture due to the sustainability philosophy of PSS. However, the acclaimed sustainability of PSS is flawed if a high environmental

impact is associated with the production of the parts that constitute the product which is offered in PSS. Therefore, it is essential to consider the environmental implications of the production of the parts that are contained in the product architecture during PD. This research identifies that cost, core-cleaning, and product serviceability are critical variables for the success of remanufacturing and PSS. The research employs pairwise assessment methodology to evaluate the compatibility of module pairs comprehensively, and obtains the modular pair compatibility indices via fuzzy system. Similarly, cost data are obtained. The study develops an optimization model that determines viable modular configuration(s) from among several alternatives in order to realize an enhanced PSS-remanufacturing business. Furthermore, the research performs lifecycle assessment (LCA) of module variants and determine the modular architecture with minimal environmental Impact. Having obtained the optimal architectures with regard to cost, core cleaning, product serviceability and environmental impacts, multi-attribute utility theory (MAUT) is engaged to collectively assess the degree of sustainability of the product architectures. The study offers analytical-based guidance to the original equipment manufacturers (OEMs) in making product architecture decisions in order to realize the sustainable PSS-remanufacturing enterprise.

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