Optimal Modular Remanufactured Product Configuration and Harvesting Planning for End-of-Life Products

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Remanufacturing is a representative product recovery strategy that can improve economic profitability and sustainability, but many companies are struggling because of the lack of understanding of the market and the design strategies for remanufactured products. Unlike the production process of new products, remanufacturing requires unique production processes, such as collecting used products and dis(re)assembly. Therefore, several factors need to be considered for the design of remanufactured products. First, when designing a remanufactured product, it is crucial to ensure that the specifications of components meet the customer's requirements because the remanufacturing uses relatively outdated components or modules. In addition, it is necessary to consider the disassembly level and order to facilitate the disassembly process to obtain the desired parts. This study proposes an integrated model to (i) find configuration design suitable for remanufactured products that can maximize customer utility based on customer online review analysis regarding End-of-Life products, and (ii) establish a harvest plan that determines the optimal disassembly operations and levels. This proposed model can be used as a decision-making tool that helps product designers find the appropriate design of remanufactured products while increasing the efficiency of the remanufacturing process. [DOI: 10.1115/1.4052389]

Keyword: life cycle analysis and design

1 Introduction

Improving global awareness of the environment and increasing pressure from environmental laws and public policies have led manufacturers to seriously consider the entire life cycle management of their products and the treatment of electronic waste. Remanufacturing has emerged as one of the effective alternatives to recover end-of-life (EoL) products. It refers to the process of extracting parts or modules from the collected EoL products, undergoing reconditioning or upgrading, and producing a tested and certified product that has almost the same performance and quality as a new product. Remanufacturing enables manufacturers to recycle EoL products to reduce production and material costs and environmental impact that may occur in the manufacturing, as well as expand their product line by producing relatively inexpensive products of the same quality [1–4].

Remanufacturing is meaningful in terms of enhancing a companies' profitability and sustainability (building a green brand image), but many companies are struggling due to a lack of understanding of the remanufacturing market and design strategies for remanufactured products [3,5]. Unlike a new product design, remanufactured products are designed based on previously released components that may be physical deterioration and (or) technological obsolescence [6–9]. Therefore, the remanufactured product design needs to consider the high recycling rate of each component as well as the value (utility) of the parts perceived by customers.

It is also important to consider the effect of the remanufactured product design on the remanufacturing process. Recently, as more products are designed in a form that is difficult to disassemble due to rapid technological development and intensifying global competition [10,11], disassemblability has become a crucial factor in remanufacturing. The order and level of the disassembly (harvesting) process performed to collect the target module for remanufactured products are important because it determines the efficiency of the entire remanufacturing process. In other words, even for parts with high customer utility, if the disassembly process is impossible or difficult, the overall benefit of remanufacturing may be reduced.

To support the proper design configuration of remanufactured products, an integrated methodology that considers customer satisfaction analysis and harvesting process simultaneously, rather than simply selecting a part with a high recycling rate, is required. However, there are few studies on the design of remanufactured products that simultaneously consider customer analysis and harvesting planning. To tackle this issue, this study proposes an integrated methodology to identify the optimal remanufactured product design to maximize customer utility through online review analysis while minimizing the disassembly (harvesting) time of EoL products. The optimization model deals with the bi-objective functions, with one objective function to maximize the customer's utility and the other to minimize the disassembly time required to extract parts from EoL products. The proposed methodology can be used as a decision support tool to help OEMs design remanufactured products under consideration of customers' utility and the efficiency of disassembly.

The rest of the paper is organized as follows: Sec. 2 reviews the relevant prior work/literature on this topic. Section 3 depicts a mathematical model for the configuration design of remanufactured products and harvesting planning. Section 4 illustrates the proposed model through a case study on a smartphone-product family. Finally, conclusions and future research are discussed in Sec. 5.

2 Literature Review

This section discusses the contributions and limitations of previous works related to the topics covered in this study:

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(i) remanufactured product design configuration, (ii) design implications from online data, and (iii) disassembly (harvesting) planning.

2.1 Product Configuration Design. Product modularity can be easily separated from other modules (components) to provide sub-assemblies and components to facilitate EoL recovery strategies [12]. Utilizing modules, product designers need to consider how to assemble the modules for a new or remanufactured product. Product configuration design optimization is the determination of the optimal combination of components (and/or modules) by selecting components from a predefined set based on several constraints to meet a specific goal [13,14]. In product design, determining product configuration is an important step. This is because this decision determines all subsequent detailed design and production process [15]. The configuration design of remanufacturing is more challenging and complex than the configuration design of new products. Therefore, research on remanufactured product configuration design is still in its early stages [16]. While most researchers focused on the manufacturing (design configuration of new products), some researchers studied the configuration design of remanufactured products considering economic and environmental objectives.

Aydin et al. [17] proposed a new methodology to address the consideration of new and remanufactured product design to maximize market share and profit. By applying the dynamic demand model and the multi-purpose optimization model, the specifications of new and remanufactured products and the timing of remanufacturing products were determined. In this study, there is a limitation of not considering the various specifications or designs of EoL products that can be used as materials for remanufacturing. Aydin et al. [18] proposed a methodology to identify sustainable product family design considering multiple life cycle approach and EoL strategies. The findings show that considering a multi-life cycle approach to designing a sustainable product line, the entire life cycle cost, the entire life cycle energy usage, and the entire life cycle water usage are significantly reduced. In this study, the number of modules that can be extracted from several EoL products was considered, but the time required in the disassembly process to extract the modules was not considered.

Kwak and Kim [2] proposed an integrated management model that includes pricing, production planning, and marketing for new and remanufactured products. In this paper, it was found that when remanufacturing was carried out with the production of new products, the profit was higher, and the environmental impact was lower than that of the case without remanufacturing. However, this study has a limitation in that the design of the remanufactured product and the collected EoL product are identical. On the other hand, Kwak [3] focused on the fact that the design of the remanufactured product may differ from the collected EoL product. Based on the assumption that some of the collected EoL products or modules can be upgraded (or downgraded) to produce a remanufactured product, Kwak [3] proposed a mixed integer programming model to find the optimal line design of new and remanufactured products. This model aimed to present the design optimization of remanufactured and new products to maximize profits while minimizing environmental impact. However, there is a limitation in this study considering only one model of EoL product.

Most of the studies mentioned above have limitations in that they do not consider the design of EoL products required for remanufacturing or consider only a single product design. However, it is important to design the optimal remanufactured product with various designs and specifications that can be used during remanufacturing, unless the EoL product design is maintained as it is during remanufacturing. In addition, little consideration was given to the efficiency of the disassembly process, an essential task in designing remanufactured products.

2.2 Design Implications From Online Data. With the increasing amount of online channels and the development of data analysis techniques, online user-generated data has been utilized in many research areas. In the field of data-driven design [19], many studies analyze the online data and draw implications for product design using various methods.

Suryadi and Kim [20] proposed a methodology for analyzing the effect of product features on the product sales rank. The authors collected customer reviews from Amazon.com and pre-processed the data. The lemmatized words were trained by the Word2Vec model and embedded into the vector distribution. From these word vectors, noun vectors were filtered and grouped by X-means clustering, K-means clustering with the automatically determined optimal cluster numbers. The Word2Vec model assigns vectors in a way that relevant words are located closer than irrelevant words, so clustering would bring similar words into the same group. After clustering, the feature clusters were identified by analyzing the frequency of cluster center words in product manual documents. Those with the frequency above a certain threshold were selected as feature words, and clusters to which feature words belong became feature clusters. Using the extracted feature words, the authors analyze the relationship between product features and sales ranks.

Tuarob and Tucker [21] presented a methodology for analyzing the changes in customer satisfaction for product features. The authors collected the Twitter mentions related to smartphone products and extracted feature-related words using an opinion mining algorithm. Then, user sentiments for these feature words were measured for different generations of products, e.g., iPhone4 and iPhone5. By observing the changes in positive and negative sentiments for each feature, the implications for product features can be obtained. Joung and Kim [22] also used sentiment analysis for analyzing the importance of product features. The authors collected the smartphone review data and extracted keywords for product features using Latent Dirichlet allocation (LDA), a probabilistic topic model that identifies hidden topics in a large amount of textual data [23]. Then, the sentiment intensity for each keyword was measured. The intensity can be an indicator for customer satisfaction for product features and the result can help product designers reflect customer preferences in product design.

In this study, the online data were used to estimate the partial utility for product parts or modules. The Word2Vec model was used to extract keywords related to the predefined parts, and term frequency (TF) was used for measuring the importance of parts.

2.3 Disassembly Planning. Another research flow related to remanufactured product design is disassembly planning. Disassembly is a systematic approach to removing a group of components or parts or sub-assemblies from a product for a given purpose and is a very crucial step in the remanufacturing process in terms of acquiring materials for production. In particular, as the release of products with designs that are difficult to disassemble has increased [11], disassemblability has become a key factor in remanufacturing.

Gungor and Gupta [24] proposed a methodology to generate disassembly sequence plans (DSPs) for the product in the presence of uncertainty, considering that unpredictable errors or variations can occur over the life of the product. Design variations that can be occurred during use may require different disassembly procedures during remanufacturing. However, this study did not consider the design decisions of remanufacturing and assumed that all parts require the same tool type for disassembly.

Cong et al. [25] proposed a method of optimizing the process of disassembling parts according to the EoL strategy for each part, focusing on the EoL process of the product. The proposed methodology was verified using a hard disk drive case study. The recovery strategy for each part of the hard disk drive was determined, and the disassembly order and disassembly level were determined. The results of this study showed that when the optimal disassembly sequence and level were applied, the total recovery profit increased and the disassembly time was shortened. Also, Francesco et al. [26] presented a new algorithm to solve a multi-objective optimization problem that maximizes parallelism, ergonomics, and worker workload balance while minimizing disassembly time and the number of product rotations.

Most studies related to disassembly planning assumed that the design of the remanufactured product is predetermined. There have been few studies that propose methodologies by integrating with product configuration design decisions. As mentioned above, however, the design of the remanufactured product may be different, and the specifications of the EoL product used for this may also vary. Therefore, research on an integrated method to determine the design of the remanufactured product using various EoL products and minimize the disassembly time that occurs according to the configuration design is required.

3 Methodology

The purpose of this paper is to identify the optimal configuration design of remanufactured products and harvesting planning that considers customers' satisfaction and disassembly efficiency. The overview of the proposed methodology is shown in Fig. 1. The first step is to collect data related to the EoL products that can be utilized for remanufacturing. The collected data in this step include data such as the configuration of the EoL products (i.e., module type and specifications), the reusability of each component, and the expected take-back quantity of the EoL products. The second step is to analyze the customers' online review of the EoL products to determine the customers' partial utility of each component or module. Since remanufactured products are made using previously released products, there are enough customer reviews regarding EoL products. Therefore, online review analysis can provide an inexpensive and quick way to understand customer perceptions of each part of each EoL product. The third step is to identify the disassembly operations to extract each component for each EoL product. In this step, the relationship between each part and the disassembly process is defined in the form of a disassembly matrix. The next step is the optimization step, and the model deals with the bi-objective optimization problem. One is to maximize the sum of the customer's partial utility (total utility), and the other is to minimize the disassembly time of EoL products. Based on the results derived through this methodology, it is expected to be able to derive an appropriate remanufactured product configuration design and make decisions on harvesting planning for EoL products simultaneously.

3.1 Customer Utility Estimation. To predict partial utility for a part of a product, in this paper, the importance of the part—the degree to which the customer is paying attention to each part—was used. The importance can be obtained from online user-generated data such as customer reviews, twitter mentions, and other social network services. In this study, online review data were used to estimate the importance of each part.

The process of part importance extraction consists of three steps: (i) data collection and pre-processing, (ii) word embedding and keyword identification, and (iii) importance analysis. First, the online review data are collected from an online shopping website. Since the collected data is the free-format text data, it is cleaned by removing punctuation and special characters. Also, all uppercase letters are converted to lowercase letters. In the next step, the resulted data is embedded by Word2Vec, and each word has its own vector representation. The keywords for predefined parts are obtained from these word vectors. As mentioned in Sec. 2, Word2Vec assigns vectors so that related words are closely located in the vector space. Based on this, the top five words closest to the designated word are extracted and then manually filtered. The specific words for product parts and keywords will be presented in the case study in Sec. 4. In the final step, the importance of each part is obtained by analyzing online reviews. Among various methods for analyzing online reviews, term frequency (TF) [20,27], a numerical statistic that reflects the importance of words in the collection documents is modified and applied. The TF model used in this study is shown in Eq. (1) where n_{ij} is the frequency of word i in document j. The value increases proportionally to the number of times a word appears in the reviews.

$$TF_i = \frac{\sum_j n_{ij}}{\sum_j \sum_i n_{ij}} \tag{1}$$

While the importance obtained for each part is used as an estimate of the customer's partial utility in this study, note that other methodologies can be applied according to the user for the utility prediction for each part.

3.2 Disassembly Matrix. In this study, a disassembly matrix D_{io} is constructed to indicate the relationship between components and disassembly operations required to extract them. Tables 1 and 2 show the disassembly matrix of the EoL products used in the case study. In the matrix, the columns represent the operations (o) required for the disassembly process of EoL product (k), O_o^k (available in Appendices A and B), and the rows refer to the components of the product. Each entry (i, o) can take the value of 0 or 1. The

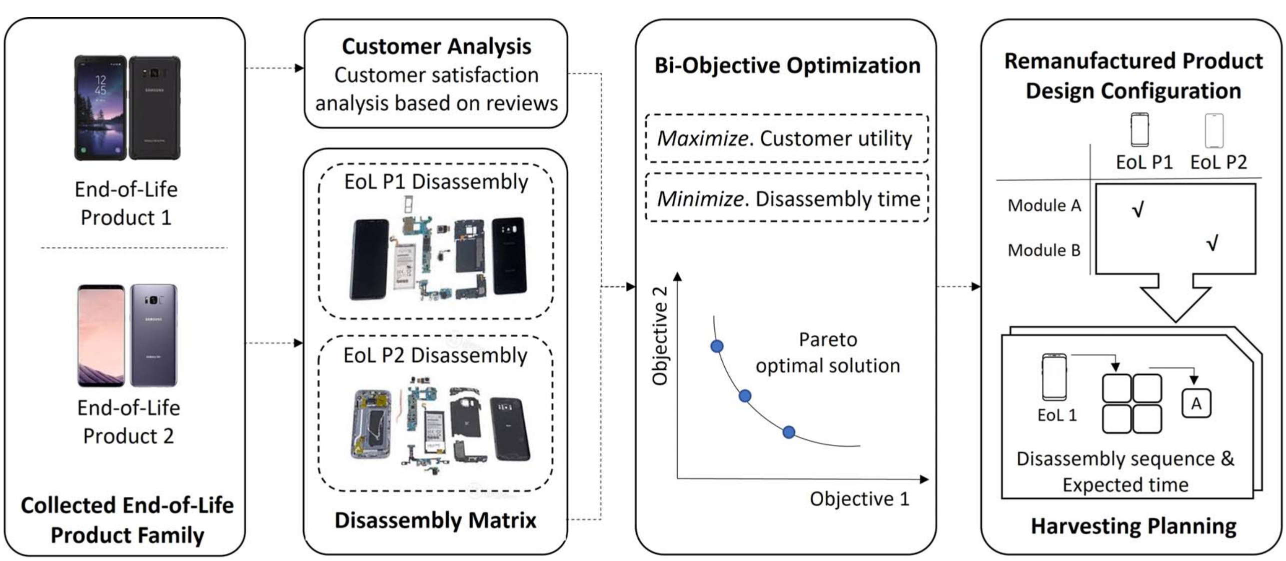

Fig. 1 Overview of the proposed methodology

Table 1 Disassembly matrix for EoL P1

Component	Disassembly operations																
	O_1^1	O_2^1	O_3^1	O_4^1	O_5^1	O_6^1	O_7^1	O_8^1	O_9^1	O_{10}^1	O_{11}^1	O_{12}^1	O_{13}^1	O_{14}^1	O_{15}^1	O_{16}^1	O_{17}^1
NFC & W/C Assembly	1	1	1	1													
Loud Speaker Assembly	1	1	1	1	1												
Sim Card Tray						1											
Earpiece Speaker	1	1	1	1	1	1	1	1	1								
Front Camera	1	1	1	1						1							
Rear Camera	1	1	1	1	1	1	1	1			1						
Headphone Jack	1	1	1	1	1	1	1					1					
Proximity Sensor	1	1	1	1	1	1	1	1					1				
Vibration Motor	1	1	1	1	1	1	1	1						1			
Fingerprint Sensor	1	1	1	1	1	1	1	1							1	1	1

Table 2 Disassembly matrix for EoL P2

Component	Disassembly operations													
	O_1^2	O_2^2	O_3^2	O_4^2	O_5^2	O_6^2	O_7^2	O_8^2	O_9^2	O_{10}^2	O_{11}^2	O_{12}^2	O_{13}^2	O_{14}^2
NFC & W/C Assembly	1	1												
Loud Speaker Assembly	1	1	1											
Sim Card Tray				1										
Earpiece Speaker	1	1	1	1	1	1	1	1						
Front Camera	1	1	1						1					
Rear Camera	1	1	1	1	1	1	1			1				
Headphone Jack	1	1	1	1	1						1			
Proximity Sensor	1	1	1	1	1	1	1					1		
Vibration Motor	1	1	1	1	1	1	1						1	
Fingerprint Sensor	1													1

value of 1 indicates that disassembly operation o is required to extract the component corresponding to i. Otherwise, the entry is 0.

Although the EoL products in Tables 1 and 2 are manufactured by the same manufacturer, these matrices show that the disassembly operations and sequences required for disassembly are different. It is because the design structure and assembly method vary between the two products. For example, to disassemble all the components indicated in column 1 of the tables, EoL P1 and EoL P2 require 17 and 14 disassembly operations, respectively. Also, this design difference affects the disassembly process required to extract individual components. In the case of extracting Near Field Communication & Wireless Charging (NFC & W/C assembly) from EoL P1, it needs to go through the disassembly operations of O_1^1 to O_4^1, but in the case of EoL P2, it can be extracted by disassembly operations of O_1^2 and O_2^2. Therefore, it is necessary to plan harvesting according to the design of the EoL product, the process of combining parts, and the design of the remanufactured product. These matrices help to identify the operations required for the extraction.

3.3 The Model for Bi-Objective Optimization.

This paper deals with a model for bi-objective optimization problems to maximize customer utility and minimize disassembly time. ϵ-constraint approach is used to solve this problem. ϵ-constraint is a representative method used when dealing with various objective functions in an optimization problem. It optimizes one of the objective functions by using other objective functions as constraints [28].

$$\begin{aligned} &\text{maximize} \quad f_1(x): \quad \sum_K \sum_J \sum_I u_{ijk} \cdot x_{ijk} \\ &\text{minimize} \quad f_2(x): \quad \sum_K \sum_J \sum_I T_{ijk}^d \cdot x_{ijk} \end{aligned} \tag{2}$$

where

$$T_{lk} \cdot n_{lok} = T_{ok}^d \quad \text{and} \quad D_{ijok} \cdot T_{ok}^d = T_{ijk}^d$$

subject to

$$\sum_I x_{ijk} = 1 \quad \forall j \tag{3}$$

$$x_{ijk} = CR_i \quad \forall i, j, k \tag{4}$$

$$\min(Q_k \cdot r_{ijk} \cdot x_{ijk}) \geq R \tag{5}$$

$$x_{ijk} \in \{0, 1\} \quad \forall i, j, k \tag{6}$$

Equations (2)–(6) represent the mathematical programming model for the integrated model of remanufactured product configuration and harvesting planning. The objective function $f_1(x)$ maximizes the sum of customers' partial utility and $f_2(x)$ minimizes the total harvesting time, as shown in Eq. (2). $f_1(x)$ represents one of the objective functions to maximize the sum of the customers' utility values (u_{ijk}) for the modules selected for the remanufacturing design ($x_{ijk} = 1$). The other objective function $f_2(x)$ indicates the sum of harvesting time (T_{ijk}^d) taken to extract modules selected for the remanufacturing design ($x_{ijk} = 1$). The harvesting time (T_{ijk}^d) is derived by multiplying the average tool (l) usage time (T_l) required for operations (e.g., Clip = 3 s per unit), the required number of the operation o with tool l (n_{lo}) (e.g., five times), and disassembly matrix (D_{io}) indicating the disassembly operation o that needs to be performed to extract the module i (see Tables 1 and 2).

The constraint shown in Eq. (3) indicates that only one module instance (x_{ijk}) can be selected among the instances (I) of each module available in the EoL products (Uniqueness constraint). If customer requirements (CR_i) are specified for a particular module instance (x_{ijk}), a constraint can be added as shown in Eq. (4). The constraint in Eq. (5) indicates that the minimum reusable quantity of each module, multiplied by the reusability of each module (r_{ijk}) and the expected take-back quantity (Q_k), should be greater than the company's remanufactured production target quantity (R). The constraint in Eq. (6) restricts design variables (x_{ijk} are binary variables).

$$
\begin{aligned}
&\text{minimize} - f_1(x)\\
&\text{subject to}\\
&g_l(x) \leq 0\\
&h_m(x) = 0\\
&f_2(x) \leq \epsilon\\
&\epsilon = f_2(x_1^*) + (f_2(x_2^*) - f_2(x_1^*)) \cdot \theta\\
&0 \leq \theta \leq 1
\end{aligned} \tag{7}
$$

This optimization problem can be transformed into Eq. (7) through the ϵ-constraint approach. The value of θ is a parameter that determines the importance of the objective functions. If θ value is 0, it is the same as the independent f_1 minimization problem. Otherwise, θ value is 1, it is the same as the independent f_2 minimization problem.

4 Case Study: Application to Smartphones

To demonstrate and test the new methodology developed in this paper, an illustrative case study is conducted on configuration design for remanufactured smartphones. According to ELDA, a tool for predicting appropriate EoL strategies based on product characteristics, it is advantageous to remanufacture or recycle through disassembly rather than other EoL strategies for electronics, which have a faster technology replacement cycle rather than product wear-out cycle [12,29]. However, the smartphone is one of the representative products that cause waste of natural resources and e-waste due to the low percentage of EoL products being recovered. Also, to protect the design of smartphones and core technologies, there are many cases where smartphones are designed in a form that makes disassembly and repair difficult, such as the use of irreplaceable parts and non-standard parts that require special tools [30]. To handle this issue, this section provides the optimal remanufactured smartphone design and disassembly sequence that simultaneously considers customer utility and the disassemble time.

4.1 Presentation of Case Study. Two models of smartphones launched by the same manufacturer were considered. The two models are composed of the same module (e.g., Front CAM, Rear CAM), but there are differences in the instance of the module (e.g., CAM instances can be megapixel: 5MP, 8MP) and the design structure of the product: (i) mid-tier smartphone (P1) and (ii) high-tier smartphone (P2).

Table 3 shows the parameter settings for the customer's utility and reusability for EoL smartphones. The smartphone-specific parts and/or modules considered in this study were selected mainly for parts with high residual value and recyclability, as shown in the first column of Table 3.

The partial utility for each of these 10 modules was obtained by analyzing online reviews. The online reviews used in the TF analysis were reviews written by customers on the Amazon site from 2017 to 2020, and the number of reviews for P1 and P2 was 938 and 931, respectively. First, the words in the review data were embedded into vectors, and the keywords for each module were extracted from these word vectors. The resulting keywords are as follows. {NFC & W/C Assembly : [nfc, wireless charging, wireless charge], Loud Speaker Assembly : [speaker, sound, volume], Sim Card Tray : [tray, ejector, eject, removal, pin], Earpiece Speaker : [speaker, sound, volume], Front Camera : [camera, picture, image], Rear Camera : [camera, picture, image], Headphone Jack : [headphone, earbud, earphone, bud], Proximity Sensor : [N/A], Vibration Motor : [vibration], Fingerprint Sensor : [fingerprint, finger]}. Next, the customer's partial utility for parts was predicted through the TF value of these keywords (Column 2-4). The TF column shows the values from Eq. (1). Note that the TF value for the proximity sensor and vibration motor is 0.000. This is because either the part has no keyword (proximity sensor) or the part was not mentioned much in the review (vibration motor). To compensate for this, an offset (0.1) was applied to the initial TF result. Then, the TF with offset was normalized so that the total utility values were summed up to 1.

Reusability indicates the possibility of reusing parts of EoL products at the time of remanufacturing and was assumed based on previous studies [31]. It is assumed that high-tier product P2 has higher reusability than mid-tier product P1. The number of EoL products that can be collected is assumed to be 15% of the sales volume of the smartphone model [30]. The number of EoL products of P1 and P2 that can be collected was set to 1.5 and 1.3 million units, respectively.

4.2 Disassembly Matrix for End-of-Life Product. Tables 1 and 2 show the disassembly matrices for the EoL product P1 and

Table 3 Parameter setting for EoL products

	P1				P2			
	Utility				Utility			
Component	TF	TF_offset	TF_norm	Reusability	TF	TF_offset	TF_norm	Reusability
NFC & W/C Assembly	0.068	0.168	0.066	0.650	0.019	0.119	0.044	0.700
Loud Speaker Assembly	0.233	0.333	0.130	0.740	0.226	0.326	0.120	0.840
Sim Card Tray	0.075	0.175	0.068	0.950	0.058	0.158	0.058	0.950
Earpiece Speaker	0.233	0.333	0.130	0.740	0.226	0.326	0.120	0.840
Front Camera	0.323	0.423	0.165	0.500	0.484	0.584	0.215	0.787
Rear Camera	0.323	0.423	0.165	0.500	0.484	0.584	0.215	0.787
Headphone Jack	0.030	0.130	0.051	0.740	0.110	0.210	0.077	0.840
Proximity Sensor	0.000	0.100	0.039	0.950	0.000	0.100	0.037	0.950
Vibration Motor	0.000	0.100	0.039	0.740	0.000	0.100	0.037	0.840
Fingerprint Sensor	0.271	0.371	0.145	0.740	0.103	0.203	0.075	0.840
Sum		2.556	1.000			2.710	1.000	
Total Reviews			938				931	
Total TF			133				155	

Note: Total Reviews: The number of reviews about a specific product. Total TF: The sum of the term frequencies for all features for all reviews.

Table 4 Data related to disassembly operations for EoL P2

		Disassembly operations (number of disassembly)													
Time per unit (s)		O_1^2	O_2^2	O_3^2	O_4^2	O_5^2	O_6^2	O_7^2	O_8^2	O_9^2	O_{10}^2	O_{11}^2	O_{12}^2	O_{13}^2	O_{14}^2
Glue[a]	60	5													5
Screw	5		11	3								1			
Clip	3					1		3		1	1	1			
Cable	5						2								
Slot	5				1				1	1	1	1	1	1	
Time per step (s)		300	55	15	5	3	10	9	5	8	8	13	5	5	300

[a]Repair guide distributed by the manufacturer.

Table 5 Optimization results for configuration design

	$\theta = 0$		$\theta = 0.3$		$\theta = 0.6$		$\theta = 0.9$		$\theta = 1$	
Components	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
NFC & W/C Assembly	0	1	0	1	0	1	1	0	1	0
Loud Speaker Assembly	0	1	0	1	0	1	1	0	1	0
Sim Card Tray	0	1	1	0	1	0	1	0	1	0
Earpiece Speaker	0	1	0	1	0	1	1	0	1	0
Front Camera	0	1	0	1	0	1	0	1	0	1
Rear Camera	0	1	0	1	0	1	0	1	0	1
Headphone Jack	0	1	0	1	0	1	0	1	0	1
Proximity Sensor	0	1	0	1	0	1	1	0	1	0
Vibration Motor	0	1	0	1	0	1	1	0	1	0
Fingerprint Sensor	0	1	0	1	0	1	0	1	1	0
Customer utility	998		1008		1008		1054		1124	
Disassembly time (s)	741		746		746		1160		1225	

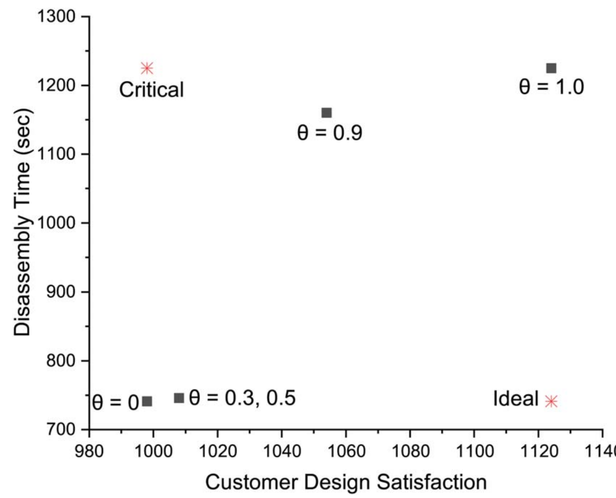

Fig. 2 Efficient frontiers of the results

P2. The matrix represents the operations required to extract components of EoL products. As shown in Tables 1 and 2, even though the two products are produced by the same manufacturer, the disassembly order and level in the part extraction process may be different.

Table 4 shows disassembly complexity for disassembly operations (T_{lk}). The disassembly complexity depends on the joint type and the type of tools required to disassemble the joint. When extracting parts that require complex disassembly operations, special equipment or processes may result in longer disassembly times and less efficiency in the overall disassembly process. For example, in the case of smartphones, the parts are combined with glue, screw, clip, cable, or slot as shown in the first column of Table 4. Among these methods, when using glue to assemble a smartphone without using external screws, special equipment (i.e., opener, suction) to remove the glue is required. Therefore, it

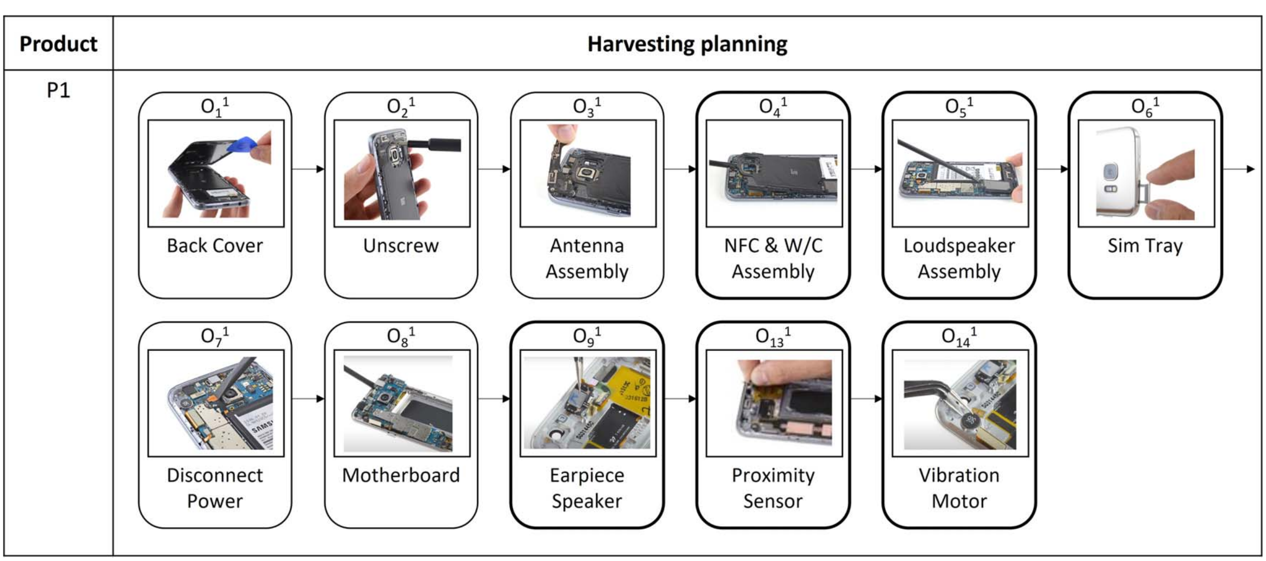

Fig. 3 Harvesting planning for EoL P1 [32,33]

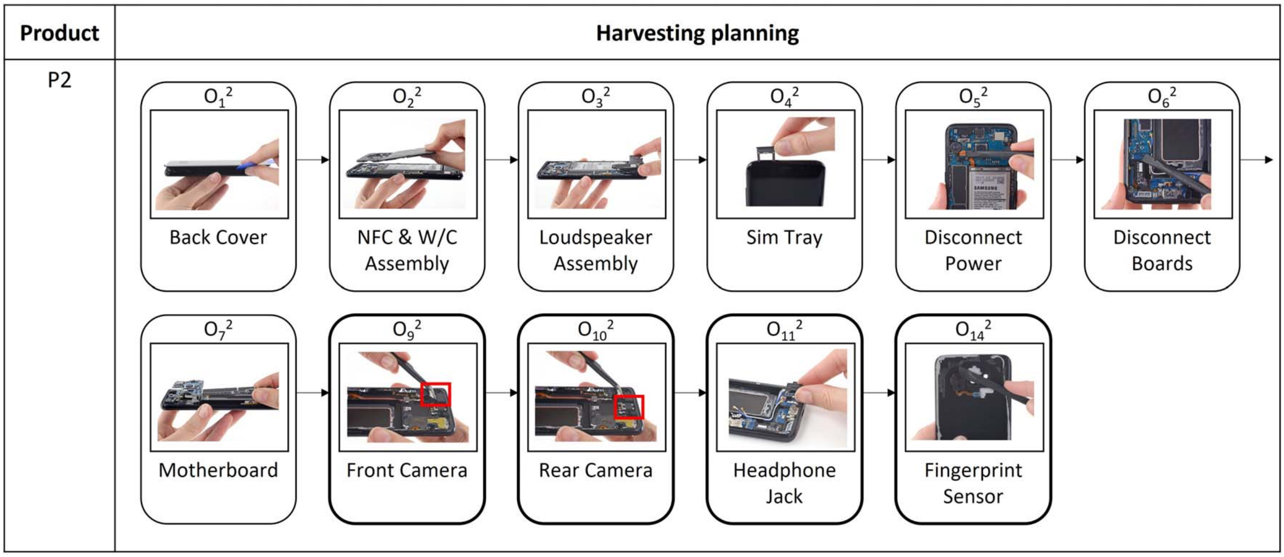

Fig. 4 Harvesting planning for EoL P2 [34]

can be confirmed that the disassembly time takes longer than other assembly methods.

4.3 Results

4.3.1 Product Design Configuration. Given the characteristics of remanufacturing that can be upgraded or combined with new parts, the design of remanufactured product can be maintained as it is (refurbishment) or changed to new designs (remanufacturing). Table 5 shows the optimization results for the optimal combination of modules that can be used in the design of remanufactured products that maximize customer satisfaction while minimizing disassembly time. Optimal product designs were identified by gradually increasing the θ value (Eq. (7)) of the optimization problem. Figure 2 shows the objective values according to θ as an efficient frontier. These results show that the design of the remanufactured product considering only customer satisfaction may not be the optimal design when considering the efficiency of disassembly simultaneously. To minimize disassembly time only ($\theta = 0$), it was optimal to use only EoL P2 for the remanufactured product. As shown in the results of this study (Table 5), when only customer utility is considered ($\theta = 1$, Design with the highest sum of partial utilities), the new design using P1 and P2 modules together is the optimal design. On the other hand, when only the disassembly time is considered ($\theta = 0$), it was optimal to design the same with the P2 product. As shown in Tables 1 and 2, the modules of EoL P1 require more disassembly operations (17 operations) than EoL P2 (14 operations) because they are assembled in a more complex form. However, when considering the customer's utility together ($0 < \theta \le 1$), it can be seen that it is optimal to use parts in both EoL P1 and P2 rather than using only the EoL P2 design.

4.3.2 Harvesting Planning. This model finds the optimal design as well as the harvesting planning of EoL products for that design. Figures 3 and 4 show the required disassembly operations of EoL P1 and P2 to produce the optimal design when θ value is 0.9. The blue-colored boxes in Figs. 3 and 4 indicate the modules that need to be extracted from each product. As shown in Figs. 3 and 4, six modules including NFC & W/C Assembly are extracted from EoL P1, and the remaining four modules are extracted from EoL P2.

According to this result, EoL P1 only needs O_1^1 to O_9^1, O_{13}^1, and O_{14}^1 operations to extract the required parts, and EoL P2 only requires O_1^2 to O_7^2, O_9^2 to O_{11}^2, and O_{14}^2 operations. Based on these results, it is possible to determine the selective disassembly sequence and level that can minimize the disassembly time for each EoL product while selecting the product design.

5 Conclusion and Future Work

This paper proposes an integrated methodology for designing a remanufactured product by comprehensively considering the customer analysis through online review and efficiency of the remanufacturing process. Considering two objectives of maximizing customer utility and minimizing harvesting time, the integrated model optimizes (i) configuration design suitable for remanufactured products and (ii) harvesting planning that determines optimal disassembly orders and levels for each EoL product. This integrated methodology allows product designers to understand the market trends and consider the efficiency of the remanufacturing process at the design stage of a remanufactured product, rather than considering only the recovery rate of the components/modules.

To demonstrate the proposed methodology, examples of the smartphone were used. Smartphones use materials with high potential value, but they have different design structures and low disassemblability, making them difficult to remanufacture. Therefore, it is necessary to apply this integrated methodology to design for remanufacturing while simultaneously analyzing customer perception and planning a disassembly. Through applying the proposed methodology, the design of an appropriate remanufactured product design considering the customers' utility and the harvesting process of extracting parts for the design simultaneously were obtained. Also, it showed that the design can be changed according to the importance of the customers' utility value and the efficiency of the remanufacturing process. These results show that it is necessary to consider the market (customer) analysis and the efficiency of the remanufacturing process at the stage of designing remanufactured products. This methodology is expected to be used as a decision-making tool for designers or companies that want to introduce remanufacturing for design strategies for remanufacturing products.

With the recent development of data analysis technology, optimal integration of product configurations based on data-driven customer analysis is a promising field for future research. In this study, the importance of each part was predicted by using the TF analysis for simplicity, but in future research, the latest methodologies that can predict the utility of customers for each part based on online data can be applied. In addition, this study did not discuss the improvement for the structure and assembly methods of EoL products. However, since the remanufacturing process depends on those design factors, the methodology for improving disassemblability of the product design for remanufacturing is expected to be a future study. Also, in this study, the utility value and harvesting time of customers were considered as objective functions, but it is likely to be possible to expand research on profitability or market share by applying the demand model and detailed cost factors in the future.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

There is no third party data used and the data will not be available for sharing.

Nomenclature

- I = index set for module instances, $i \in I$
- J = index set for modules, $j \in J$
- K = index set for End-of-Life (EoL) products, $k \in K$
- L = index for disassembly tools, $l \in L$
- O = index set for disassembly operations, $o \in O$
- R = target production quantity of the remanufactured product
- n_{lo} = average number of uses of tool l during disassembly operation o
- r_{ijk} = reusability of module instance i of module j from EoL product k
- u_{ijk} = customer utility for module instance i of module j from EoL product k
- x_{ijk} = design variable for module instance i of module j from EoL product k is selected in the design configuration (=1) or not (=0)
- D_{io} = disassembly matrix, the entry represents 1 if disassembly operation o is required to extract module instance i and 0 if not.
- Q_k = expected take-back quantity of EoL product k
- T_l = average usage time per use of disassembly tool l (sec)
- T^d_{ijk} = disassembly time it takes to extract module instance i of module j from EoL product k
- T^d_o = disassembly time it takes to perform operation o
- CR_i = customer's requirements for module instance i
- θ = parameter that determines the importance of objectives

Appendix A: Disassembly Operations for End-of-Life P1

Disassembly operations	
O^1_1	Disassemble back Cover
O^1_2	Unscrew
O^1_3	Disassemble Antenna assembly
O^1_4	Disassemble NFC, W/C Assembly
O^1_5	Disassemble Loud Speaker Assembly
O^1_6	Disconnect Sim tray
O^1_7	Disconnect Power
O^1_8	Disassemble Motherboard
O^1_9	Disassemble Earpiece Speaker
O^1_{10}	Disassemble Front Camera

Continued

Disassembly operations	
O^1_{11}	Disassemble Rear Camera
O^1_{12}	Disassemble Headphone Jack
O^1_{13}	Disassemble Proximity Sensor
O^1_{14}	Disassemble Vibration Motor
O^1_{15}	Disassemble Battery
O^1_{16}	Disassemble Display
O^1_{17}	Disassemble Fingerprint Sensor

Appendix B: Disassembly Operations for End-of-Life P2

Disassembly operations	
O^2_1	Disassemble back Cover
O^2_2	Disassemble NFC, W/C Assembly
O^2_3	Disassemble Loud Speaker Assembly
O^2_4	Disassemble Sim Tray
O^2_5	Disconnect Power
O^2_6	Disconnect motherboard and daughterboard
O^2_7	Disassemble Motherboard
O^2_8	Disassemble Earpiece Speaker
O^2_9	Disassemble Front Camera
O^2_{10}	Disassemble Rear Camera
O^2_{11}	Disassemble Headphone Jack
O^2_{12}	Disassemble Proximity Sensor
O^2_{13}	Disassemble Vibration Motor
O^2_{14}	Disassemble Fingerprint Sensor

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