

Disassembly-To-Order Systems

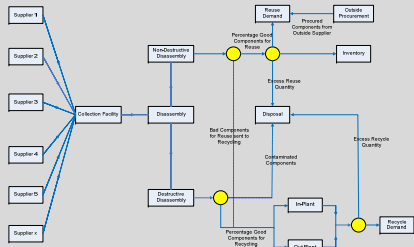


Dynamic Programming for Solving Disassembly-to-Order System Under Stochastic Yields, Limited Supply, and Quantity Discount

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Introduction

- In a disassembly-to-order (DTO) system, a wide variety of EOL products are purchased or taken back from end users in order to be disassembled to satisfy the demand for components
- Products and subassemblies are disassembled into individual components as customers demand for specific components arrive
- Two types of Disassembly:
 - Complete Disassembly
 - Selective Disassembly
- Process of Disassembly:
 - Destructive
 - Non-destructive



- DTO system is considered
 - A variety of returned products are disassembled to fulfill demand for components
- Several factors are considered before disassembling products
 - EOL products are received in a variety of conditions
 - Leading to uncertainties in the process
 - Products are supplied by a number of suppliers
 - Wide range of products, product conditions, product prices
- Suppliers capacity
 - Number of products they can offer
- Suppliers quantity discount schedule
 - Total purchase to increase their competitive edge

We developed a DTO model using Dynamic Programming (DP) for multiple periods which take into consideration the mentioned system uncertainties and variability

The main objective was to determine optimal number of take-back EOL products in every period from each supplier to fulfill the demand of components while maximizing total profit of the system

Objective Function

$$\text{Max } \tau = \sum_{n=1}^N (S_n^{(1)} + D_n^{(1)}) + \sum_{n=1}^N (e_n^{(2)} + D_n^{(2)}) - \sum_{n=1}^N (1 - DR_{j,n}) \sum_{i=1}^I p_{i,n} \sum_{k=1}^K Q_{i,k,n}^{(1)} - \sum_{n=1}^N Q_{i,k,n}^{(2)} + cdd_{i,n} - \sum_{n=1}^N Q_{i,k,n}^{(3)} + cnd_{i,n} - \sum_{n=1}^N ch_{i,n} + Q_{i,k,n}^{(4)} - \sum_{n=1}^N cpr_{i,n} + Q_{i,k,n}^{(5)} - \sum_{n=1}^N (Q_{i,k,n}^{(6)} + circ_{i,n}) - \sum_{n=1}^N (Q_{i,k,n}^{(7)} + corc_{i,n}) - \sum_{n=1}^N cdp_{i,n} + Q_{i,k,n}^{(8)}$$

Inventory Management of End-of-Life Products using Stochastic Dynamic Programming

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Problem Objective Function

$$f_n^*(S_n, X_n) = \text{MAX}_{-} f_n(S_n, X_n)$$

At any given stage n , the best decision would be that will result in the maximum generated total profit

* The goal is to develop a model that will determine systematically liquidation vs. hold strategy of the current OHI with the aim to maximize the total system's profit

Mathematical Model (cont'd)

The following expressions are used in the model:

$$PR_{i,j}^*(q_1) = \text{MAX}_{-0,1} V_{i,j}^*(x, r, k)$$

$$PR_{i,j}^*(q_2) = \text{MAX}_{-0,1} V_{i,j}^*(x, r, k)$$

The most attainable profit generated from holding/liquidating EOL

$$V_{i,j}^*(0, r, k) = -C_{i,k,j}^{hold} + Q_{i,k,j}^{chic}$$

$$V_{i,j}^*(1, r, k) = -C_{i,k,j}^{hold} * (Q_{i,k,j}^{chic} - Q_{i,k,j}^{pic}) + P_{i,k,j}^{pic} * Q_{i,k,j}^{pic} + C_{i,k,j}^{pic} * Q_{i,k,j}^{pic}$$

Represents the net profit generated from holding/liquidating core product given any quality and period

$$V_{i,j}^*(0, r, k) = -C_{i,k,j}^{hold} + Q_{i,k,j}^{chic}$$

$$V_{i,j}^*(1, r, k) = -C_{i,k,j}^{hold} * (Q_{i,k,j}^{chic} - Q_{i,k,j}^{pic}) + P_{i,k,j}^{pic} * Q_{i,k,j}^{pic} + C_{i,k,j}^{pic} * Q_{i,k,j}^{pic}$$

Represents the net profit generated from holding/liquidating parts given any quality and period

$$f_n(S_n, X_n) = V_{i,j}^*(x, r, k) + PR_{i,j+1}^*(q_1)$$

$$f_n(S_n, X_n) = V_{i,j}^*(x, r, k) + PR_{i,j+1}^*(q_2)$$

Immediate profit generated from holding/liquidating, plus the maximum expected future profit for period $n-1$ onward

Stage: n=5	States (Sn)	Profit Generated From Option r					Decision Optimal
		r=1	r=2	r=3	r=4	r=5	
1K-2K	OHI						r=5nXn Xn
2K-3K	2639	18842.46	18209.21	21956.48	18367.44	12561.64	21956.48 r=3
3K-4K	3639	25982.46	23944.62	28638.93	24563.25	15283.80	28638.93 r=3
4K-5K	4639	32241.05	29225.70	36045.03	29735.99	27277.32	36045.03 r=3
>5000	5639	28200.00	31500.00	30850.00	28700.00	27200.00	31500.00 r=2

Profit generated based on quantity and type of liquidation channel

Note: r=0 column is a zero column

Analysis of a Kanban Controlled Disassembly Line with Sensor Embedded Products

M. Ali Iqin and Surendra M. Gupta

Introduction

- The use of sensor embedded products (SEPs) is a promising approach to deal with the uncertainty in disassembly yield.
- SEPs involve sensors implanted during the production process.
- These sensors facilitate the data collection process by monitoring critical components of a product.
- The data collected through sensors can be used to
 - Predict the component or product failures during product lives.
 - Estimate the remaining lives and conditions of components at the EOL of the product.
- In this study, we analyze the use of sensors in the detection of failed or missing components in a product before disassembling it.
- Two separate experimental design studies based on Orthogonal Arrays (OAs) are carried out for the cases with and without SEPs.
- The results of paired-t tests comparing two cases based on different performance measures are presented.

System Description

Table 1 Component Characteristics

Component	Code	Testing Time (min.)		Volume (cf)	Station
		Mean	Std.Dev.		
Memory	A	2	0.2	0.008	1
Hard Disk	D	10	2	0.016	2
Motherboard	E	5	1	0.263	3

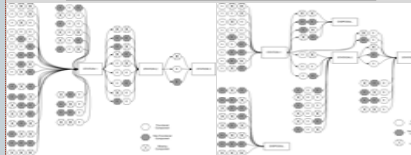


Figure 1 Routing of EOL Products without Sensors

Figure 2 Routing of EOL Products with Sensors

Design of Experiments Study

Table 2 Factor Levels

Number	Factors	Levels		
		1	2	3
1	Disposal cost increase factor for EOL computers	0.15	0.20	0.30
2	Mean demand rate for Memory (components per hour)	10	15	20
3	Mean demand rate for Hard Disk	10	15	20
4	Mean demand rate for Motherboard	10	15	20
5	Mean arrival rate of EOL computers (products per hour)	10	20	30
6	Mean disassembly time for station 1 (minutes)	0.25	0.50	0.75
7	Mean disassembly time for station 2	0.50	0.75	1.0
8	Mean disassembly time for station 3	1	1.5	2
9	Backorder cost rate	0.40	0.60	0.80
10	Disassembly cost per minute (\$)	1	2	3
11	Holding cost rate	0.10	0.20	0.30
12	Weight for Memory (pounds)	0.1	0.3	0.5
13	Weight for Hard Disk	1	2	3
14	Weight for Motherboard	1	2	4
15	Price for Memory (\$)	10	20	30
16	Price for Hard Disk	25	50	75
17	Price for Motherboard	50	100	150
18	Disposal cost per pound (\$)	0.30	0.40	0.50
19	Maximum inventory level	5	10	15
20	Waste weight factor	0.20	0.30	0.40
21	Probability of a non-functional Memory	0.10	0.20	0.30
22	Probability of a non-functional Hard Disk	0.10	0.20	0.30
23	Probability of a non-functional Motherboard	0.10	0.20	0.30
24	Probability of a missing Memory	0.05	0.10	0.15
25	Probability of a missing Hard Disk	0.05	0.10	0.15
26	Probability of a missing Motherboard	0.05	0.10	0.15

Results

Table 3 Paired-t Test Results for Various Performance Measures

Performance Measure	95% Confidence Interval on Mean Difference	t-value
Holding Cost	(-42.25, -23.44)	-7.00
Backorder Cost	(-20258, -8577)	-4.93
Disassembly Cost	(-136629, -26998)	-11.11
Disposal Cost	(-20424, -13485)	-9.80
Test Cost	(-134667, -114138)	-24.31
Transportation Cost	(-115.84, -85.83)	-13.48
Total Cost	(-206423, -168891)	-20.06
Total Revenue	(-15983, -18508)	-4.45
Profit	(-229084, -38021)	9.59

Advanced Disassembly-To-Order with Sensor Embedded Products

Order Ondermir and Surendra M. Gupta

Introduction: Issues with Traditional Disassembly-to-Order Model (TDOM)

- End-of-life products (EOLPs) do not show typical qualities. This is due to different:
 - maintenance frequencies,
 - upgrades,
 - working conditions (light use, intensive use) and
 - environmental conditions (hot, cold, dusty, clean environments).
- Some of the components in an EOLP may be replaced or eliminated.
- Sophisticated demands cannot be met
- Problems stem from the lack of information. If one could get advanced information about the status of the product, it could prove to be quite invaluable in making EOL management decisions.

Advanced DTO Model (ADTOM)

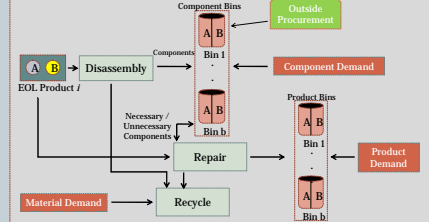


Figure 1 Advanced DTO system utilizing the data collected by sensors

Numerical Example

Table 1 Non-operable components (**) and remaining-life times (years) of operable components.

EOLP #	Model	Components														
		A	A3	B	C	D	E	F	F2	F3	F4	F5	G	G2	G3	
1	2	**	**	4.9	**	**	**	**	**	**	**	**	**	**	**	
2	6	3.5	**	0.4	**	**	**	1.1	**	7.0	**	**	**	**	**	
3	5	5.0	**	3.7	**	**	**	2.4	**	4.1	**	**	**	**	**	
4	9	**	**	1.5	**	**	**	4.7	**	4.1	**	**	**	**	**	
199	7	**	**	2.3	**	**	**	4.4	**	3.4	**	**	**	**	**	
200	9	**	**	4.3	**	**	**	4.4	**	2.7	**	**	**	**	**	

Table 2 Product types, component demands and material yields

Product Type	Components														
	A	A2	A3	B	B2	B3	C	C2	C3	C4	D	D2	E	E2	E3
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
3	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
4	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
5	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
6	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
8	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
9	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
10	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Demand/day	21	12	15	21	9	12	18	21	15	18	21	39	18	15	18

Results

Table 3 Cost comparison of the two models

	ADTOM	TDOM
Disassembly Cost (\$)	399.50	731.23
Procurement Cost (\$)	3733.33	3986.67
Recycle Cost (\$)	30.10	49.91
Total Cost (\$)	4162.93	4767.80

Benefits of ADTOM = $V = C_{TDOM} - C_{ADTOM} = 4767.80 - 4162.93 = 5604.87$ / day

Percent improvement = $I = \frac{C_{TDOM} - C_{ADTOM}}{C_{TDOM}} = \frac{4767.80 - 4162.93}{4767.80} = 0.127$

