Performance Analysis of Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order System

Ammar Y. ALOQAHTANI 1, Surendra M. GUPTA 2, and Kenichi NAKASHIMA 3

1 Department of Industrial Engineering, King Abdulaziz University, Jeddah 22254, Saudi Arabia
2 Department Mechanical and Industrial Engineering, Northeastern University, Boston, MA, 02115 U.S.A
3 Department of Industrial Engineering and Management, Kanagawa University, Yokohama, 221-8686, Japan

Abstract: In product recovery the disassembly process has an important role since it allows for separation and retrieval of desired parts and materials. End-of-life (EOL) products with missing and/or nonfunctional components increase the uncertainty associated with disassembly yield. Sensor-embedded products (SEPs) eliminate a majority of uncertainties involved in EOL management by providing life-cycle information of products. This information includes the content of each product and component conditions, and enables the estimation of remaining useful life of the components. Once the data on the products are captured, it is possible to make optimal EOL decisions without any preliminary disassembly or inspection operations.

This paper presents an Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order (AR-TODTORTO) model with disassembly precedence relationships among components of an air conditioner (AC). It also inspects and analyzes the impact of using smart sensors in End-of-Life products (EOLPs) on system performance. Various experimental design studies are conducted based on orthogonal arrays (OAs). The customers’ demands may be satisfied either by purchasing new components, reassembling components from the returned used products, refurbishing products, or remanufacturing used products based on customers’ needs. Discrete event simulation models are used to calculate various performance measures under different experimental conditions.

Key Words: Sustainable manufacturing, Reverse supply chain, Remanufacturing, Sensor embedded products, RFID.

1. Introduction
Currently, the number of studies raising interest in the end-of-life (EOL) stage of a product, has gained much attention from researchers. This is due, on one hand, to environmental factors, government regulations and public demands, and on the other hand, to potential economical profits that could be obtained by implementing reverse logistics and product recycling resolutions. Manufacturers try to cope with consumer awareness towards environmental issues and stricter environmental legislation by setting up facilities which involve the minimization of the amount of waste sent to landfills by recovering materials and components from returned or end-of-life products (EOLPs).

Remanufacturing processes of EOLPs include cleaning, disassembling, sorting, inspecting and recovering, or disposal. The recovery process could be implemented for product, components or material. Based on the condition of the EOLPs there are several stages for the recovery process: product recovery (refurbishing, remanufacturing, repairing), component recovery (cannibalization), and material recovery (recycling).

Disassembly is the first fundamental step in remanufacturing, recycling, and disposing. Disassembly is the process of separating the product into its components and materials using non-destructive, semi-destructive, or destructive operations. The main objective of disassembly is to support the goal of recovery processes by minimizing manufacturers’ dependency on natural resources and their rate of depletion.

In recent years, the concept of disassembly-to-order (DTO) has gained attention. It targets to satisfy component and material demands by cannibalizing the EOLPs by determining the optimum number of EOLPs to disassemble. Meanwhile, products without embedded smart sensors generally provide no information about the state of EOL components until the end of the disassembly process. At that point each component needs to be tested. This could have a significant effect on the cost-effectiveness of disassembly. Additionally, time and resources spent on disassembling non-functional components is a wasted effort that will increase the disassembly and backorder costs. High backorder costs could be mitigated by increasing the components safety stock levels resulting in higher holding costs.

Another fundamental step for product recovery is repairing EOLPs. In some cases repairing the EOLP may need a non-functional component to be replaced. It could also require disassembly of functional and non-functional components due to disassembly precedence relationships before replacement. The recovered product may be sold as a remanufactured or a used product based on the final condition.

The sensors are implanted during the manufacturing process of sensor-embedded products (SEPs) for tracing, predicting and gathering useful product information (e.g., product identity, type of components, remaining service life, remanufacturing...
ing history, non-functional, replaced, or missing components) at the time of return. These sensors smooth the data collection process prior to disassembly of an EOL product which leads to savings in testing, disassembly, disposal, backorder, and holding costs.

This paper investigates an Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order (ARTODTORTO) facility with disassembly precedence relationships among components of an air conditioner (AC). It also examines and analyzes the impact of embedded sensors in EOL products on system performance. Different experimental design studies are conducted based on orthogonal arrays (OAs). The customers’ demands may be satisfied either by purchasing new components, using components recovered from returned products, refurbishing products, or remanufacturing products based on customers’ needs. Discrete event simulation models are also used to calculate various performance measures’ values under different experimental conditions.

The next section presents a literature review in the relevant areas. The objective of the study is stated in Section 3. Section 4 describes the ARTODTORTO model. Design-of-experiments study is presented in Section 5. Results of the experiments are discussed in Section 6. Finally, Section 7 presents some concluding remarks.

2. Literature Review
This section provides a literature review on the issues considered in this research. First, a brief review on environmentally conscious manufacturing and product recovery are presented. Then, a discussion on sensor-embedded products studies is offered.

2.1 Environmentally Conscious Manufacturing and Product Recovery
Comprehensive reviews of issues in environmentally conscious manufacturing and product recovery are presented by Gungor and Gupta [9] and Ilgin and Gupta [14]. The most widespread aspect in remanufacturing research area is disassembly due to its significant role in any recovery system. The studies of disassembly issues could be classified into five main categories (viz., scheduling, sequencing, disassembly line balancing, disassembly-to-order and automated disassembly).

Scholars have deliberated these different categories of disassembly processes including: scheduling [2],[3],[11], sequencing [1],[32], disassembly line balancing [31], disassembly-to-order [18],[23],[25],[29],[30], and automated disassembly [4],[20],[37]. For different aspects of disassembly, see the book by Lambert and Gupta [28].

ARTODTORTO system built in this study is based on disassembly-to-order researches. Ondemir and Gupta [33] proposed a multi-criteria decision making model for advanced repair-to-order and disassembly-to-order system which deals with products that are embedded with sensors and RFID tags. Kongar and Gupta ([22],[23],[24],[25]) presented preemptive goal programming (PGP), fuzzy goal programming (FGP), linear physical programming (LPP), and multi objective tabu search models for the disassembly-to-order problem and illustrated implementations of their models in various circumstances. Gupta, Imtanavanich, and Nakashima [12] proposed an artificial neural network model in order to solve the DTO problem.

Remanufacturing has also been researched recently by many authors because traditional production planning approaches fall short in a product recovery setting. Lage and Godinho Filho [27] reviewed 76 journal articles published on remanufacturing between 2000 and 2009. Georgiadis and Athanasiou [7] presented the impact of two-product joint lifecycles on the capacity planning of remanufacturing networks. The authors put emphasis on the inherent uncertainties of remanufacturing systems and proposed a systems dynamics model and design of experiments for capacity planning. A study by Georgiadis and Athanasiou [8] deals with long-term demand-driven capacity planning policies in the reverse channel of closed-loop supply chains with remanufacturing, under high capacity acquisition cost coupled with uncertainty in actual demand, sales patterns, quality and timing of end-of-use product returns. The authors studied the system’s response in terms of transient flows, actual/desired capacity level, capacity expansions/contractions and total supply chain profit, employing a simulation-based systems dynamics optimization approach. For different aspects of remanufacturing, see the book by Ilgin and Gupta [17].

2.2 Sensor Embedded Products
The expansion of technology has allowed manufacturers to build sensors in smaller sizes and at lower cost. The acquisition of the essential life-cycle components of a product with sensors embedded is presented by Zeid et al.[39] and Vadde et al.[38]. Other researches aim to explore whether the use of embedded sensors would improve the efficiency of product life-cycle management. A comprehensive survey on the commercial sensor systems used in the health management for electronic products and systems was reported by Pecht [35]. Fang et al.[5] reviewed the current practices toward the development of embedded sensors in products in two primary categories, namely, embedding sensors in products and representing and interpreting sensor data.

To provide easy access for retrieving, updating, and managing of information in the product life-cycle, radio-frequency identification (RFID) tags have been studied by Kiritsis et al. [21], and Parlidak and McFarlane [34]. The practical and economic impact of using RFID in alleviating the quality uncertainty associated with the remanufacturing processes has been investigated by Kulkarni et al.[26]. Ferrer et al.[6] described an application of RFIDs where active RFIDs can be used for easy identification and localization of components within a remanufacturing facility, while passive RFIDs can be permanently tagged onto components of remanufacturable products at the beginning of their service life.

3. Objective of this Study
The objective of this study is to examine and determine the influence of SEPs and RFID tags on the various performance measures (viz., disassembly cost, disposal cost, backorder cost, holding cost, testing cost, transportation cost, total cost, total revenue, and profit) and to find how to process EOLPs to meet products, components and materials demands using the Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order (ARTODTORTO) system. There are four main objectives for ARTODTORTO system to optimize
(i.e. minimize the total cost, minimize the number of disposed items, maximize material sales revenue, and maximize customer’s satisfaction level by meeting the demand).

4. Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order System Description

The ARTODTORTO system considered in this study is a product recovery system. Based on the condition of EOL air conditioner (AC), it will go through a series of recovery operations as shown in figure 1. Refurbishing and Repairing processes may require reusable components to meet the demand of the product. This requirement satisfies the internal and the external component demand. Both will be satisfied using disassembly of recovered components.

![Table 1 AC Components and precedence relationship](image)

| Component Name | Station | Code | Precedence relationship |
|----------------|---------|------|-------------------------|
| Evaporator     | 1       | A    |                         |
| Control box    | 2       | B    |                         |
| Blower         | 3       | C    | A, B                    |
| Air guide      | 3       | D    | A, B, C                 |
| Motor          | 4       | E    | A, B, C, D              |
| Condenser      | 5       | F    |                         |
| Fan            | 5       | G    | F                       |
| Protector      | 6       | H    |                         |
| Compressor     | 6       | I    | H                       |

EOL ACs arrive at the ARTODTORTO system for information retrieval using radio frequency data reader which are stored in the facility’s database. Then the ACs go through a six-station disassembly line. Complete disassembly is performed to extract every single component. Table 1 shows the precedence relationships between the AC components. There are nine components in an AC consisting of evaporator, control box, blower, air guide, motor, condenser, fan, protector, and compressor as shown in figure 2. Exponential distributions are used to generate disassembly times at each station, interarrival times of each component’s demand, and interarrivel times of EOL AC. All EOLPs after retrieval of the information are shipped either to station 1 for disassembly or, if EOLP needs only repair for EOLPs after retrieval of the information are shipped either to station 1 for disassembly or, if EOLP needs only repair for EOLPs, then destructive disassembly is used such that the other components’ functionality will not be damaged. Therefore, unit disassembly cost for a functional component is higher than nonfunctional component. After disassembly there is no need for component testing due to the availability of information on components’ conditions from sensors. It is assumed that the demands and life cycle information for EOLPs are known. It is also assumed that retrieval of information from sensors costs less than actual inspection and testing. ARTODTORTO system demand, disassembly, refurbishing and remanufacturing flow charts for sensor embedded ACs are shown in figure 3, figure 4, figure 5 and figure 6 respectively.

Recovery operations differ for each SEP based on its condition and estimated remaining life. Recovered components are used to meet components and spare parts demands, while recovered or refurbished products are used for product demands. Also, material demands are met using recycled products and components. Recovered products, and components are characterized based on their remaining life times and are placed in different life-bins (e.g. 1 year, 2 years, etc.) waiting to be retrieved via a customer demand. Underutilization of any product or component could happen when it is qualified for a higher life-bin and is placed in a lower life bin because the higher life bin is full. Any product, component or material inventory which is greater than the maximum inventory allowed is assumed to be extra and is used for material demand or disposed.

In order to meet the product demand, repair and refurbish options could also be chosen. EOLP may have missing or nonfunctional (broken, zero remaining life) components that need to be replaced or replenished during the repairing or refurbishing process to meet certain remaining life requirement. EOLP may also consist of components having lesser remaining lives than desired, and for that reason might have to be replaced.

5. Design-of-Experiments

According to a series of comprehensive studies done for the quantitative evaluation of the performance of SEPs on a disassembly line (Ilgin and Gupta in [13],[15],[16]), SEPs had a favorable resolve to handle remanufacturing uncertainty. To test this claim on ARTODTORTO a simulation model was built to represent the entire system and its behavior was observed under different experimental conditions. Arena version 14.5 was used to build the discrete-event simulation models. A total of 69 factors were identified, at 3 levels, viz., low, intermediate and high levels. The reason for the proposed three-level design was to model the possible curvature in the response function and to handle the case of nominal factors at 3 levels. The parameters, factors and factor levels are given in Table 2 and Table 3.

A full-factorial design with 69 factors at 3 levels would require an extensive number of experiments (viz., $8.34e+32$). To reduce the number of experiments to a practical level, orthogonal arrays (OAs) were used [36]. OAs provide the way of conducting the minimal number of experiments. In most cases orthogonal array is more efficient when compared to many other statistical designs. The minimum number of experiments that are required can be calculated based on the degrees of freedom, $N$, as follows [36]:

$$N = 1 + \sum_{i=1}^{\text{variables}} ((\# \text{of levels of variable } i) - 1)$$
number of experiments must be greater than or equal to system’s degrees-of-freedom, N. Precisely, \( L_{139}(3^{69}) \) OA was chosen since the degrees of freedom for ARTODTORTO system is 139. That means, it requires 139 experiments to accommodate 69 factors with three levels each. OAs assume that there is no interaction between any two factors.

Arena software version 14.5 was used to build the discrete-event simulation model and calculate all the cost and revenue parameters corresponding to each of the 139 experiments. Furthermore, for validation and verification purposes animations of the simulation models were built along with multiple dynamic and counters plots. Ten replications with six months (eight hours a shift, one shift a day and 5 days a week) were used to run each experiment.

Arena models calculate the profit using the following equation

\[
\text{Profit} = SR + CR + SCR - HC - BC - DC - DPC - RPC - RMC - TPC
\]

where SR is the total revenue generated by the Product, component and material sales during the simulated run time, CR is the total revenue generated by the collection of EOL ACs during the simulated run time, SCR is the total revenue generated by selling scrap components during the simulated run time, HC is the total holding cost of products, components, material and EOL ACs during the simulated run time, BC is the total backorder cost of products, components and material during the simulated run time, DC is the total disassembly cost during the simulated run time, DPC is the total disposal cost of components, material and EOL ACs during the simulated run time, RPC is the total repair cost during the simulated run time, RMC is the total remanufacturing cost of products during the simulated run time, and TPC is the total transportation cost during the simulated run time.

In each AC three types of scraps are recovered and sold, viz., evaporator and condenser are sold as copper scrap, chassis and metal cover are sold as steel scrap and blower, fan and air guide are sold as fiberglass. All the other components are considered as waste components. Scrap revenue from steel, copper and fiberglass components is calculated by multiplying the weight in pounds by the unit scrap revenue of each metal type. Similarly, disposal cost is calculated by multiplying the waste weight by the unit disposal cost. The time to retrieve information from sensors is assumed to be 20 second per AC. The transportation cost is assumed to be $ 50 for each trip of the truck. There are different prices in the secondary market of recovery product due to different level of quality.

6. Results

In order to have a quantitative assessment of the impact of SEPs on ARTODTORTO system performance, the design-of-experiments scheme presented in the previous section was im-
implemented. Table 4 and Table 5 show a sampling of the 139 experimental results.

Table 4 Cost measures of the ARTODTORTO system

| Exp. | Total Repair cost | Total Recycling cost | Total Holding cost | Total Disposing cost |
|------|-------------------|----------------------|--------------------|----------------------|
| 1    | $334,142          | $222,761             | $445,522           | $111,381             |
| 2    | $299,766          | $399,688             | $99,922            |                      |
| 3    | $285,410          | $190,273             | $380,547           | $95,137              |
| ...  | ...               | ...                  | ...                | ...                  |
| 137  | $314,805          | $206,268             | $412,536           | $103,134             |
| 138  | $314,805          | $209,870             | $419,740           | $104,935             |
| 139  | $283,244          | $188,829             | $377,658           | $94,415              |
| Avg. | $302,053          | $201,369             | $402,738           | $100,684             |

From Table 4 and Table 5 it is clear that the average total revenue is greater than the average of the total cost for all 139 experiments and the average profit is more than 270 thousand dollars. Thus, the ARTODTORTO system is economically viable when using sensor embedded products (SEPs) and RFID tags to eliminate the effect of uncertainties in quality, quantity and timing of returned products.

The presented air conditioner (AC) case study illustrates how the information collected and stored on the embedded sensors can be used to fully recover the product so as to satisfy the demands for used components, remanufactured products and recycled materials.
7. Conclusion
In this paper, an Advanced Remanufacture-To-Order, Disassembly-To-Order and Refurbishment-To-Order (ARTODTORTO) system was investigated. The ARTODTORTO system uses information technology devices in a demand-driven environment to reach the optimum disassembly,
repair, disposal, recycling, refurbishing, remanufacturing and inventory plans.

A case example of air conditioner was considered to illustrate the application of the proposed approach and a discrete-event simulation model was built using Arena 14.5 software package. Separate design-of-experiment studies based on OAs were carried out to assist and monitor the behaviors and sensitivity of different parameters.

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### Table 3: Parameters used in the ARTODORTO system

| Factor                                      | Unit            | Levels 1 | Levels 2 | Levels 3 |
|---------------------------------------------|-----------------|----------|----------|----------|
| Mean arrival rate of EOL ACs                | Products/hour   | 10       | 20       | 30       |
| Probability of Repair EOLPs                 | %               | 5        | 10       | 15       |
| Probability of a nonfunctional control box  | %               | 10       | 20       | 30       |
| Probability of a nonfunctional motor        | %               | 10       | 20       | 30       |
| Probability of a nonfunctional fan          | %               | 10       | 20       | 30       |
| Probability of a nonfunctional compressor   | %               | 10       | 20       | 30       |
| Probability of a missing control box       | %               | 5        | 10       | 15       |
| Probability of a missing motor              | %               | 5        | 10       | 15       |
| Probability of a missing fan                | %               | 5        | 10       | 15       |
| Probability of a missing compressor        | %               | 5        | 10       | 15       |
| Mean non-destructive disassembly time for station 1,2,3 & 5 | Minutes | 0.75  | 1        | 1.25     |
| Mean non-destructive disassembly time for station 4 | Minutes | 0.50  | 0.75     | 1        |
| Mean non-destructive disassembly time for station 6 | Minutes | 1.00  | 1.5      | 2        |
| Mean destructive disassembly time for station 1,2,3 & 5 | Minutes | 0.40  | 0.5      | 0.65     |
| Mean destructive disassembly time for station 4 | Minutes | 0.30  | 0.45     | 0.6      |
| Mean destructive disassembly time for station 6 | Minutes | 0.6   | 0.75     | 1        |
| Mean Assembly time for station 1,2,3 & 5     | Minutes | 1.00  | 1.25     | 1.5      |
| Mean Assembly time for station 4             | Minutes | 0.75  | 1        | 1.25     |
| Mean Assembly time for station 6             | Minutes | 1.25  | 1.5      | 1.75     |
| Mean demand rate Evaporator                 | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Control Box            | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Blower                 | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Air Guide              | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Motor                  | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Condenser              | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Fan                    | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Protector              | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for Compressor             | Parts/hour      | 10      | 15       | 20       |
| Mean demand rate for 1,2 & 3 Years AC       | Products/hour   | 5       | 10       | 15       |
| Mean demand rate for Refurbished AC         | Products/hour   | 5       | 10       | 15       |
| Mean demand rate for Material               | Products/hour   | 5       | 10       | 15       |
| Percentage of Good Parts to Recycling       | %               | 95      | 0.85     | 0.75     |
| Mean Metals Separation Process              | Hour            | 1.00    | 1.25     | 1.5      |
| Mean Copper Recycle Process                 | Minutes         | 1.00    | 1.25     | 1.5      |
| Mean Steel Recycle Process                  | Minutes         | 1.00    | 1.25     | 1.5      |
| Mean Fiberglass Recycle Process             | Minutes         | 1.00    | 1.25     | 1.5      |
| Mean Dispose Process                        | Minutes         | 0.50    | 0.75     | 1        |
| Maximum inventory level for AC               | Products/hour   | 10      | 15       | 20       |
| Maximum inventory level for Refurbished AC  | Products/hour   | 10      | 15       | 20       |
| Maximum inventory level for AC Component    | Products/hour   | 10      | 15       | 20       |

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Ammar Y. ALQAHTANI

is a research assistant of industrial engineering at King Abdulaziz University in Jeddah, Saudi Arabia. He holds a BSc. and MSc. degrees in Industrial Engineering and nowadays he is persuading his PhD. in Industrial Engineering at Northeastern University. His research interests are in the areas of environmentally conscious manufacturing, product recovery, reverse logistics, Closed-loop supply chain and simulation.

Surendra M. GUPTA

is a Professor of Mechanical and Industrial Engineering and the Director of the Laboratory for Responsible Manufacturing, Northeastern University. He received his BE in Electronics Engineering from Birla Institute of Technology and Science, MBA from Bryant University, and MSIE and Ph.D. in Industrial Engineering from Purdue University. He is a registered professional engineer in the State of Massachusetts. Dr. Gupta’s research interests are in the areas of Production/Manufacturing Systems and Operations Research. He is mostly interested in Environmentally Conscious Manufacturing, Reverse and Closed-Loop Supply Chains, Disassembly Modeling and Remanufacturing. He has authored or co-authored well over 475 technical papers published in books, journals and international conference proceedings. His publications have been cited by thousands of researchers all over the world in journals, proceedings, books, and dissertations. He has traveled to all seven continents viz., Africa, Antarctica, Asia, Australia, Europe, North America and South America and presented his work at international conferences on six continents. Dr. Gupta has taught over 100 courses in such areas as operations research, inventory theory, queuing theory, engineering economy, supply chain management, and production planning and control. Among the many recognitions received, he is the recipient of outstanding research award and outstanding industrial engineering professor award (in recognition of teaching excellence) from Northeastern University as well as a national outstanding doctoral dissertation advisor award.

Kenichi NAKASHIMA

is a Professor in the Department of Industrial Engineering and Management at Kanagawa University, Japan. He received his BE, MS and PhD in Industrial Engineering from Nagoya Institute of Technology, Nagoya, Japan, in 1990, 1992 and 1995, respectively. From 1995 to 1996, he was a Research Associate in the Department of Industrial Management, Osaka Institute of Technology. He was an Assistant Professor from 1996 to 2000 and an Associate Professor from 2000 to 2010 in the Department of Industrial Management, Osaka Institute of Technology. He was also a visiting Assistant Professor at MIT in 1998. Dr. Nakashima received the Research Award for young researchers from Japan Industrial Management Association in 1997. He has served as members of technical committees of international conferences. His research interests include dynamic programming, Markov decision processes, production management and management information systems. His papers have appeared in International Journal of Production Research, International Journal of Production Economics and IEEE Transactions on Systems, Man and Cybernetics (Part A).