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Product Resynthesis: Knowledge Discovery of the Value of End-of-Life Assemblies and Subassemblies

The trends of increasing waste and comparatively low growth of waste treatment methodologies have created the need for better utilization of the products we deem unfit for use. The options available for utilizing end-of-life (EOL) products are currently restricted to reusing, recycling, remanufacturing*, and* permanent disposal*. In this work, the authors propose a new EOL option called* resynthesis *that utilizes existing waste from EOL products in a novel way through the synthesis of assemblies/subassemblies across multiple domains (i.e., consumer electronics, health care, automotive, etc.). The* resynthesis *of assemblies/subassemblies is achieved by quantifying their similarities (*form *and* function*) across multiple domains. A mixed-integer linear model is developed to determine the optimal EOL strategy for each component/subassembly. As a means of verifying the EOL decision, the value of the "new"* resynthesized *product is compared with the value that would be derived if the individual subassemblies were* reused*,* remanufactured*,* recycled*, or* disposed*. A case study involving an electronic mouse is used to validate the proposed methodology and to demonstrate its practicality as an alternate enterprise level EOL option.* [DOI: 10.1115/1.4025526]

1 Introduction

In the United States alone, more than 30 million computers and 129 million phones are disposed of each year, resulting in a tremendous amount of electronic waste (e-waste). In 2009, over 2 million tons of electronic devices such as computers, computer accessories, televisions, and cell phones were discarded. The Environmental Protection Agency (EPA) indicates that approximately only 25% of these unwanted electronics were recycled, of which 38% were computers, 17% were television sets, and 8% were mobile devices [1]. According to the EPA's estimations, only about 15–20% of electronic component-based waste is treated with EOL decision-making, with the remainder of these electronics going directly to landfills and incinerators [1]. Undoubtedly, there is an urgent need to mitigate this problem by ensuring the full utilization of these discarded products.

Sustainable design focuses on eliminating the negative impacts of design artifacts on the environment through skillful design methodologies that consider the natural environment as an inherent factor in designing new products or altering old ones [2]. Presently, the sustainability practices that industries employ are limited to *reusing/repurposing*, *recycling*, *remanufacturing*, or simply *disposing*. *Reusing* is the act of using an item for more than one lifecycle by subjecting it to minor repair (if needed) for the same function [3]. *Repurposing* is simply another form of *reusing* that involves modifying a single product for a different purpose without significantly reforming it. *Repurposing* can apply to multiple product domains, although its main usage is in pharmaceuticals and fabrics [4]. Throughout this paper, *repurposing* is treated as a subset of *reusing* and hence will not be considered separately. *Recycling* is the breaking down of an EOL product into raw materials which are then used to make new products [3]. *Remanufacturing* involves the repair or replacement of worn out or obsolete components and modules [5]. According to the EPA, the *recycling*, *reuse*, and *remanufacturing* industry is comprised of a large number of companies [6]. *Disposal* involves collecting and depositing EOL products in landfills. *Disposal* can also result in incineration, which is the combustion of organic substances and waste [7]. Although organized *disposal* can be very useful in discarding hazardous waste, the negative environmental effects involved in these disposal methods demand attention [8]. The annual revenues generated by the *recycling* industry is far more than the *reuse* and *remanufacturing* industries, indicating that *recycling* is a more preferred EOL option for manufacturers [6]. This is in part due to the fact that manufacturers tend to use Design for Assembly and Manufacturing, which makes it difficult for parts to be *reused* or *remanufactured* [9]. *Recycling*, however, has economic and environmental shortcomings, since it requires energy to break down products (assemblies) into their fundamental raw materials [10,11]. Furthermore, certain products/components have hazardous chemicals/materials, making them extremely difficult to recycle [12,13]. The cost to *recycle* may also be a prohibitive factor in product *recycling* efforts due to the complexities of the material extraction process [14]. The *resynthesis* EOL option proposed in this work aims to mitigate these challenges by utilizing existing waste from EOL products in a novel way through the synthesis of existing assemblies/subassemblies across multiple domains.

By definition, the term *synthesis* is the systematic combination of otherwise different elements to form a coherent whole [11]. In the context of product design and development, *product synthesis* represents the actual manufacturing/assembly process of a product, since a product is a coherent assembly of otherwise distinct materials/subassemblies. Taking into account the limitations of existing EOL options and acknowledging the definition of *synthesis*, the authors introduce a new dimension of product sustainability called product *resynthesis*. Product *resynthesis* is the creation of a product that is distinct from its parent assembly/subassembly or that adds functionality to an existing product through the

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combination of different EOL products (assembly or subassembly) or both. Product *resynthesis* differs from *repurposing* because unlike *resynthesis*, *repurposing* does not create a novel product through the *synthesis* of multiple parent products/components (assemblies/subassemblies); it simply creates a new application domain for an existing EOL product [15]. The "new" product is simply the original product used in a different way; therefore, it is practically *reused*. *Resynthesis*, on the other hand, involves partially/completely modifying the design of the parent product(s) and would involve several machining/manufacturing processes to create a new product. Considering the existing EOL sustainability options, *recycling* is not always economically and environmentally viable [10,14], while *reusing* and *remanufacturing* do not incorporate DFMA [9]. *Resynthesis* aims to overcome these limitations by identifying viable candidate assemblies/subassemblies that, when combined, enhance the functionality and overall value of EOL products.

Up until now, existing research methodologies focused on product sustainability have overlooked the potential advantages of *resynthesizing* EOL products since they only consider the above four EOL options. Industries and leading organizations today have identified sustainability as an integral facet of their business strategy, not only to uphold their enterprise value but also to grow and prosper. In other words, an organization can enhance its revenue and market share by employing a strong sustainability strategy, which can aid their engagement with key stakeholders (such as employees and communities) and protect their license to operate, reduce costs, manage risks, and increase operational efficiencies [16]. The new dimension to EOL decision-making will be compared with existing EOL options such as *reuse*, *remanufacturing*, *recycling*, and *disposal*. This presents enterprise decision makers with a new EOL option for their products and provides opportunities for value-addition and/or new product development, which may prove more efficient, more effective, and ultimately more profitable.

This paper is organized into five sections. The current section provides an introduction to sustainable design and the motivation for the proposed methodology. Section 2 discusses the relevant literature involved in this work. Section 3 describes the methodology proposed in order to form an economically and environmentally feasible subassembly combination based on various similarity parameters. A case study is presented in Sec. 4 that illustrates the applicability of the proposed methodology in a realistic product design setting. Finally, Sec. 5 summarizes the major conclusions drawn from this work and describes potential future work in this field.

2 Literature Review

Sustainable design aims to replace the consumption of materials and to reduce environmental pollution and wasted resources while simultaneously meeting specific needs of consumers and enterprise decision makers [17]. This section reviews the literature relevant to this work by first discussing the formation of a component (subassembly) database using disassembly techniques (Sec. 2.1). In Sec. 2.2, literature relating to modularity explains the interactions between/among assemblies and subassemblies. Next, Sec. 2.3 reviews mathematical models aimed at quantifying the relationship/compatibility between assemblies/subassemblies using product similarity based techniques. Finally, literature addressing the EOL decision-making process for a given database of subassemblies is presented in Sec. 2.4.

2.1 Disassembly Sequence Implementation. Different subassemblies of a product may possess different reliabilities and accordingly can have different EOL values. Therefore, it is essential to incorporate product disassembly strategies for components (subassemblies) and to apply various EOL decisions (*reuse*, *remanufacturing*, *recycling*, and *disposal*) to individual components. Kara et al. develop the concept of selective disassembly, which requires the disassembly of selected products that can be potentially *reused* [18]. According to their model, a disassembly sequence for some selected products with minimal removal of their components is determined. Gonzalez and Adenso-Diaz propose a recurrent algorithm to determine the optimal EOL strategy based on the product's bill of materials and graphical CAD/CAM representations [19]. Their model determines to what extent the product should be disassembled and what the EOL decision for each disassembled component should be. Lambert defines the disassembly process as a sequence of single operations for separating a single part (atomic subassembly) from a product (assembly) or separating into two different subassemblies [20]. Kwak et al. define an EOL subassembly as "a feasible subset of components that can be recovered or disposed without further disassembly according to a single EOL option" [21]. Zwingmann et al. apply a constraint programming approach to efficiently solve the combinatorial problem of finding the feasible subassemblies [22]. Kang et al. propose an algorithm for the automatic derivation of a transition matrix based on a product's architecture [23]. Lambert explains the complexities of a transition matrix using simple illustrations involving elementary mechanical linkages and an AND/OR graph [24]. Kang et al. similarly propose an algorithm to derive the disassembly structure of a product based on part-oriented precedence relationships that is then represented as a transition matrix [23]. Mapping both financial and sustainability considerations across industry sectors can reveal the interaction of sustainability opportunities and risks [25]. Pandey and Thurston present a model that minimizes the variability and environmental impact of EOL products [26]. The environmental impact values are computed using SIMAPRO [27].

The literature review presented in this section is limited to the four EOL options of *reuse*, *remanufacture*, *recycle*, and *dispose*. Unfortunately, these four EOL options do not consider the added value that may exist through the novel combination of assemblies/subassemblies of EOL products. The methodology proposed in this paper introduces a new dimension of EOL decision-making called *resynthesis* that quantifies the relationships between assemblies/subassemblies and proposes novel combinations that may result in higher profit margins compared to the four EOL options of *reuse*, *remanufacture*, *recycle*, and *dispose*.

2.2 Modularity-Based Product Design. After determining all possible subassemblies, the relationship between different combinations needs to be examined. Since the proposed methodology aims to suggest possible candidates for sustainable product design, there is a need to investigate existing modularity-based product design literature. Gershenson et al. define modularity as that which is generated from the decomposition of a product into subassemblies and components [28]. Products can be regarded as modular systems when they can be disassembled into a number of subassemblies that may be mixed and matched in various kinds of similar *domain* compositions, where a *domain* is defined as the set of products with similar utility functions and usages [29]. Modules (building blocks) are almost synonymous with subassemblies, with the distinguishing factor being the need for modules to be easily attached and detached from assemblies when needed [30]. In this paper, the meaning of modularity is based on engineering design studies, as the research primarily focuses on EOL products.

Allen and Carlson-Skalak define a module as a component or pack of components that can be detached from the product without destruction as a unit, which provides a nonidentical function required for the product to operate as desired [30]. Ulrich and Eppinger assert that when subassemblies are represented as functional elements of the product with interactions between them, the product under review has the most modular architecture, whereas Fujita and Ishii define a module as a standard model for minimizing the number of functions per component [31,32]. Walz defines a module as a standardized unit comprised of multiple dimensions for product flexibility and variety in use [33]. These above

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definitions do not take into consideration the interactions between components. Gershenson et al. further define life-cycle modularity as modules and interactions generated from the stages and components based on product life-cycle, such as development, testing, manufacturing, assembly, packaging, shipping, service, and retirement [34]. This study is based on Gershenson and Prasad's individual research [35,36]. Zhang and Gershenson expand on these models to better understand the product retirement process [37]. Sosale et al. discuss modularity with the concept of *recycling* in their product design research but fail to address the implications of *reusability* and *remaufacturability* to draw comparisons amongst them [38].

Many modularity studies are also derived from Suh's design axiom and establish an understanding about maintaining independence of functional requirements [35,39]. The theory suggests that each product function should be aimed at maintaining functional independence so that it results in a certain correlation between *form* and *function*. The *form* is defined as the physical representation from a geometric perspective, which consists of the outline and features, such as edges and angles, of the object under survey [35]. The *function* in consideration is derived based on the utilitarian purpose of the object relating to its technical specifications [40]. Huang and Kusiak also employ the axiom to design digital circuit modules having electrical end user applications [41]. However, Cheng finds that designing sophisticated products based on the independence axiom alone, where the compatibility of subassemblies is required, is not sufficient, as components outside the module were ignored [17]. Gershenson et al. further update the definition of independent modules by considering modules to contain a large set of components that have small dependencies on components and similarities to other components not in the module [34]. Similarities include the *form* in the physical aspect of subassemblies and *function* in the interactions between them.

Modular product design uses modules as standard units to build products with an increase in the feasibility of component use, product change, and product variety [41]. This relates to product life-cycle decision-making, as modular designs enable the grouping of components into detachable modules and increase the availability of products for *reuse*, *recycling, remanufacturing*, and *disposal* [38]. The geometric *form* and *functional* similarity between modules in an assembly can significantly influence the feasibility of the EOL strategy pursued. Therefore, by quantifying the *form* and *function* similarity across EOL product domains, enterprise decision makers can determine whether the proposed product *resynthesis* EOL option is a viable sustainability strategy when compared to the traditional four EOL options of *reuse*, *recycling, remanufacturing*, and *disposal*.

2.3 Cross-Domain Product Design. The term *Bisociation* was originally coined by Koestler to describe a synthesis of elements drawn from two previously unrelated matrices of thought into a new matrix of meaning by way of a process involving comparison [42]. In the context of product design, Tucker and Kang propose the term *Bisociative Design* as a design methodology that aims to quantify hidden, previously unknown design synergies across seemingly unrelated product domains [43]. Their work helps present candidate design solutions for next generation product platforms by searching large-scale product databases exhibiting *form* and *function* similarities across seemingly unrelated product domains.

Bio-inspired design is a relatively new body of research that aims to search and identify biological solutions that may aid in solving engineering design problems [44]. The methodology inspires designers to build design concepts based on cross domain knowledge between biology and engineering systems [45]. However, in *Product Resynthesis*, assemblies/subassemblies from EOL products already exist (as opposed to concepts) with an overall objective being to discover the value of EOL assemblies/subassemblies rather than subjecting them to *reuse*, *remanufacture*, *recycle*, or *disposal*.

The similarities in *form* and *function* act as quantitative metrics to evaluate the degree of compatibility between two products from different domains. The existence of EOL products spanning multiple domains makes traditional comparison metrics (commonality metrics, design structure matrix (DSM) models, etc.) difficult to implement in these scenarios. Consequently, product similarity metrics built upon the concept of *bisociation* have the potential to mitigate these challenges. Nagel et al. propose a system of bisociative interestingness measures through systematic evaluation methods, where designers and engineers can check the similarity between two products in a cognitive manner [46]. However, cognitive similarities are hard to employ in a system that requires numerical quantitative metrics for comparisons. Furthermore, the scale and scope of large-scale product design databases (millions of products) make qualitative cognitive evaluations of product domains cumbersome and impractical. The approach to quantifying *form* similarity proposed in this work overcomes these limitations by quantifying the geometric compatibility of possible subassembly combinations of EOL products in large, high dimensions. The *function* similarity quantifies the degree of functional interaction between assemblies/subassemblies of different products and their intended use in the market space. *Resynthesizing* can therefore be applied to the EOL products from a *bisociative* perspective through *form* and *function* analysis. Tierny et al. propose a partial retrieval algorithm that enables two different components to be attached based on *form* similarity by using comparative analysis techniques, such as the implementation of reeb graphs, to evaluate the *form* [47]. Although their research suggests the evaluation of a product's *form* based on the graphical representation (image outline) as opposed to a geometric analysis, the *functional* aspects of the products have not been discussed.

Furthermore, their work does not address quantifying product similarities in the context of EOL decision-making. In this work, the authors present a mathematical model that quantifies the value of combining assemblies/subassemblies based on the similarity of their *form* and *function* in an effort to determine the optimal EOL strategy that maximizes enterprise objectives while satisfying customer needs in the market space. This will be explained in detail in the following sections. AQ2

2.4 EOL Decision Making. In this section, the authors demonstrate how *bisociative design* methods can be incorporated into the EOL decision-making process. Several models have been proposed in the literature for determining the optimal EOL strategies for the components of a product. The model introduced by Mangun and Thurston develops a product portfolio approach that determines the time at which a product should be taken back and identifies the EOL decision for the components, i.e., whether they should be *reused*, *remanufactured*, *recycled*, or *disposed* [3]. The objective of the model is to maximize total multi-attribute utility for a portfolio comprised of three distinct market segments, namely, technophiles, utilitarian, and green consumers [3].

Lee et al. discuss a multi-objective methodology for determining appropriate EOL options for manufactured products set against conflicting objectives of minimizing environmental impact and minimizing loss (or maximizing gains) [48]. Johnson and Wang introduce a procedure that integrates economic factors into the scheduling of disassembly operations for Material Recovery Opportunities, which is defined as the opportunities to reclaim postconsumer products for *recycling*, *remanufacturing*, and *reuse* [49]. Behdad and Thurston employ a graph-based integer linear programming problem combined with multi-attribute utility analysis to identify the best set of tradeoffs among disassembly times and resulting cost under uncertainty. Their methodology also identifies the probability of not incurring damage during disassembly and reassembly time, the resulting cost under uncertainty, and the probability of not incurring damage during reassembly [50]. Remery et al. propose a new EOL Scenario Evaluation Methodology, which provides a method for evaluating the various EOL options in the early design phase [51]. Bufardi et al. propose a multicriteria decision aid to help decision makers select the best compromise EOL alternative based on their preferences and the performance of EOL alternatives with respect to the relevant environmental, social, and economic criteria [52]. Pandey and Thurston use a heuristic nondominated sorting genetic algorithm to identify the optimal component-level EOL decisions for multiple stakeholders [5].

While the aforementioned literature propose methodologies for addressing sustainable product design, they are limited to investigating solutions for single-domain products (for example, a product that is applicable only to the automotive domain) as opposed to comparisons between many product domains, which reduces the scale of applications that are otherwise possible. Also, the authors only considered assembled components and have not considered the subassemblies that make up the final product during evaluation.

The product *resynthesis* methodology proposed in this paper explores multiple products and their respective possible subassembly configurations during evaluation. Section 3 introduces the proposed product *resynthesis* methodology as a novel EOL option for enhancing overall enterprise level objectives.

3 Methodology

This section presents a detailed description of the proposed methodology starting with the formation of a large-scale database of compatible subassembly combinations (candidates). Next, *form* and *function* similarity models are introduced that quantify the relationship between different assemblies/subassemblies. The values of the *resynthesized* combinations are used to determine the optimal EOL decisions for the remaining subassemblies. The objective function and constraints in the optimization model will also be introduced. An overview of the proposed methodology is illustrated in Fig. 1. From a conceptual standpoint, all products hereafter will be referred to as "assemblies" and components as "subassemblies" in this paper.

3.1 Creating a Database of Assemblies. The first step in the methodology is to access a large database of assemblies (Fig. 2). *Form* data can be obtained from digital 3D CAD models (shown in Fig. 2) of all assembled components and their subassembly combinations existing in a company's product design database. For older and other EOL assemblies/subassemblies without existing 3D CAD models, geometric capture tools such as a 3D scanner (or for simpler analysis—2D image projections) could be used to acquire the *form* data. *Function* data can be obtained from official specifications/technical manuals. Textual patent data may also serve as a source for extracting functional descriptions of design artifacts [53]. Researchers have determined that it is more efficient and profitable to selectively disassemble an assembly as opposed to considering all possible assembly configurations (irrespective of the disassembly sequence) [54].

3.2 Determining Possible Disassembly Options. Lambert proposes the disassembly graph of a product represented as a transition matrix T [20]. This matrix represents the transitions caused by the possible disassembly operations. The cells of the matrix are represented by T_{ik}, where i refers to the different subassemblies

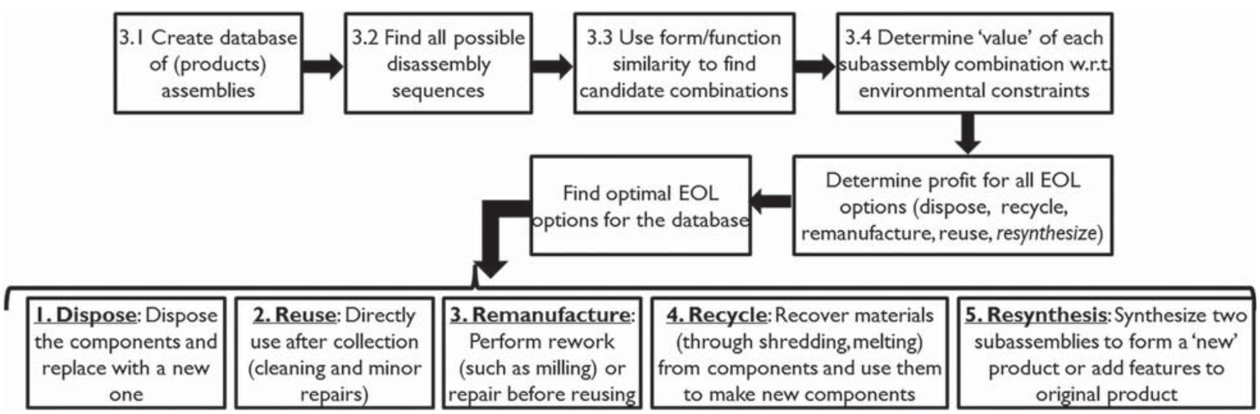

Fig. 1 Overall EOL methodology incorporating product resynthesis in sustainable product design

Sample Product	Sample Image	Form Data – 3D	Function Data - text
Whiteboard Marker			write, color, non-toxic ink, plastic casing, odor-free ink, non-dry tip
Cellular Phones			3g/4g LTE, Bluetooth, Wifi, 2100 mHa battery, GPS, speaker, 8.1 MP camera

Fig. 2 Sample product database consisting of form and function data

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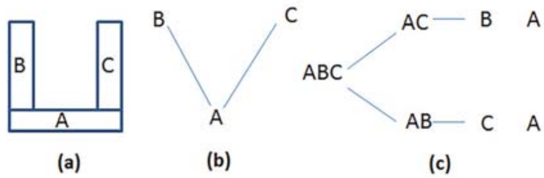

	0	1	2	3	4
ABC	1	-1	-1	0	0
AB	0	1	0	-1	0
AC	0	0	1	0	-1
A	0	0	0	1	1
B	0	0	1	1	0
C	0	1	0	0	1

(d)

Fig. 3 (*a*) Assembly of ABC, (*b*) correlation triangle, (*c*) subassembly possibilities for ABC, and (*d*) transition matrix for ABC

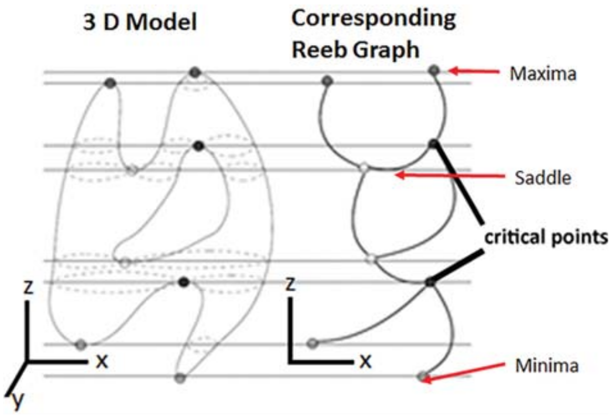

Fig. 4 Reeb graph sample visualization [58]

(rows) and index k refers to the disassembly actions (columns). This is generated for each assembly and subassembly possibility. Furthermore, $T_{ik} = -1$ indicates that action k disassembles subassembly i, and $T_{ik} = 1$ means that action k creates subassembly i. Other elements of the matrix are 0 (no action takes place).

Figure 3(*a*) illustrates a conceptual assembly schematic for a product made up of subassemblies A, B, and C, while Fig. 3(*d*) shows the related transition matrix. Figures 3(*b*) and 3(*c*) indicate the correlation triangle between the subassemblies and the various possible subassemblies that can be generated for the ABC model outlined in Fig. 3(*a*). Here, $T_{00} = 1$ implies that action 0 ($k = 0$) generates the assembly ABC $i = 0$, i.e., ABC. Also, $T_{01} = -1$, thus action 1 ($k = 1$), disassembles assembly ABC ($i = 0$). Similarly, $T_{11} = 1$ and $T_{51} = 1$ imply that action 1 ($k = 1$) generates subassemblies AB ($i = 1$) and C ($i = 5$), and so on. The model does not restrict products to be disassembled up to their atomic (bill of materials) levels. Selective or partial disassembly is considered in order to avoid unnecessary disassembly costs. The feasible levels of disassembly are determined through the transition matrix, while the optimal level is obtained based on the final objective function (taking into account the costs of disassembly) solution.

3.3 Determining Compatible Sets. The issue of quantifying compatibility between assemblies is resolved by considering the *form* similarity (geometric) and *function* similarity (textual) that have been defined in Sec. 2 (and Fig. 2). This enables the evaluation of physical as well as *function* compatibility and interactions.

3.3.1 Quantifying Form Similarity. To understand the *form* of assemblies, it is crucial to consider three-dimensional representations of components in the form of mesh data and proceed to label the *form* of each combination of subassemblies present in them. This is done by converting mesh data in the form of three-dimensional models to Reeb graphs, which provides a graphical representation of the *form* of each model. The Reeb graph as a shape retrieval technique has limitations as explained by Bespalov et al. and is domain specific to a large extent [55]. The authors in this work have employed a generic reeb graph technique adopted by Doraiswamy and Natarajan to evaluate the *form* of the products [56], although the proposed methodology is not limited to Reeb graph techniques to quantify *form* similarity. Other shape geometry retrieval solutions as discussed by Iyer et al. can also be employed within domains to evaluate *form* and to compare products [57]. Figure 4 shows the 3D object on the left and its corresponding Reeb graph on the right. The generation of a Reeb graph represents the connectivity of the various level sets of a 3D model where each level set (represented by lines parallel to the horizontal in Fig. 4) is the projected 2D section of the model at varying distances from a base reference plane.

The method employed to determine the Reeb graph is based on the determination of isosurface parameters at increasing level set values (along *Z*-axis) through the generated image model [59]. Based on the generated graphs for the various components, graphical similarities, which are a representation of the similarities in *form* between graphs, are calculated for each possibility. The process to efficiently generate and compare the Reeb graph topologies is carried out based on research by Doraiswamy and Natarajan [59]. Based on *Morse's theory* of surface manifolds, which studies the differential equation of the topology, the Reeb graph is computed using a step-wise iteration, as described in Fig. 5.

The first step involves the sorting of vertices or coordinate points in the point cloud mesh data that make up the 3D model in increasing order of their function value from a set reference plane (the *XY* plane is considered the reference for explanation). For the purpose of simple validation, all points in the mesh of the 3D model are assumed to have equal weights or functional value. The next step involves establishing the Reeb graph function, which has an initial value of "NULL" and, as the algorithm is iterated, stores the critical point data. The output of the Reeb graph is generated based on this function. The computational step checks the isosurface parameter at each node and continuously returns

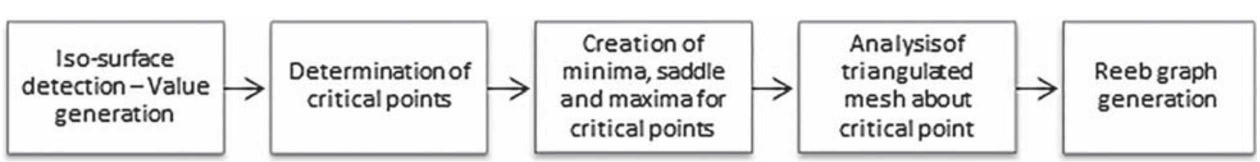

Fig. 5 Reeb graph computation for estimation of form similarity between combinations of assemblies and subassemblies

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Table 1 Sample output of a Reeb graph

Object –Level set data		
Saddle	Maxima	Minima
1	0	2
2	0	4
3	6	5
—	—	—
—	—	—
15644	15655	15623

Table 2 Matrix representation: subassembly function descriptions

		Subassembly function description			
		Subassembly 1	Subassembly 2	…	Subassembly F
Descriptive Terms	Term 1	$C^{1,1}$	$C^{1,2}$	…	$C^{1,n}$
	Term 2	$C^{2,1}$	$C^{2,2}$	…	$C^{2,n}$
	—	—	—	…	—
	—	—	—	…	—
	Term T	$C^{m,1}$	$C^{m,2}$	…	$C^{m,n}$

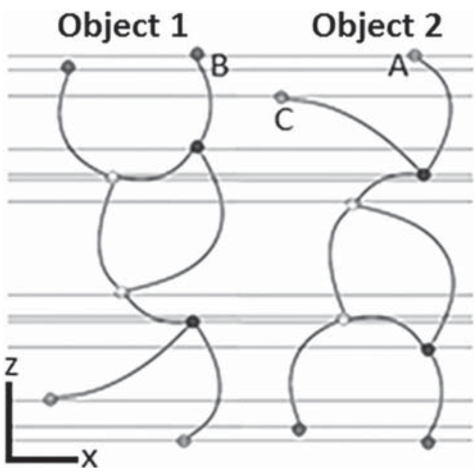

Fig. 6 Reeb graph comparison on increasing level set values (*z*-axis) for different configurations

the critical values to the Reeb graph function. The final step generates the output of the Reeb graph, a sample of which is shown in Table 1.

The input is represented as a 3D triangular mesh that is generated by rendering the image dataset for a definite number of tetrahedral blocks [56]. The generated Reeb graphs for the various combinations of subassemblies consist of critical points classified into saddle, maxima, or minima based on the mesh analysis of each combination [56]. These are determined based on the value of the isosurface at each point. *Maxima* are points with only lower isosurface values, and *minima* are those with only higher values. *Saddle points* are either points with multiple higher or lower isosurface values. An enumerative process listing all of these points is shown in Table 1. The values in the columns indicate the increasing level set values for saddle, maxima, and minima for the 3D model. More than one critical point configuration per level set value is possible depending upon the topology of the model. Comparisons are drawn based on the basic evaluation of generated Reeb graphs through critical point similarities that best represent the structure of the components.

Similarity measures between two 3D models are therefore based on the similarities in the level sets and critical point distributions of the Reeb graphs of the models, as depicted in Fig. 6. Point A and point B of the different objects lie on the same level set and are both *maxima* points. This similarity adds to the similarity function value of the two objects, whereas point C, which is also a maxima point on a different level set, does not add value to the function due to the lack of a corresponding similar nodal value on the other object.

The similarity values that are generated are based on the number of similar nodal level sets found between two Reeb graphs of different components. This is done by an iterative process to compare the critical points for each similar level set. The ratio of the similar points to the total points generated (scale of 0 to 1) in the Reeb graph data set gives the similarity ratio for each iterative comparative model. These similarity values generated indicate the level of similarity between configurations. For example, a configuration having ten different level sets and a similarity value of 0.4 indicate that four out of the ten level sets have similar values.

3.3.2 Quantifying Function Similarity. The *function* similarity between subassemblies is measured based on the textual specifications provided by each individual component in the bill of materials or the user manual. Through the disassembly processes of the EOL products, assemblies can either be made up of single or multiple parts. These specifications include technical descriptions of assemblies/subassemblies consisting of descriptive words/values. Since words can have different meanings given the context, an appropriate text mining algorithm must be employed. It is also possible to have similar meanings between two different words. For instance, “chip” and “processor” are not the same word, but the semantics can be similar when both terms are employed in a computer engineering context describing a central processor unit and integrated circuit, respectively. However, these terms also have different meanings in the adjective form. In this case, chip can also be regarded as the material fragments that are cut by machine tools. However, traditional text mining techniques based on term frequency (e.g., document indexing) may not distinguish the term chip based on semantics [60]. DSM concepts have been employed in engineering to investigate the relationships between engineering systems and subsystems [61]. This method quantifies these relations based on feedback provided by experts in the field. However, DSM-based approaches may not be suitable for analyzing large-scale databases comprised of thousands or millions of assemblies/subassemblies, since it may require more time and cost when compared to automated data querying techniques.

Latent semantic analysis (LSA) is a text mining algorithm that employs single value decomposition (SVD) techniques in an effort to extract hidden/semantic meanings of words when given specific contexts. To compare the *functional* similarity between subassemblies, the technical description of each subassembly is first represented in matrix form, as seen in Table 2. Each column j in Table 2 represents a subassembly (j), while each row i represents a descriptive term (i) used to describe the *function* of subassembly (j). Each cell contains the frequency (C_{ij}) with which a term (i) appears in the technical description of subassembly (j), where:

- Semantic term vector (each row of Table 2)

$$\mathbf{Term}(i) = [C_{i,1}, \ldots, C_{i,n}] \tag{1}$$

- Subassembly function description vector (each column of Table 2)

$$\mathbf{Function}(j) = \begin{bmatrix} C_{1,j} \\ \cdot \\ \cdot \\ \cdot \\ C_{m,j} \end{bmatrix} \tag{2}$$

Table 2 can be defined as **X**, where $C_{i,j}$ represents the frequency of a particular term in the description of each subassembly function

$$\mathbf{X} = \begin{bmatrix} C_{1,1} & \cdots & C_{1,n} \\ \vdots & \ddots & \vdots \\ C_{m,1} & \cdots & C_{m,n} \end{bmatrix} \tag{3}$$

The SVD of **X** can therefore be represented as [62]

$$\mathbf{X} = \mathbf{T_0 S_0 D_0'} \tag{4}$$

where **X** is the term (*T*) by function (*F*) matrix (i.e., $\mathbf{X} = T \times F$), $\mathbf{T}_0$ represents the term (*T*) by rank (*r*) matrix, having orthogonal, unit-length columns ($\mathbf{T}_0' \, \mathbf{T}_0 = \mathbf{I}$), $\mathbf{S}_0$ is the diagonal matrix of singular values ($r \times r$), *r* is the rank of $\mathbf{X} \leq \min\,(T, F)$, and $\mathbf{D}_0$ is the rank (*r*) of function (*F*) matrix, having orthogonal, unit-length columns ($\mathbf{D}_0' \, \mathbf{D}_0 = \mathbf{I}$) (i.e., $\mathbf{D}_0 = r \times F$).

In order for the LSA algorithm to be practical for large-scale database applications, computation complexity issues have to be considered. It is possible that very large corpora can be reconstructed with only a limited number of dimensions by selecting *k* largest singular values in the diagonal matrix during the SVD process [62]. The corresponding singular vectors from matrices $\mathbf{T}_0$ and $\mathbf{D}_0$ derive the rank *k* approximation of the original matrix **X** where $k < r$. The resulting lower dimension approximation of the original **X** matrix is considered to be the *semantic space*, which then allows the quantification of the relationship between different subassemblies using measures such as the cosine similarity. The similarity between two subassemblies can be computed as follows:

$$\cos(\mathbf{D_j}, \mathbf{D_q}) = \frac{\mathbf{d_j} \times \mathbf{d_q}}{\|\mathbf{d_j}\| \|\mathbf{d_q}\|} \tag{5}$$

where

$$\mathbf{d_j} = \mathbf{D_j' T_k S_k^{-1}} \tag{6}$$

$$\mathbf{d_q} = \mathbf{D_q' T_k S_k^{-1}} \tag{7}$$

$\mathbf{D}_j$ is a subassembly function description in the *j*th column ($\mathbf{D}_j' \, \mathbf{D}_j = \mathbf{I}$), $\mathbf{D}_q$ is a subassembly function description in the *q*th column ($\mathbf{D}_q' \, \mathbf{D}_q = \mathbf{I}$), *k* is a rank approximation, $\mathbf{T}_k$ represents the term (*T*) by rank (*k*) approximation of $\mathbf{T}_0$, $\mathbf{S}_k$ is the diagonal matrix of (*k*) approximated singular values ($k \times k$), $\mathbf{d}_j$ is a vector coordinate of documents in the *j*th column of the *semantic space*, $\mathbf{d}_q$ is a vector coordinate of documents in the *q*th column of the *semantic space*.

While the theoretical bound of the cosine similarity metric ranges between (−1, 1), in the context of document classification, the range is limited to (0,1), where 0 represents no correlation in the descriptions between two documents, and 1 represents a perfect match in the descriptions between two documents [62]. The similarity between terms (e.g., chip and processor) can be computed (and if similar, clustered) by changing the values from each Eqs. (6) and (7) to $\mathbf{T_i' D_k S_k^{-1}}$, $\mathbf{T_p' D_k S_k^{-1}}$; where each $\mathbf{T}_i$ ($\mathbf{T_i' \, T_i} = \mathbf{I}$) and $\mathbf{T}_p$ ($\mathbf{T_p' \, T_p} = \mathbf{I}$) is a term in the *i*th row and *p*th row, respectively; each $\mathbf{t}_i$ and $\mathbf{t}_p$ is a vector coordinate of terms from *i*th row and *p*th row from the *semantic space*, respectively; and $\mathbf{D}_k$ represents the function description (**D**) by rank (*k*) approximation of $\mathbf{D}_0$ matrix.

The following example demonstrates how the LSA algorithm can be used to quantify subassembly functional similarities. In this example, 11 terms are selected to describe 4 subassemblies (documents $\mathbf{D}_1$, $\mathbf{D}_2$, $\mathbf{D}_3$, and $\mathbf{D}_4$.); using terms A, B, C, D, E, F, G, H, I, J, and K. It is assumed that each subassembly is described by at least one of these terms. To lower the dimension of reconstructed matrix $\mathbf{X}_k$, *k* is given as 2

$$\mathbf{X} = \begin{array}{c|cccc|} & D_1 & D_2 & D_3 & D_4 \\ A & 0 & 1 & 1 & 1 \\ B & 0 & 0 & 1 & 1 \\ C & 0 & 1 & 0 & 0 \\ D & 0 & 0 & 1 & 0 \\ E & 0 & 1 & 0 & 0 \\ F & 1 & 1 & 0 & 1 \\ G & 0 & 1 & 1 & 1 \\ H & 0 & 1 & 1 & 1 \\ I & 1 & 1 & 0 & 1 \\ J & 1 & 0 & 2 & 0 \\ K & 1 & 0 & 1 & 1 \end{array} \qquad \mathbf{T}_2 = \begin{vmatrix} 0.3966 & 0.1282 \\ 0.2860 & -0.1507 \\ 0.1106 & 0.2790 \\ 0.1523 & -0.2650 \\ 0.1106 & 0.2790 \\ 0.3012 & 0.2918 \\ 0.3966 & 0.1282 \\ 0.3966 & 0.1282 \\ 0.2443 & 0.3932 \\ 0.3615 & -0.6315 \\ 0.3428 & -0.2522 \end{vmatrix}$$

$$\mathbf{S}_2 = \begin{vmatrix} 4.2055 & 0.0000 \\ 0.0000 & 2.4155 \end{vmatrix} \qquad \mathbf{D}_2 = \begin{vmatrix} 0.2391 & -0.2450 \\ 0.4652 & 0.6738 \\ 0.6406 & -0.64 \\ 0.5622 & 0.276 \end{vmatrix}$$

X is the original matrix as seen in Eq. (3). $\mathbf{T}_2$, $\mathbf{S}_2$, and $\mathbf{D}_2$ are attained by the SVD process using Eq. (4) where $k = 2$. By employing Eq. (5) the similarity between $\mathbf{D}_1$ and $\mathbf{D}_3$ is 0.6615, where each vector, $\mathbf{D}_1$ and $\mathbf{D}_3$, has the following coordinates (0.2391, −0.2450), (0.6406, −0.6402), respectively, based on Eqs. (6) and (7). By quantifying the latent semantic functional similarities between different subassemblies, factors such as software compatibility and hardware and generational variations (e.g., DVDs to Blu-ray) can be captured in the resulting EOL model.

3.4 Optimal EOL Decision. The *form* and *function* similarity values obtained from Secs. 3.3.1 and 3.3.2 will help determine the optimal *resynthesis* option/strategy for a given EOL product. There are several assumptions made for the model proposed in this paper:

- All EOL products that are collected are assumed to be in working order.
- The reliability and effective age of the take-back products are based on manufacturer specifications.
- Only the *primary function* of each take-back product is factored in this model, i.e., multifunction EOL products are not taken into account.

Figure 7 shows the *form–function* similarity graph for two subassemblies based on the *form–function* similarity metrics presented in Secs. 3.3.1 and 3.3.2.

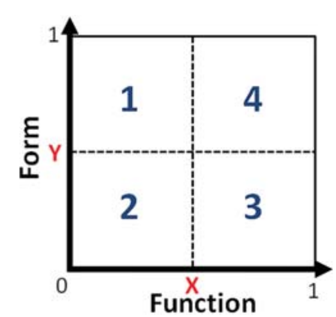

Fig. 7 Form–function similarity graph

Table 3 Form similarity

Form	Assembly A	Assembly B
Assembly A	—	Y
Assembly B	Y	—

Table 4 Function similarity

Function	Assembly A	Assembly B
Assembly A	—	X
Assembly B	X	—

The following are the *resynthesis* alternatives that are quantified based on the magnitude of the similarity values. If the *form* similarity value (varying between 0 and 1) is greater than Y, then it is said to be *high*, otherwise *low*. If the *function* similarity value (also varying between 0 and 1) is greater than X, then it is said to be *high*, otherwise *low*.

Classification 1: *Form* (high), *Function* (low): This presents a suitable candidate for *resynthesis* by combining two products (assemblies) or components (subassemblies), or adding *functionality* to an existing product (assembly).

Classification 2: *Form* (low), *Function* (low): Not well suited for product *resynthesis*.

Classification 3: *Form* (low), *Function* (high): Possibility of product substitution exists depending upon the costs of both products (assemblies), implying that if an assembly can perform the same function for a lower cost, it can replace an assembly having a higher cost.

Classification 4: *Form* (high), *Function* (high): Either of the product decisions in Eqs. (1) and (3) can be applied.

In order to explain the concept behind the four classifications above, assume that product_A and product_B are products (assemblies) for which EOL decisions are to be made. Let π_A and π_B be the profits (per unit) obtained from A and B, considering that they are *remanufactured*, *reused*, *recycled*, or *disposed*. Let us consider *resynthesis* as an EOL option, such that the *resynthesis* of A and B form product C. Conceptually, *resynthesis* becomes the preferred EOL decision if the following conditions are fulfilled:

$$\pi_C + \pi_{\text{Residuals}} \geq \pi_A + \pi_B \tag{8}$$

where $\pi_{\text{Residuals}}$ = the profit attained from the remaining subassemblies of A and B that are not used in *resynthesis* post disassembly (and are remanufactured, *reused*, *recycled*, or *disposed*), $\pi_C = (\text{Price})_C - (\text{Cost})_C$, $(\text{Price})_C$ = Price of *resynthesized* product C (*resynthesis* of A + *resynthesis* of B), $(\text{Cost})_C$ = Cost incurred to create *resynthesized* product C (*resynthesis* of A + *resynthesis* of B) can be obtained by determining the costs of each operation outlined in Table 5.

In other words, *resynthesis* is justified in the above case since it is more profitable to *resynthesize* A and B to form C than it is to *remanufacture*, *reuse*, *recycle*, or *dispose* of them. Two components (subassemblies) with unique functions (extremely dissimilar or low *function* similarity) when combined to form a new product such that their functions are retained leads to a higher value for the resulting product [63,64]. A new functionality implies that a customer can consolidate different products that were traditionally bought separately into one product. For example, a cell-phone with added functions/features such as a camera, GPS, etc., would have a higher value since it incorporates the functions of other products into itself. Also, if two subassemblies have a high form similarity, it is economically easier to integrate them since they can potentially share a common module/platform to form a new product [65].

Consider the extreme case of two assemblies having *form* and *function* similarity matrices as seen in Tables 3 and 4.

Classification 1: If A and B have a high *form* similarity ($Y = 1$), then $(\text{Cost})_C$ = "low" [60], and if they have a low *function* similarity ($X = 0$), then $(\text{Price})_C$ = "high" [65], thus the value of the final *resynthesized* assembly is at its maximum, therefore, π_C = high. For example, a smart phone and the keypad of a microwave have a high *form* similarity while their *function* similarity is low. If an EOL smart phone and microwave were to be *resynthesized*, the end product will be a microwave with all functionalities of the smart phone embedded into (both hardware and software) it as seen in Fig. 8.

Thus, the final value (price) of the *resynthesized* microwave would significantly increase possibly resulting in higher profit as compared with other EOL options.

Classification 2: Similarly, if A and B have low *form* similarity ($Y = 0$), then $(\text{Cost})_C$ = high [65], and if they have a low *function* similarity ($X = 0$), then $(\text{Price})_C$ = high [66]; thus, the profit obtained from product C will be low (π_C = "low") due to extreme

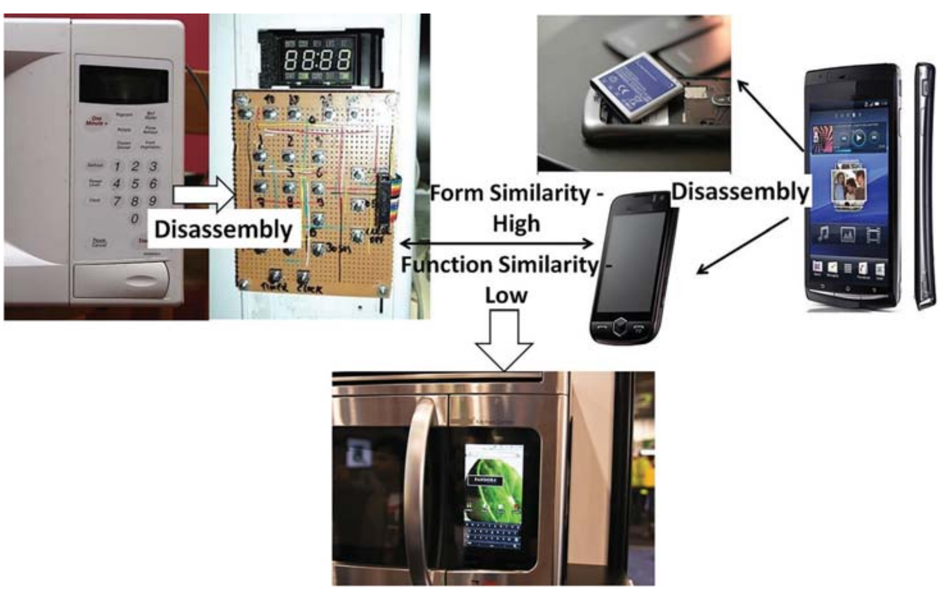

Fig. 8 Example of a candidate for resynthesis

Fig. 9 Example of low form, low function similarity

Fig. 10 Example of low form, high function

Fig. 11 Example of high form, high function

dissimilarity (an increase in potential *resynthesis* cost) even though their functions are dissimilar (as seen in Fig. 9).

Classification 3: If A and B have a low form similarity ($Y=0$), then $(\text{Cost})_C = \text{high}$, and if they have a high function similarity ($X=1$), then $(\text{Price})_C = \text{low}$. Thus, $\pi_C = \text{low}$ since a *resynthesis* of these two products would be expensive (due to the low form similarity) and at the same time, would not provide additional functionality beyond the original products, as seen in the example in Fig. 10.

Classification 4: If A and B are identical and are the same product (*form* similarity $Y=1$, *function* similarity $X=1$) then if we are to form a product C by combining the assemblies/subassemblies of A and B, $\text{Cost}_C = \text{Cost}\ (\textit{resynthesis}_A + \textit{resynthesis}_B) = $ "low", because it is certainly easier to incorporate *functions* of A into B or vice versa [65]. Also, in this case, it is assumed that the value of product C would not exceed the value of A or B since product C does not provide any additional functions beyond what is already provided by either product A or B. For example, if we have two identical laptops (with comparable reliabilities as seen in Fig. 11), both their *form* and *function* similarity would be close to 1 (depending upon their internal configuration).

Thus, if we are to form an assembly incorporating components (subassemblies) from both, say by replacing one's battery with the other, the final product will not have a value higher than the sum of their individual values. As a reminder, the assumption made here is that the subassemblies are of comparable reliabilities.

Based on the conceptual explanations above, classifications (1) and (4) are the most suitable for *resynthesis*, while classifications (2) and (3) are the least suitable candidates for *resynthesis*. For this paper, classification (1) (from Fig. 8) of "*high form and low function similarity*" is considered the best "candidate" for *resynthesis* strictly from an economic perspective due to the examples presented above. If two subassemblies have a high form similarity, then it is certainly easier to physically integrate (or combine) them, thus saving expenditure on design planning and actual fabrication [65,67]. In the case of (2) and (3), due to low *form* similarity, the design and production costs increase [65]. Also, if the two subassemblies have different *functions*, then their combination can retain both *functions*, thus creating a final product with an added value, since the customer would be willing to pay more for a product which has auxiliary features in addition to its primary features/functions [66]. This distinguishes (1)

Table 5 Operations associated with the five postrecovery options

Operation	Decision				
	Dispose	Reuse	Remanufacture	Recycle	Resynthesize
Collection	X	X	X	X	X
Transportation to disposal centers	X				
Dismantling	X		X	X	X
Refining	X			X	X
Machining			X		X
Disposal of waste	X				
Assembling					X

from (4), outlining its favorability. In this work, it is assumed that the enterprise decision makers set the constraint for the values of X and Y (in Fig. 7) as to what is considered high/low similarity.

There are various operations associated with all five postrecovery options that determine the cost of performing that operation and its environmental impact (Table 5). SIMAPRO can provide environmental impact values for all the processes outlined in Table 5. The mathematical model takes into account the costs and environmental impacts associated with each of the above operations. The aim of the objective function is to maximize the total enterprise profit, given the sustainable EOL decisions, while taking into account environmental constraints.

3.4.1 Mathematical Model. Objective function

Maximize

$$M \times \left\{ \sum_{l=1}^{L} \sum_{j=1}^{5} \sum_{i=1}^{I} (P_{ijl} \cdot y_{ijl}) - \sum_{l=1}^{L} \sum_{k=1}^{K} (Cv_k \cdot x_{kl}) - \sum_{k=1}^{K} (Cf_k \cdot z_k) \right\} \quad (9)$$

where i is the feasible EOL subassembly for a total of I feasible EOL subassemblies, j is the EOL option ($j = 1, 2, \ldots, 5$), and k id the feasible disassembly transition for a total of K Feasible disassembly transitions, l is the product type (e.g., $l = 1$: Product A, $l = 2$: Product B, and so on for a total of L products), x_{kl} is the quantity of subassemblies of product type l that will be disassembled by transition k, y_{ijl} is the number of feasible subassembly i of product type l that are considered EOL (j), z_k is the binary variable that shows whether disassembly transition k is done or not, Cf_k is the fixed cost of a facility used for disassembly transition k (USD), Cv_k is the variable cost relating to subassemblies of product type l that will be disassembled by transition k (USD), P_{ijl} is the price requested by applying EOL option j for feasible subassembly i of product l (USD), M is the total volume of returned products (can also be modeled as a vector of demands for returned products).

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$$\sum_{i=1}^{I} \sum_{j=1}^{5} (E_{ij} d_{ij}) \leq \varepsilon \quad \text{(Environmental feasibility)} \quad (10)$$

$$\sum_{k} T_{ikl}\, x_{kl} = \sum_{i} y_{ijl} \quad \text{(Feasibility with respect to quantity)} \quad (11)$$

$$x_{0l} = Q_l \quad \text{(Initial quantity)} \quad (12)$$

where d_{ij} is the binary variable that shows whether subassembly i is treated with EOL decision j, T_{ikl} is the value of cell (i, k) in transition matrix of product type l (it can be -1, 0, or 1), Q_l is the total quantity of product type l (units), E_{ij} is the environmental impact when subassembly i is treated with EOL option j, x_{0l} is the quantity of subassemblies of product l, at $k = 0$, i.e., initial quantity of product l, and ε is the environmental impact limit defined by the manufacturer such that it meets environmental policy standards.

The objective function maximizes the profit that can be obtained for a given set of EOL products. Fixed and variable costs are considered, while the price and quantity of the EOL decision determines the revenue generated. The first term in Eq. (9) ($P_{ijl} \cdot y_{ijl}$), summed over i, j, and l, is the total revenue earned by executing EOL options for product subassemblies. The second term is the sum of variable costs of disassembly, and the third term is the disassembly fixed cost. The quantity or volume of returned products (M) can be determined using models used in Refs. [68,69] in Eq. (10), and the values of E_{ij} are obtained using SIMAPRO. The type of operation (energy consumed, by-products, effluents produced, and so on) involved in carrying out EOL option j for subassembly i determines the value of E_{ij}. The unit of measuring the environmental impact is mPt (millipoints), which is the impact of 1 kg of a substance on the environment. This is based on the material type of the subassemblies and the manufacturing process associated with the EOL decision [70]. In order to determine the value of the new product, there are two cases that need to be taken into account:

(1) If the price of the final product can be estimated from similar products existing in the market space.
(2) If option 1 is unavailable in the market, then the resulting *resynthesized* product is unlike the original assemblies and therefore, the prices of the individual subassemblies are simply added to obtain the market price of the *resynthesized* product.

The mixed-integer linear programming problem is first solved with only four EOL decisions (*reuse, recycle, remanufacture*, and

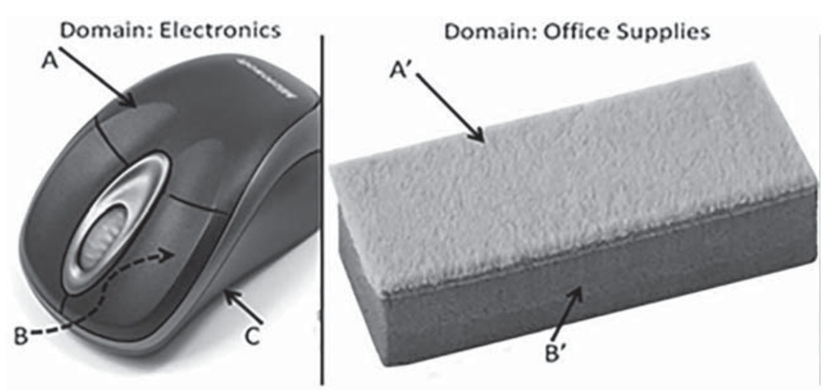
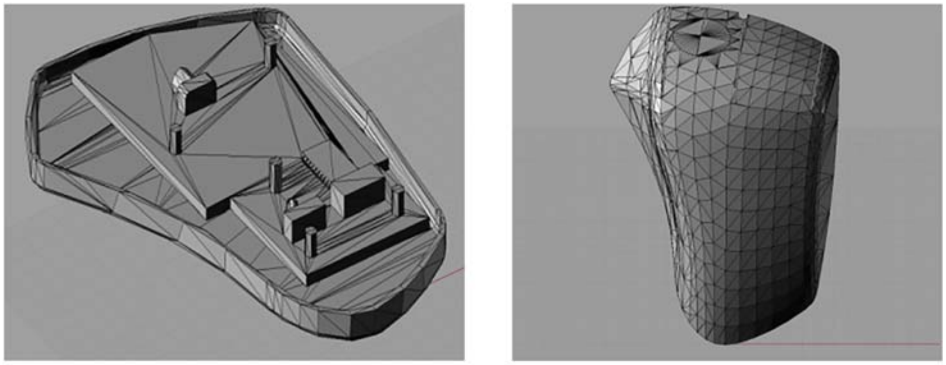


Fig. 12 Electronic computer mouse and white board eraser



(a) (b)

Fig. 13 (*a*) 3D mesh of base and microchip and (*b*) 3D model of the outer casing

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Table 6 Mouse assembly matrix and Eraser assembly matrix

(a)		(b)	
Part	Subassembly name	Part	Subassembly name
A	Mouse Casing (Top)	A′	Eraser (Base)
B	Microchip (PCB)	B′	Eraser Casing
C	Mouse Base		

dispose) similar to Ref. [71]. Once the compatible candidates for *resynthesis* have been identified, the overall enterprise profit is then calculated (with *resynthesis* as an EOL option) and compared with the original model that only included four EOL decisions (*reuse, recycle, remanufacture*, and *dispose*). The complexity of the optimization model is in polynomial time $O(n^2)$.

4 Application: Electronic Mouse Case Study

This section presents the application of the proposed methodology using a case study of an electronic computer mouse and a white board eraser as seen in Fig. 12.

This case study considers an ordinary computer mouse that is obsolete. The various components of the computer mouse include outer casing (A), inner microchip board (B), and base covering (C) (Fig. 12). The white board eraser consists of just two components, namely, eraser head (A′) and eraser body (B′) (Fig. 12). Combinations of subassemblies, such as BC and AC (3D wire meshes shown in Figs. 13(*a*) and 13(*b*)), are generated and also considered during the proposed application of *resynthesis*.

4.1 EOL Product Variables and Parameters. As explained in Sec. 1, the quantity of electronic mice discarded in 2009 was over 2 million. This serves as the design parameter for the mixed-integer linear program used to model the case study. Therefore, $l = \{1, 2\}$ and $M_1 = M_2 = 2{,}000{,}000$. The main components of the mouse and the eraser are shown in Tables 6, respectively. The transition matrices for the two products are shown in Tables 7.

Another input for the model is the EOL option price matrices for the mouse and the eraser, which indicate the estimated revenue from making each feasible EOL decision for each subassembly. Therefore, *reuse*, *remanufacture*, *recycle*, and *resynthesize* for EOL products results in positive net profit (whenever cost < price), while disposal results in a negative profit, as this is a cost incurred by the enterprise.

Table 8 shows the costs associated with the collection and processing of the two products. The costs are obtained using the data AQ6 in Raibeck et al. (the data apply to all types of polymers, including the polymers that the products in this case study are made

Table 7 Transition matrix for mouse and Eraser

(a)

ℵk	0	1	2	3	4	5	6
ABC	1	−1	−1	−1	0	0	0
AB	0	1	0	0	−1	0	0
AC	0	0	1	0	0	−1	0
BC	0	0	0	1	0	0	−1
A	0	0	0	1	1	1	0
B	0	0	1	0	1	0	1
C	0	1	0	0	0	1	1

(b)

ℵk	0′	1′
A′	1	−1
A′	0	1
B′	0	1

Table 8 Cost for processing mouse and eraser per unit [72]

Operation	Cost in USD
Collection	2
Transportation to disposal centers	0.35
Dismantling	0.05
Refining	0.32
Machining	0.6
Disposal of waste	0.05
Assembling	0.58

from) [44]. For estimating the cost associated with each EOL decision, the operations associated with each EOL decision have been indicated in Table 5.

For providing an appropriate baseline for the example, estimates were derived using the cost data in Table 8, and operations associated with each EOL option.

4.2 Form–Function Similarity Quantification. The *form* similarity matrix for both components is computed by comparing the critical points of both models. The similarity is calculated based upon Reeb graph comparisons of various models. Critical points, which indicate the varying level set values, are mapped on both models, and the degree of similarity between models is a measure of the number of similar level sets to the total number of level sets (Fig. 14). Each node in Fig. 14 indicates a level set value. For example, the similarity value of 0.452 (highlighted in Table 9) is derived from a similarity of 397 level set regions out of a total of 879 between the mouse assembly AC and the eraser head A′.

The *function* similarity between each assembly/subassembly is quantified by employing the cosine similarity metric, with the vectors derived from LSA that represent *functions*. For instance,

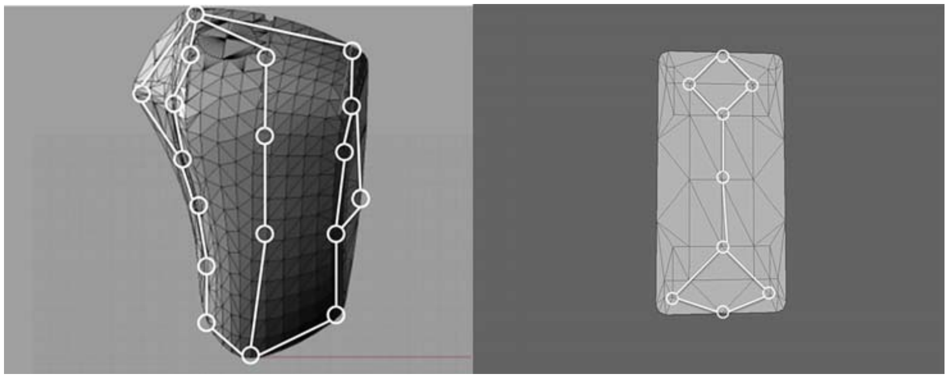

Fig. 14 Illustration of reeb graph overlaid in mouse component AC and eraser head A′

Table 9 Form and function similarity comparison matrix

Component		Eraser casing – B′	Eraser head – A′	A′B′
Mouse top - A	Form	0.282	0.074	0.300
	Function	0.480	0.060	0.270
Microchip - B	Form	0.130	0.129	0.130
	Function	0.020	0.010	0.000
Mouse base - C	Form	0.159	0.452	0.156
	Function	0.320	0.230	0.350
AB	Form	0.282	0.074	0.300
	Function	0.060	0.020	0.040
AC	Form	0.301	0.452	0.377
	Function	0.350	0.230	0.360
BC	Form	0.159	0.449	0.163
	Function	0.170	0.140	0.200

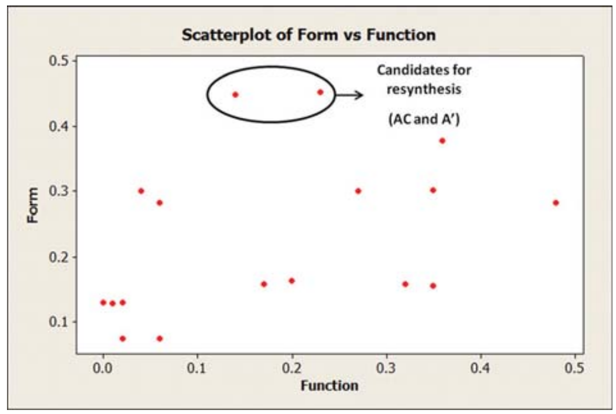

Fig. 15 Plot of function versus form from Table 9

the similarity value of 0.230 (highlighted in Table 9) is calculated by quantifying the functional descriptions (from patent data) of the subassemblies, succinctly represented below [72,73]:

- Function of AC: "An ergonomic mouse…to support a proximate end of a finger,…, stability for user…"
- Function of A′: "An eraser for removal of dry ink dust…includes fabric layers…"

In this case, AC and A′ have a high *form* similarity and low *function* similarity, as indicated by the green highlighted cells in Table 9. This presents an opportunity to add a *function* to an existing product from the database of products, as described in Fig. 2, and *resynthesize* to form a new product with enhanced *functions*. To illustrate this statement, in the case study, this translates to physically attaching A′ to the subassembly AC and creating a new product which will have a new *form* configuration and enhanced functionality that are a set of *functions* inclusive of *functions* from A, C, and A′.

Figure 15 presents a graphical representation of *form–function* similarity values created in Table 9. From here, candidates for *resynthesis* can be identified as those which lie in region 1 having high *form* and low *function* similarity values.

The *form* similarities between the subassemblies are calculated based on the similarities between the generated Reeb graphs for each possible combination. The time taken for each comparison varies upon the size of the model and generally takes anywhere from 1 to 60 s running on an Intel Core i7 3.00 GHZ processor with 16 GB ram. This similarity is a measure of physical interchangeability or physical addition that is enabled by geometric similarity. From Table 9, the subassembly combination AC and A′ can be physically added based on the geometry similarities that exist between the two. AC is given preference over BC due to a higher *form* similarity value, even though BC has a lower *function* similarity with A′.

The *function* similarities between subassemblies of Table 9 are calculated using the LSA algorithm. The time taken for each comparison varies upon the size of the model and generally takes anywhere from 1 to 2 s for each similarity computation between the components of the mouse and the eraser when running on a machine with similar specifications as that used to calculate form similarity. The *functions* are taken from the technical description of the mouse and eraser. The *functions* are further divided into modules which relate to the components of each product. In this case study, the *function* of each component A, B, C, A′, and B′ represents the *functions* of the components of the mouse and eraser. Therefore, the *functions* of assembled components such as AB or A′B′ in Table 9, are the aggregation of *functions* from each of the subassemblies A, B, A′, and B′.

Function and *form* similarities have been calculated for each comparison to support the optimal candidate combination that is required for *resynthesis*.

4.3 Results and Discussion. The final *resynthesized* assembly is shown in Fig. 16. Risk Optimizer and Excel Solver were used to model the case study which included 2,000,000 units of each product, i.e., mouse and eraser.

For the environmental constraint, the value for ε was taken as 2000 based on the mpt values of various processes in SIMAPRO [27]. The results (x_{kl} and d_{ij}) are tabulated in Tables 10 and 11.

Table 10 indicates that ABC should be dissembled down to AC (and BC in cases where *resynthesis* is economically or environmentally not optimal) and B. AC is then treated with the EOL decision of *resynthesis*.

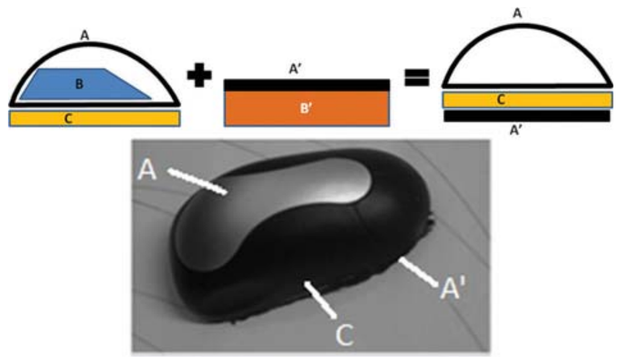

Fig. 16 Schematic and possible final assembly based on product resynthesis

Table 10 The optimal number of subassembly modules and related EOL decision for mouse

i\j	Dispose	Reuse	Remanufacture	Recycle	Resynthesize
ABC	0	0	0	0	0
AB	0	0	0	0	0
AC	0	0	0	0	1800000
BC	0	100000	0	0	0
A	0	100000	0	100000	0
B	0	0	400000	1500000	0
C	0	0	0	100000	0

Table 11 The optimal number of subassembly modules and related EOL decision for eraser

i\j	Dispose	Reuse	Remanufacture	Recycle	Resynthesize
A′B′	0	0	0	0	0
A′	0	0	0	200000	1800000
B′	0	200000	100000	1700000	0

The objective function value is $4,065,000, and the optimal solution indicates that the transitions described in Tables 10 and 11 should be pursued.

The operations that should be carried out are also indicated along with the quantity allocated. For example, for subassembly BC, 100,000 units are reused, which would mean that the internal microchip (B) and base (C) were intact and hence can be *reused* (possibly by combining them with other mouse casings, i.e., A). It can also be observed that only AC is *resynthesized*, because for *resynthesis*, it is essential to have optimal *form* and *function* similarity values and be economically viable, properties that other subassembly combinations do not possess. Likewise, Table 11 shows that A′B′ should be disassembled into A′ and B′, and the operations that should be carried out with them are also indicated.

In order to validate the significance of *resynthesis*, the model was first solved without considering *resynthesis* as a postrecovery option. Thus, only four EOL options (*dispose, reuse, remanufacture*, and *recycle*) are considered, and the LP is solved with $j = 1$, 2, 3, and 4. As discussed in Sec. 2 of this work, existing research has traditionally only focused on these four EOL options.

However, while maintaining the rest of the parameters, the objective function value obtained in the case of only the four EOL options is $3,248,000, which is 20% lower compared to the $4,065,000 profit when *resynthesis* is added as an EOL option. The case study presented in this section takes into account only a small fraction of the total available EOL products. *Resynthesis* applied on a larger scale has the potential of significantly improving enterprise sustainable operations and mitigating harmful effects on the environment.

5 Conclusions and Future Work

This paper proposes a new postrecovery method of *resynthesis* using disassembly methods, product similarity/modularity, and profit-based optimization. A mixed-integer linear optimization model is used to solve the EOL decision model, and an example using a mouse-shaped whiteboard eraser is presented. The results reveal the economic and environmental benefits of using *resynthesis* as a postrecovery option for EOL sustainable design. A validation analysis showed that *resynthesis* can be a better EOL decision from a pure economic standpoint with certain environmental benefits. One of the examples of resynthesis applications at present can be found in Ref. [74].

The results from this research can be extended by sharing EOL operations as well as disassembly operations between products, considering cases of products having multiple functions and uncertainties such as quality and reliability, and effective age of the take-back products can be added to the model. Anticipating EOL decisions can result in significant design modifications. Therefore, determining the specific redesign guidelines according to the results of the model can be investigated in future research directions.

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