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# COST-BENEFIT ANALYSIS OF SENSOR-EMBEDDED PRODUCTS BASED DISASSEMBLY-TO-ORDER SYSTEM

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## ABSTRACT

Due to environmental awareness and realization of cost savings, disassembly-to-order (DTO) concept has become popular. One of the main obstacles to making optimal DTO decisions is the uncertainty involved in end-of-life products (EOLPs). This uncertainty is due to the lack of information about the condition and the quantity of EOLPs returned. This uncertainty can be removed by sensors monitoring the products in their life-cycle. However, DTO systems utilizing these sensors will be more costly to establish and maintain.

This paper presents economic justification of establishing advanced disassembly-to-order (DTO) systems in which sensor-embedded end-of-life products are disassembled in order to fulfill sophisticated demands for both components and materials.

## INTRODUCTION

As a reverse logistics concept, disassembly-to-order (DTO) has become a popular research area over the recent years. DTO aims to fulfill component and material demands by cannibalizing the EOLPs. The goal of DTO is to determine the optimum number of EOLPs to be disassembled in order to fulfill the demand for components and materials such that some desired criteria of the system are satisfied. However, EOLPs originating from many sources in which they were subject to different operating environments, usage patterns and customers upgrades do not show typical qualities. Therefore, DTO's outcome is, in fact, fraught with errors. This is due to the unpredictable, hence uncertain nature of EOLPs. Sensor-embedded products based disassembly-to-order systems address this issue.

A sensor-embedded product (SEP) contains sensors that monitor the product during its life cycle and record the product life-cycle data. By facilitating data collection during product usage, sensors enable the prediction of product or component failures and estimation of the remaining life of components as the products reach their EOL. This allows decision makers to make optimal DTO plans which also fulfill sophisticated demands based on remaining life of the components [12]. Determination of the optimal solution to the DTO problem is obviously the most important advantages to the sensor-embedded product based DTO systems along with time savings, avoiding inspections and unnecessary disassemblies, and efficient inventory management. Moreover, these advanced DTO systems treat each EOLP individually. By means of this feature, not only the number of EOLPs but also the specific EOL products to disassemble could be optimally determined. Thus, sensor-embedded products based DTO systems are expected to have lower operational cost than that of traditional DTO systems. However, an advanced DTO system utilizing the data collected by the sensors will be more costly to establish and maintain. In order for companies to invest on this concept, the benefits of these systems should more than outweigh the cost of the data collection technology and prove to be justifiable (i.e. profitable).

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In this paper, economic justification of establishing advanced disassembly-to-order (DTO) systems is presented. Traditional DTO models (TDTOM) set the benchmark of economic performance against which to evaluate the advanced DTO model (ADTOM). Benefits of ADTOM over the benchmark are evaluated using cost-benefit analysis. In economical analysis of these two systems, we determined the difference between these two models' operational costs. What is obtained is the benefit of ADTOM. Therefore, the benefit of ADTOM (i.e. the value of life cycle information, *V)* can be calculated as follows; $V = C_{TDTOM} - C_{ADTOM}$, where $C$ is the total operational cost of a system.

## LITERATURE REVIEW

Disassembly problems have been discussed by many authors. Gupta and Taleb [4] proposed an algorithm for planning the disassembly of a discrete, well-defined product structure. The algorithm determines the quantity and schedule of disassembly of a product to fulfill the demand for its various parts. In their follow-up papers, Taleb and Gupta [15] extended the methodology to include the disassembly of multiple product structures. Lambert [9], Pnueli and Zussman [14] and Moore et al. [10] conducted research on disassembly planning. Gungor and Gupta [2] [3] addressed the problems of disassembly processes and disassembly sequence planning. Inderfurth and Langella [7] presented a probabilistic DTO model and proposed heuristic methods to obtain deterministic yields.

Product life cycle data collection is a relatively new idea. Hence, a limited number of papers are available in the literature. Parlikad and McFarlane [13] showed qualitatively that the availability of product information has a positive impact on product recovery decisions. Vadde et al. [17] proposed a complete disassembly system utilizing sensor-embedded products and conducted a simulation study to present how better solutions could be obtained. Ketzenberg [8] measured and evaluated the value of information through three information-known cases that separately address different types of uncertainties: demand, recovery yield, and capacity utilization. Ondemir and Gupta [11] proposed a mathematical DTO model utilizing life-cycle data in order to fulfill remaining life time based sophisticated component demands. In its follow up paper [12], authors extended the model in order to meet the sophisticated product demands by using repair option.

## PROBLEM DEFINITION

Reverse logistics operations are much more complex than those of forward logistics. A lot of complexity stems from high degrees of uncertainties in the quality and quantity of products [1]. Traditional deterministic DTO models determine how many EOLPs to disassemble assuming that all EOLPs of the same type show the same properties (conditions, component yields), even though EOLPs may have been used under completely different circumstances. This assumption allows decision maker to decide the number of EOLPs to be processed based on the initial bill of materials. In real life, however, each EOLP shows different characteristics due to the working conditions, usage patterns, maintenance, etc. which it has been subject to. Since none of these are known prior to disassembly, with the current methods, it is impossible to know exactly how many useful components exist in the EOLP inventory and what their conditions are. To address this issue, researchers proposed probabilistic models using probability distribution of the component yields [7]. Probabilistic models, once the probability distributions are known, provide good estimations for the number of components hidden in the whole EOLP inventory. Therefore, these models can tell how many useful components could be recovered if the whole or a certain portion of EOLP inventory is disassembled. This process, unfortunately, requires the disassembly of all EOLPs including those which do not have any components that are satisfactory to meet the demand specifications. In other words, there is a predicted and admitted waste of time, labor and hence money involved. The only way to deal with this problem is to know which EOLP contains what prior to disassembly.

Besides, as remanufactured and refurbished products gain popularity in the market, demands get more sophisticated and occur based on the remaining life of used products or components. In this case, methods based on bill of materials are obviously useless. Probabilistic yield models are also incapable of addressing the issue, because the actual problem turns into determination of which EOLPs to disassemble in order to fulfill the remaining-life based demands.

An ADTOM can address afore mentioned issues. However, an advanced will be more costly to establish and maintain. Hence, the main problem is to determine the value of extra information obtained by sensors. In order for the model to prove to be profitable, cost of the information must be lower than its value. The nomenclature for the both models is given in Table 1.

**TABLE 1: NOMENCLATURE**

| | | | |
|---|---|---|---|
| **Parameters:** | | $\pi b_{tj}$: | Broken component $j$ yield rate of an EOLP of type $t$, |
| $b, i, j,$ $k, t$: | Running numbers, | $c_{1j}$: | Disassembly cost of component $j$, |
| $n$: | Number of EOLPs on hand, | $c_{2j}$: | Recycling cost of component $j$, |
| $m$: | Number of components dealt with, | $c_3$: | Disassembly cost of a broken component, |
| $B$: | Number of life-bins desired, | $c_{jb}$: | Outside procurement cost of a component $j$ that has a remaining life of b years. |
| $K$: | Number of material types dealt with, | **Variables:** | |
| $T$: | Number of product types dealt with, | $\bar{x}_i$ : | Takes the value 1 if EOL $i$ is disassembled, zero otherwise, |
| $a_{ij}$: | Parameter taking the value one if component $j$ is available and useful in EOLP $i$, | $x_{ijb}$: | Takes the value 1 if component $j$ in EOLP $i$ is disassembled into remaining-life-bin $b$, zero otherwise, |
| $f_{ij}$: | Parameter taking the value one if component $j$ is non-operable in EOLP $i$, | $z_t$: | Number of disassembled EOLPs of type $t$ |
| $y_{jk}$: | Material $k$ yield of component $j$, | $r_{jb}$: | Number of operable $j$ components in remaining-life-bin $b$ that are recycled, |
| $cd_{jb}$: | Demand for component $j$ | $l_{jb}$: | Number of $j$ components procured from outside into remaining-life-bin $b$. |
| $md_k$: | Demand for material $k$, | | |
| $rem_{ij}$: | Remaining life of component $j$ in EOLP $i$, | | |
| $\pi_{tj}$: | Component $j$ yield rate of an EOLP of type $t$, | | |

## SENSOR-EMBEDDED PRODUCTS BASED DTO MODEL

The advanced DTO model (ADTOM) constructed in this paper is a pure integer linear program. The goal of the model is to determine which EOLPs to disassemble, repair, or recycle. The model is constructed for completely modular products. In other words, all components are assumed to be independently assembled on a base (chassis). The mathematical model is shown below.

$$\min z = \sum_{i=1}^{n}\left(\bar{x}_i \sum_{j=1}^{m}\left(c_{1j}a_{ij} + c_3 f_{ij}\right)\right) + \sum_{j=1}^{m}\left(c_{2j}\left(\sum_{b=1}^{B}\left(r_{jb}\right) + \sum_{i=1}^{m}\left(f_{ij}\bar{x}_i\right)\right)\right) + \sum_{j=1}^{m}\left(\sum_{b=1}^{B} c_{jb} l_{jb}\right) \tag{1}$$

subject to,

$$\sum_{\forall \{i | rem_{ij} \geq b\}} \left(a_{ij} x_{ijb}\right) + l_{jb} - r_{jb} \geq cd_{jb}, \forall j, b \tag{2}$$

$$\sum_{j=1}^{m} y_{jk} \left(\sum_{b=1}^{B}\left(r_{jb}\right) + \sum_{i=1}^{m}\left(f_{ij}\bar{x}_i\right)\right) \geq md_k, \forall k \tag{3}$$

$$\sum_{b=1}^{B} x_{ijb} = \bar{x}_i, \forall i, j \tag{4}$$

$$\bar{x}_i, x_{ijb} \geq 0 \text{ and binary } (0,1), \forall i, j \tag{5}$$

$$r_{jb}, l_{jb} \geq 0 \text{ and integer, } \forall j, b \tag{6}$$

Equation (1) defines the objective function by minimizing the sum of total disassembly cost, total recycling cost and total outside component procurement cost, respectively. Equation (2) represents the constraints that assure that the total number of procured and disassembled components of type $j$ is greater than or equal to the demand for components of type $j$. Equation (3) represents constraints that assure that the material demand is fulfilled. Material demand is fulfilled by recycling all broken (non-operable) components. If the demand cannot be satisfied this way, operable parts will be recycled as well. Model utilizes non-operable parts first by means of the objective function. It must be noted that the disassembly cost of a non-operable component would be less than that of an operable component. Besides, in case of operable component shortage, recycling operable components may force the model to procure components from outside. This obviously leads to a higher total cost. Equation (4) represents constraints that make sure that all components are taken out if an EOL is disassembled and that a component is placed in no more than one life-bin. Since a product may fit in all bins (see Eq(2)). Equation (5) and (6) are non-negativity and variable-type constraints.

## GENERIC INTEGER DTO MODEL WITH DETERMINISTIC YIELD

Traditional DTO model (TDTOM) which sets the benchmark of economic performance is shown below. Equation (7) defines the objective function by minimizing the sum of total disassembly cost, total recycling cost and total outside component procurement cost, respectively. Equations (8) and (9), again, make sure that the component and material demands are fulfilled. Finally, Eq. (10) represents non-negativity and variable-type constraints.

$$\min z = \sum_{t=1}^{T}\left( x_t \sum_{j=1}^{m}\left( c_{1j}\pi_{tj} + c_3\pi b_{tj} \right)\right) + \sum_{j=1}^{m}\left( c_{2j}\left( r_j + \sum_{t=1}^{T}\left( \pi b_{tj} x_t \right)\right)\right) + \sum_{j=1}^{m} c_j l_j \tag{7}$$

subject to,

$$\sum_{t=1}^{T} \left( \pi_{tj} x_t \right) + l_j - r_j \geq cd_j, \forall j \tag{8}$$

$$\sum_{j=1}^{m} y_{jk}\left( r_j + \sum_{i=1}^{m} \left( \pi b_{tj} x_t \right)\right) \geq md_k, \forall k \tag{9}$$

$$x_t, r_{jb}, l_{jb} \geq 0 \text{ and integer, } \forall j, b, t \tag{10}$$

## ECONOMIC ANALYSIS

Economic analysis was conducted by comparing ADTOM with TDTOM. Difference between the total operational costs was considered as the benefit of the new system or the value of the extra information. In order to compare ADTOM with TDTOM, ADTOM was adjusted so that the demands based on remaining life of the components would not be considered. This way ADTOM would be placed on the same page with TDTOM, since TDTOM is not capable of handling sophisticated demands.

For numerical results, we assumed a return rate of 200/day for the EOLPs. A total of 200 EOLPs, were virtually created. 10 different product types, each of which consists of a number of components out of

17 alternatives, were defined. Table 1 shows product types and corresponding components along with component demands and material yields. Each component in each virtually generated product has a probability of being reusable. This probability uniformly distributed between 65% and 90%. Each non-reusable component had a 90% probability of being broken. The remaining 10% were considered as missing parts. Material demands were 16 and 35 lbs. for plastic and steel, respectively (1 lbs≈0.454 kg).

**TABLE 2: PRODUCT TYPES, COMPONENT AND MATERIAL DEMANDS**

| Components | A | | | B | | | C | | | | D | | E | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Product Type | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | C3 | C4 | D1 | D2 | E1 | E2 | E3 | E4 | E5 |
| 1 | X | | | X | | | X | | | | X | | X | | | | |
| 2 | | X | | X | | | X | | | | X | | X | | | | |
| 3 | | | X | | X | | X | | | | X | | | X | | | |
| 4 | | X | | X | | | | | X | | | X | | | | X | |
| 5 | X | | | | | X | | X | | | | | X | | | | |
| 6 | X | | | | X | | | | | | X | | | X | | | |
| 7 | | | X | | X | | | | X | | | | | X | | | |
| 8 | | | X | X | | | | | X | | | | X | | X | | |
| 9 | | X | | | | X | | X | | | X | | | | | X | |
| 10 | | | X | | | X | | | | X | | X | | | | | X |
| Demand | 21 | 12 | 15 | 21 | 9 | 12 | 18 | 21 | 15 | 18 | 21 | 39 | 18 | 15 | 18 | 18 | 21 |
| Steel (lbs) | 1 | 1 | 1 | 0 | 0 | 0 | 1.5 | 1.5 | 1.5 | 1.5 | 0.5 | 0.5 | 0 | 0 | 0 | 0 | 0 |
| Plastic (lbs) | 0 | 0 | 0 | 1.5 | 1.5 | 1.5 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 2.5 | 2.5 | 2.5 | 2.5 |

## RESULTS

ADTOM was evaluated using the virtually generated EOLP data given above while TDTOM was fed the exact yield rates drawn from the mentioned data. Optimal solutions and total operational costs of the two models are shown in Table 2.

**TABLE 3: COST COMPARISON OF THE TWO MODELS**

| | ADTOM | TDTOM |
|---|---|---|
| Disassembly Cost ($) | 399.500 | 731.229 |
| Procurement Cost ($) | 3733.333 | 3986.667 |
| Recycle Cost ($) | 30.100 | 49.908 |
| Total Cost ($) | 4162.933 | 4767.804 |

Hence, the benefits obtained by establishing a sensor-embedded product based DTO system, *V*, can be determined as; $V = C_{TDTOM} - C_{ADTOM} = 4767.804\ -\ 4162.933\ =\ \$604.871/day$. Therefore, cost of sensors per product should not exceed $3.024. Percent improvement in the results, *I*, can be calculated as;

$$I = \frac{C_{TDTOM} - C_{ADTOM}}{C_{TDTOM}} = \frac{4767.804\ -\ 4162.933}{4767.804}\ =\ 0.127$$

Results also show that, EOLPs on hand were not sufficient to fulfill the demand. Consequently, procurement cost took the largest portion in total cost. If this was not the case, in other words, if there were more EOLPs to disassemble, then percent improvement would have been much higher.

## CONCLUSIONS

In this paper, economic justification of sensor-embedded product based DTO systems is presented. Analysis was conducted by comparing the operational costs of two disassembly-to-order (DTO) models described in the paper, namely, advanced DTO model (ADTOM) and traditional DTO model (TDTOM). Cost advantage to ADTOM was simply determined by calculating the difference between the operational costs. It was found out that, according to the given data, ADTOM brings out a cost saving of $604.871 a day. Hence, TDTOM is inferior to ADTOM; even though the exact component yield rate is fed to TDTOM. This result proves sensor-embedded product based DTO system to be profitable as long as the cost of sensors per product does not exceed $3.024. Once the other benefits of original ADTOM, such as fulfilling sophisticated demand, is considered, daily benefits should be found much higher than $604.871. Since, no monetary equivalent to sophisticated demand fulfillment could be found in the literature, this benefit will remain qualitative.

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