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Mehmet Ali Ilgin  
*Northeastern University*

Surendra M. Gupta  
*Northeastern University*

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Laboratory for Responsible Manufacturing

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## **Contact Information**

Dr. Surendra M. Gupta, P.E.  
Professor of Mechanical and Industrial Engineering and  
Director of Laboratory for Responsible Manufacturing  
334 SN, Department of MIE  
Northeastern University  
360 Huntington Avenue  
Boston, MA 02115, U.S.A.

(617)-373-4846 **Phone**  
(617)-373-2921 **Fax**  
gupta@neu.edu **e-mail address**

<http://www.coe.neu.edu/~smgupta/> **Home Page**

## **DISASSEMBLY OF SENSOR EMBEDDED PRODUCTS WITH COMPONENT DISCRIMINATING DEMAND**

**Mehmet Ali ILGIN**, Northeastern University, Boston, MA 02115, 617-373-7635,  
ilgin.m@neu.edu

**Surendra M. GUPTA**, Northeastern University, Boston, MA 02115, 617-373-4846,  
gupta@neu.edu

### **ABSTRACT**

There is a high level uncertainty associated with disassembly yield due to existence of unfunctional and/or unneeded components in end of life products. Sensors embedded in critical components of a product can deal with this uncertainty by providing information on the type and condition of the components prior to disassembly. This study presents a quantitative assessment of the impact of sensor embedded products (SEPs) on the various performance measures of a kanban-controlled washing machine disassembly line. First, separate design of experiments studies based on orthogonal arrays are performed for the cases with and without SEPs. Then, the results of paired-t tests comparing two cases based on different performance measures are presented.

### **1. INTRODUCTION**

Increasing environmental awareness and stricter government regulations on the recycling of end-of-life (EOL) products force manufacturers to establish specific facilities for product recovery which can be defined as recovery of materials and parts from returned or EOL products via recycling and remanufacturing. Disassembly is an important process in product recovery since it allows for the selective separation of desired parts and materials (Ilgin and Gupta [2]). Regarding the condition and type of a component in an EOL product, there are several questions which increase the uncertainty in disassembly yield: a) Is the component functional? b) Is the component missing? c) What is the type of the component? If these questions are answered prior to the disassembly of the component, unnecessary disassembly of a non-functional or unneeded component can be avoided. Sensors embedded in products can answer these questions prior to disassembly. By using the sensor information on the condition and type of the components in EOL products, the routing of products through the disassembly line can be changed.

The use of sensor-based technologies on after-sale product condition monitoring is an active research topic. Starting with the study of Scheidt and Shuqiang [8], different methods of data acquisition from products during product usage were presented by the researchers (Karlsson [3], Karlsson [4]; Klausner, et al. [6]; Petriu, et al. [7]). In all of these studies, the main idea is the use of devices with memory to save monitoring data generated during the product usage. Although most of these studies focus on the development of sensor embedded product (SEP) models, only few researchers presented a cost-benefit analysis. Klausner, et al. [5] analyzed the trade-off between the higher initial manufacturing cost caused by the use of an electronic data log in products and cost savings from the reuse of used motors. Simon, et al. [9] improved the

cost-benefit analysis of Klausner, et al. [5] by considering the limited life of a product design. They showed that, in that case, servicing provides more reusable components compared to EOL recovery of parts. Vadde, et al. [11] investigated the effectiveness of embedding sensors in computers by comparing several performance measures in the two scenarios-with embedded sensors and without embedded sensors. The performance measures considered include average life cycle cost, average maintenance cost, average disassembly cost, and average downtime of a computer. However, they do not provide a quantitative assessment of the impact of SEPs on these performance measures. Moreover, since only one component of a computer (hard disk) was considered, the disassembly setting does not represent the complexity of a disassembly line which is generally used to disassemble EOL computers. By extending Vadde, et al. [11], Ilgin and Gupta [1] analyzed the effect of SEPs on the performance of an EOL computer disassembly line which is used to disassemble three components from EOL computers, namely, memory, hard disk and mother board. Due to relatively simple structure of an EOL computer, they did not consider the precedence relationships among the components. However, disassembly of a particular component is restricted by one or more components in some products. That is why, these products are disassembled according to a route determined based on the precedence relationships. Another disassembly scenario that was not investigated in Ilgin and Gupta [1] is the component discriminating demand which occurs when customers demand a specific type of a particular component. Due to changes made by customer or service personnel during product usage, it is very difficult to determine the type of a component in a conventional EOL product prior to disassembly. However, the sensors embedded in SEPs can determine the type of components prior to disassembly. This prevents the disassembly of unneeded component types while decreasing the backorder costs of the highly demanded component types.

In this study, we extend Ilgin and Gupta [1] by investigating the quantitative impact of SEPs in case of product disassembly with precedence relationships and component discriminating demand. Specifically, we consider a kanban controlled washing machine (WM) disassembly line. Two separate Design of Experiments (DOE) studies based on Orthogonal Arrays (OAs) are carried out for the cases with and without SEPs. In the calculation of various performance measure values under different experimental conditions, detailed Discrete Event Simulation (DES) models of both cases are used. Then, the results of paired-t tests comparing two cases based on different performance measures are presented.

## **2. SYSTEM DESCRIPTION**

A three-station EOL WM disassembly line is analyzed in this study. The components disassembled at different stations and the precedence relationships among the components can be seen in Table 1. Disassembly times at stations, demand inter-arrival times for components and EOL WM inter-arrival times are all exponentially distributed. There are three motor types and two circuit board types disassembled at station 2 and station 3, respectively. The demand arrives for a specific type of a component at a station. For instance, if a customer orders a type 1 circuit board, type 1 circuit board inventory at station 3 is checked. If there is no type 1 circuit board, the order is backordered. A type 2 circuit board cannot be used as a substitute for a type 1 circuit board. A conventional WM visits all stations. Following the disassembly at each station, components are tested. The testing times are normally distributed with the means and standard

deviations presented in Table 2. A sensor embedded WM visits only the stations which are responsible for the disassembly of functional components and predecessor components of these components. Moreover, following the disassembly of a component, there is no testing due to sensor information on the condition of the component. Another advantage provided by sensors is the identification of component types prior to disassembly. In case of sensor embedded WMs, the component types in a WM can be determined in the beginning of the line. Based on this information, disassembly of WMs involving a specific component type which is demanded more can be prioritized at a station.

Excess product, subassembly and components are disposed of by a small truck with a load volume of 425 cubic feet. Whenever the total volume of the excess product, subassembly and component inventories become equal to the truck volume, the truck loaded with excess inventory is sent to a recycling facility. Any product, subassembly or component inventory which is greater than *maximum inventory level* is assumed to be excess. Component volumes are given in Table 2. The volume of an EOL WM is taken as 20 cubic feet. Multi Kanban System (MKS) developed by Udomsawat and Gupta [10] is used to control the disassembly line.

**Table 1.** Precedence relationships among the disassembled components.

Part Name	Code	Precedence Relationship	Station
Metal Cover	A	-	1
Circuit Board	B	A	2
Motor	C	A,B	3

**Table 2.** Specifications for the disassembled components.

Part Name	Code	Testing Time		Volume (cft)	Demanded ?	Number of Different Types	Disposal Classification
		Mean	Std. Dev.				
Metal Cover	A	-	-	1.344	No	-	Steel scrap
Circuit Board	B	5	1	0.015	Yes	3	Waste
Motor	C	10	2	0.137	Yes	2	Waste

### 3. DESIGN OF EXPERIMENTS STUDY

In order to present a comprehensive and quantitative evaluation of the SEPs on the performance of the WM disassembly line, we compare the case with SEPs against the case without SEPs under different experimental conditions. The factors and factor levels are given in Table 3. A full factorial design with 35 factors requires an extensive number of experiments. Therefore, experiments were designed using OAs which allow for the determination of main effects by making a minimum number of experiments. Specifically, L81 OA was chosen since it requires 81 experiments while accommodating 40 factors with three levels. Discrete Event Simulation (DES) models of both cases were developed using Arena 11 to determine profit value together with various cost and revenue parameters for each experiment. Each DES experiment was carried out for 60480 minutes, the equivalent of six months with one eight hour shift per day.

The following equation presents the formula used in the DES models for the calculation of profit value.

$$\text{Profit} = \overbrace{(SR+CR + SCR)}^{\text{Total Revenue}} - \overbrace{(HC+BC+DC+DPC+TC+TPC)}^{\text{Total Cost}} \quad (1)$$

Where SR is the total revenue generated by the component sales during the simulated time period (STP), CR is the total revenue generated by the collection of EOL WMs during the STP, SCR is the total revenue generated by selling scrap components, HC is the total holding cost of components, EOL WMs and subassemblies during the STP, BC is the total backorder cost of components during the STP, DC is the total disassembly cost during the STP, DPC is the total disposal cost of components, EOL WMs and subassemblies during the STP, TC is the total testing cost during the STP, TPC is the total transportation cost during the STP.

Metal cover and other steel components (e.g., drum, front and side metal frames) are sold as steel scrap. Motor, circuit board and all the other small components are regarded as waste components. In order to determine total weight of small components such as screws, cables, total weight of the main components is multiplied with a *small component weight factor*. In order to calculate the disposal cost of a waste component, the weight is multiplied with the *disposal cost per pound*. Disposal cost for subassemblies and products are calculated by multiplying the total weight of waste components with the *disposal cost per pound*. Disposal cost for subassemblies and products are increased by a factor called *disposal cost increase factor for EOL WMs*. Scrap revenue for metal cover is calculated by multiplying the weight with the *scrap revenue per pound*. In the calculation of scrap revenue for subassemblies and products, total weight of scrap-able components is multiplied with the *scrap revenue per pound*. Scrap revenue for subassemblies and products are decreased by a factor called *scrap revenue decrease factor for EOL WMs*. The time required to retrieve information from the sensors is assumed to be testing time. Duration of this retrieval process is taken as 10 seconds per WM. The operating cost associated with each trip of the truck is assumed to be \$50. For each EOL WM, the facility demands a \$15 collection fee.

#### 4. RESULTS

Employing the results of DOE studies, various paired-t tests were performed on different performance measures. Table 4 presents the 95% confidence interval, t-value and p-value for each test. According to this table, SEPs achieve statistically significant savings in holding, backorder, disassembly, disposal, testing and transportation costs while they provide statistically significant improvements in total revenue and profit.

**Table 3.** Factor levels in DOE study.

No.	Factors	Levels		
		1	2	3
1	Disposal cost increase factor for EOL WMs	0.05	0.10	0.15
2	Scrap revenue decrease factor for EOL WMs	0.05	0.10	0.15
3	Mean demand rate for Circuit Board Type 1 ( <i>components per hour</i> )	2	4	6
4	Mean demand rate for Circuit Board Type 2 ( <i>components per hour</i> )	2	4	6
5	Mean demand rate for Circuit Board Type 3 ( <i>components per hour</i> )	2	4	6
6	Mean demand rate for Motor Type 1( <i>components per hour</i> )	2	4	6
7	Mean demand rate for Motor Type 2( <i>components per hour</i> )	2	4	6
8	Mean arrival rate of EOL WMs ( <i>products per hour</i> )	10	20	30
9	Mean disassembly time for station 1 ( <i>minutes</i> )	0.25	0.50	0.75
10	Mean disassembly time for station 2 ( <i>minutes</i> )	0.75	1	1.25
11	Mean disassembly time for station 3 ( <i>minutes</i> )	0.75	1	1.25
12	Backorder cost rate	0.40	0.60	0.80
13	Disassembly cost per minute (\$)	1	2	3
14	Testing cost per minute (\$)	0.40	0.50	0.60
15	Holding cost rate	0.10	0.20	0.30
16	Weight for Metal Cover ( <i>pounds</i> )	8	12	16
17	Weight for Circuit Board ( <i>pounds</i> )	0.5	1	1.5
18	Weight for Motor ( <i>pounds</i> )	5	10	15
19	Weight of other components ( <i>pounds</i> )	80	100	120
20	Price for Circuit Board Type 1(\$)	20	40	60
21	Price for Circuit Board Type 2(\$)	30	50	70
22	Price for Circuit Board Type 3(\$)	40	60	80
23	Price for Motor Type 1(\$)	50	75	100
24	Price for Motor Type 2(\$)	100	125	150
25	Disposal cost per pound (\$)	0.30	0.40	0.50
26	Scrap revenue per pound (\$)	0.15	0.20	0.25
27	Maximum inventory level	5	10	15
28	Small component weight factor	0.05	0.10	0.15
29	Probability of a non-functional Circuit Board	0.10	0.20	0.30
30	Probability of a non-functional Motor	0.10	0.20	0.30
31	Probability of a missing Circuit Board	0.05	0.10	0.15
32	Probability of a missing Motor	0.05	0.10	0.15
33	Probability of Type 1 Circuit Board	0.20	0.30	0.40
34	Probability of Type 2 Circuit Board	0.20	0.30	0.40
35	Probability of Type 1 Motor	0.40	0.50	0.60

## 5. CONCLUSIONS

A viable solution approach to deal with the disassembly yield uncertainty is SEPs which involve sensors implanted during the production process. In this study, we analyzed the impact of SEPs on the various performance measures of a WM disassembly line. First, separate DOE studies based on OAs were performed for the cases with and without SEPs. Then paired-t tests were carried out in order to compare two cases for various performance measures. According to the test results, SEPs increase total revenue and profit while providing significant reduction in total cost.

**Table 4.** Comparison of SEPs against conventional products based on paired-t test results.

<b>Performance Measure</b>	<b>95% Confidence Interval on Mean Difference (Sensor –No Sensor)</b>	<b>t-value</b>	<b>p-value</b>
Holding Cost	(-48.3281, -30.8654)	-9.02	0.000
Backorder Cost	(-40766.6, -27392.4)	-10.14	0.000
Disassembly Cost	(-18926.2, -13308.2)	-11.42	0.000
Disposal Cost	(-44018.5, -36241.0)	-20.54	0.000
Test Cost	(-105743.4, -93996.0)	-33.84	0.000
Transportation Cost	(-3714.70, -3227.89)	-28.38	0.000
Total Cost	(-206132, -181282)	-31.02	0.000
Total Revenue	(187627, 263997)	11.77	0.000
Profit	(372333, 466537)	17.72	0.000

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