DISASSEMBLY SEQUENCING USING TABU SEARCH

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ABSTRACT End-of-life disassembly has developed into a major research area within the sustainability paradigm, resulting in the emergence of several algorithms and structures proposing heuristics techniques such as Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Neural Networks (NN). The performance of the proposed methodologies heavily depends on the accuracy and the flexibility of the algorithms to accommodate several factors such as preserving the precedence relationships during disassembly while obtaining near-optimal and optimal solutions. This paper improves a previously proposed Genetic Algorithm model for disassembly sequencing by utilizing a faster metaheuristic algorithm, Tabu search, to obtain the optimal solution. The objectives of the proposed algorithm are to minimize (1) the traveled distance by the robotic arm, (2) the number of disassembly method changes, and (3) the number of robotic arm travels by combining the identical-material components together and hence eliminating unnecessary disassembly operations. In addition to improving the quality of optimum sequence generation, a comprehensive statistical analysis comparing the previous Genetic Algorithm and the proposed Tabu Search Algorithm is also included.

Keywords: Disassembly Sequence, Electronics Disassembly, End-of-Life Management, Heuristics, Optimization, Robotics Applications, Tabu Search.

INTRODUCTION

Products in today's market can be generally classified into two categories: efficient and responsive. Efficient products are considered to have a stable and constant demand, supply, pricing, and they tend to move slowly in the supply chain. However, the demand, supply and price for responsive products fluctuate often and these products are characterized by relatively larger profit margins due to their time sensitive nature. This sensitivity requires them to move faster in the forward supply chain to ensure customer satisfaction. With similar logic, the useful life time of responsive products tend to be much shorter than their efficient counterparts due to macro environmental changes, viz., globalization and technological advances. Therefore, reverse distribution systems become instrumental in retrieving these products from the market for subsequent reuse, recycling, or proper disposal. Within responsive products, electrical and electronic equipment (EEE) is the largest growing waste stream requiring economically and environmentally solid and efficient reverse logistics and supply chain operations. EEE uses large quantities of natural resources including substantial amounts of precious metals such as gold, silver, and copper during their production. Furthermore, EEE is composed of several components and subassemblies that can be reused even if the whole product might not be technologically valid. Together with the precious material content, the functionality of these partial structures makes recycling and reuse activities

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economically valid. Reuse, recycling, or proper disposal of any product generally requires disassembly of the end-of-life product. The efficiency of disassembly operations is a crucial factor in the success of any reverse flow. Since using human labor to disassemble these products adds more cost and time to the overall system, the need for utilizing automated solutions become apparent. In addition, the process of disassembly is complicated and carries various risk factors due to the hazardous substances embedded in these products. In some instances, disassembly is also required to replace or fix components that are not accessible by humans, making robotic solutions to the problem the only alternative.

The problem of generating an optimal sequence for disassembly operations is rather challenging due to the uncertainty of the process. EEE is subject to various changes in their original bill-of-materials due to technological advances. For instance, a component inside a personal computer may be altered over time due to an upgrade or a change, such as replacing the RAM capacity. Another, perhaps more important, challenge that contribute to the complication of disassembly operations is the fact that the majority of products are not designed for disassembly; thus requiring destructive disassembly operations in some instances and prohibiting the reuse of still functioning components.

This paper aims at handling the uncertainty and aforementioned challenges via introducing two modules: A sensory system and an online Tabu search algorithm. The sensory system is used to identify the depth of the product with the help of a digital camera capturing product images for processing and detecting the components. The Tabu search algorithm then generates an optimum online real time disassembly sequence using this information, hence overcoming the uncertainty in the product structure.

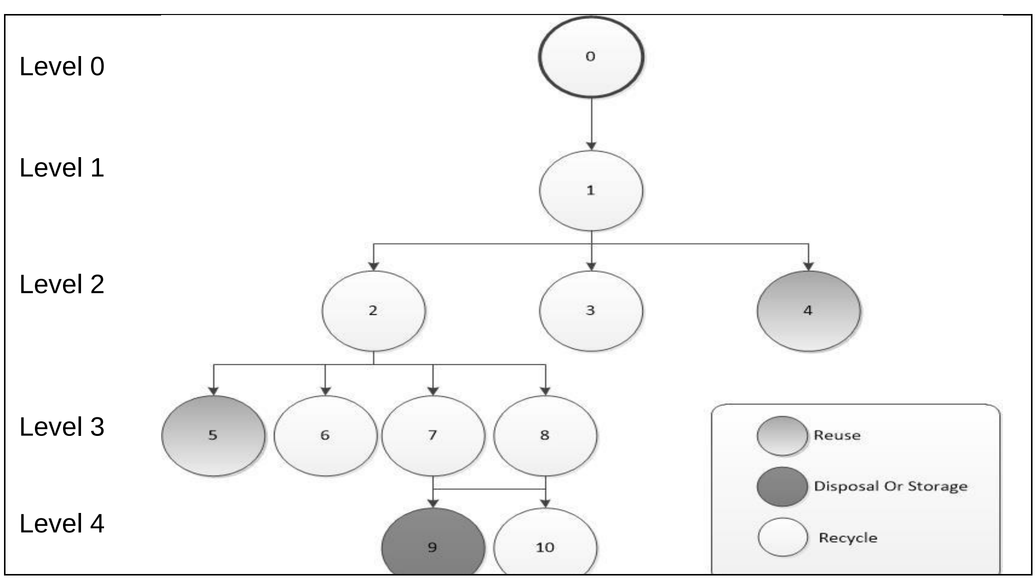

Figure 1. Bill-Of-Materials (BOM) for the EOL product

Figure 1 demonstrates the bill of materials (BOM) of the end-of-life product and depicts the product structure used in this paper. The proposed solution includes a robotic manipulator with a digital camera and utilizes range sensing and component segmentation algorithms. Table 1 lists all the components in the product including their material content and the required disassembly operation (destructive (D) or non-destructive (ND)).

The Tabu Search (TS) algorithm utilized in this paper was first proposed by Fred Glover [1] in 1986 to overcome the Local Optimal Search (LS) problem and enabling global Optima search. Tabu Search generally includes two memories, namely, short and long term memory. The short term memory prevents the reversal of the recent moves. The long term frequency memory reinforces attractive components, forcing the algorithm to move towards more preferable solutions. The algorithm also generates a Tabu list prohibiting returns to previously searched paths. Tabu Search is an extension of classical LS methods. In fact, basic TS can be seen as simply the combination of LS with short-term memories. The recycle back in the moves is prevented by using the memories (Tabu Lists). It follows that the two first basic elements of any TS heuristic are the definitions of its search space and its neighborhood structure [1].

Table 1. End-of-life Product Components, Material Content and Required Disassembly Techniques

Component Number	Description	Material	Disassembly Method
0	Robot reference point		
1	Side cover	Aluminum (A)	D
2	Power supply	Copper(C)	D
3	Sound card	Plastic (P)	ND
4	Modem card	Plastic (P)	ND
5	CPU	Plastic (P)	ND
6	Hard drive	Aluminum (A)	ND
7	CD drive	Aluminum (A)	ND
8	Zip drive	Aluminum (A)	ND
9	RAM	Plastic (P)	ND
10	Drives slot	Aluminum (A)	D

LITERATURE REVIEW AND BACKGROUND

Evolutionary algorithms have been recognized to be well-suited to multiobjective optimization since early in their development [2]. Given that the EOL disassembly embodies several objectives to ensure its efficiency, multiobjective evolutionary algorithms have been extensively used for the EOL disassembly scheduling and/or sequencing problems [3].

Kongar and Gupta [4] considered the case of complete disassembly utilizing both destructive and non-destructive methods. Their paper presented an algorithm for establishing partial and non-destructive disassembly sequences of products, where the recycling and industrial maintenance requires a non-destructive methodology for automatic disassembly. Furthermore, the authors introduced a new representation for the component included in the disassembly based on assemblies of components, not the material. Their method helps in finding the optimum disassembly sequence faster within the process of disassembling products, based on the information from the design process. Therefore, the algorithm could be used in new product design as well as for recycling and product maintenance.

McGovern and Gupta [5] focused on the disassembly line balancing problem aiming at increasing the process productivity while reducing the number of workstations used. To achieve this, their work utilized a genetic algorithm to obtain the optimal or near-optimal solution for the disassembly sequencing.

ElSayed et al. [6] used a Genetic Algorithm with precedence preservative crossover (PPX) to find the optimum or near-optimum disassembly sequence for complete disassembly The objective of the proposed GA is to minimize the total fitness function by minimizing (i) the traveled distance, (ii) the number of disassembly method changes, and (iii) by combining the identical-material components together, eliminating unnecessary disassembly operations. Following this, a roulette wheel is employed to select the sequence of parents in the next generation. The objectives include, (1) minimizing the number of workstations and hence, minimizing the total idle time, (2) ensuring workstation idle times are similar, (3) removing hazardous parts early in the disassembly sequence, (4) removing high-demand parts before low-demand parts, and (5) minimizing the number of part removal direction changes required for disassembly. The authors also introduced a new efficiency measurement tool combining Line Efficiency (LE) and Smoothness Index (SI).

Torres et al. [7] proposed a cell with a degree of automation in non-destructive product disassembly. The authors also employed computer vision for object detection in addition to a modeling system for the products. The modeling system provides information regarding the type of products and the main components of the product architecture.

ElSayed et al. [8] proposed an online Genetics Algorithm (GA) that aims at handling uncertainty in the EOL product structure. The algorithm consists of two modules: (i) a sensory-driven visual and range acquisition recovery system, and (ii) an online genetic algorithm (GA) model. The object detection converts objects from 3D to 2D structures via a camera-based algorithm resulting in $2\frac{1}{2}$ D images. The proposed algorithm finds the optimal disassembly sequence while reducing the time required to disassemble the product.

Xing et al. [9] conducted a survey that reviews the application of soft computing to remanufacturing. The survey aimed at finding answers to various remanufacturing software questions such as the main problems within remanufacturing systems and existing remanufacturing techniques. The survey utilized the data provided by the library of the University of Johannesburg, South Africa. The results were categorized into two basic groups; disassembly and remanufacturing.

Kalayci and Gupta [10] introduced a Tabu Search (TS) algorithm to solve the Disassembly Line Balancing Problem (DLBP) with multiple objectives. The DLBP described in the paper consists of multiple objectives requiring the assignment of disassembly tasks to a set of ordered disassembly workstations while satisfying the disassembly precedence constraints and optimizing the effectiveness of several measures. The authors aimed at reducing the number of disassembly steps required to minimize the total idle time for all workstations. They also assigned the removal of hazardous and high demand components maximum priority.

Torres et al. [11] proposed two types of cooperation among robot arms aiming to manage the task between multiple robots. In the first cooperation, two or more robots cooperate to achieve the same task. In the second type, several tasks are achieved by different robots at the same time. The entire design was built based on a decision tree. The main goal in their follow up work [12] is to retrieve materials from the EOL product via destructive disassembly.

Kuren [13], to find an optimum disassembly path for EOL products, proposed a disassembly cell prototype and presented a case study for mobile phone disassembly. Since a destructive method was used in this paper, the need to used precedence relationships has been eliminated in the proposed solution.

This work is a follow up on the algorithms in Kongar and Gupta [4]. The proposed genetic algorithm includes PPX (Precedence Preservation Crossover) to respect the hierarchical structure of the EOL product. The main objective of the algorithm is to minimize the Makespan by minimizing the number of direction changes, disassembly method changes and combining the identical-material components.

PROPOSED METHODOLOGY

The proposed algorithm aims at minimizing the uncertainty in the disassembly process via two techniques: (1) A sensory system, and (2) an online real-time Tabu Search module. The sensory system consists of a robotic manipulator, a digital camera and an image processing algorithm. The camera captures the images of components and/or subassemblies accessible at each level (Fig. 1) and identifies the depth of each available entity. The Tabu Search (TS) algorithm then uses this information to determine the optimal disassembly sequence for the current level. Since the visibility and accessibility of components are altered following each disassembly operation, the Tabu Search algorithm seeks another optimal sequence for the newly generated EOL product structure. The sensory system captures product images after every removal, providing the Tabu Search algorithm with accurate online real-time data. This loop continues until all the components demanded for recycling and reuse are removed. Unwanted components are also subject to disassembly, if and only if their removal would lead to accessibility of desired components, i.e., the components demanded for reuse or recycling. This condition prohibits unnecessary movements and hence reduces the overall Makespan.

The Tabu Search algorithm is motivated by multiple objectives while searching for the best possible sequence within each layer. The algorithm ensures that (1) the distance traveled by the robot arm, (2) the number of disassembly method changes, i.e., from *ND* to *D* or vice versa, and (3) the number of material changes are minimized. Objective (3) is achieved by grouping the components that are made out of identical materials and increases the overall makespan via a panelizing constant if the following component to be disassembled consists of different material. A literature example is considered to demonstrate the functionality of the proposed algorithm.

NUMERICAL METHODOLOGY

The Tabu Search algorithm was applied to the numerical example provided in Table 1 for the product provided in Figure 1. One thousand independent runs were completed to test the Tabu Search and to compare the solutions with the previously published Genetic Algorithm results provided in Kongar and Gupta [4]. Tabu Search results proved to be significantly better than the Genetic Algorithm results.

In order to validate the reliability of results, various statistical test were conducted using SPSS, Excel, Matlab and the Arena Simulation software. The SPSS output of the summary statistics for 1,000 random runs for Tabu Search (TS) and Genetic Algorithm (GA) are provided in Table 2. The superiority of Tabu Search is clearly evident from the table. For example, the median and mode for Tabu Search runs in milliseconds (187.5, 197.65625) are significantly less than the median and mode of the Genetic Algorithm runs (406.25, 402.9844).

CONCLUSION

Tabu Search run times are significantly less than Genetic Algorithm run times, hence providing faster solutions to the disassembly sequencing problem.

Table 2. Summary Statistics for Tabu Search (TS) and Genetic Algorithm (GA) Run Times in milliseconds

	Tabu Search (TS)	***Genetic Algorithm (GA)***
Mean	197.65625	402.9844
Standard Error	2.033077929	1.125706
Median	187.5	406.25
Mode	156.25	390.625
Standard Deviation	64.29156917	35.59795
Sample Variance	4133.405867	1267.214
Kurtosis	0.3840795	6.296531
Skewness	0.95576832	1.572811
Range	328.125	328.125
Minimum	78.125	296.875
Maximum	406.25	625
Sum	197656.25	402984.4
Count	1000	1000
Confidence Level (95.0%)	3.989593024	2.20902

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