Disassembly and Reassembly Sequence Planning Tradeoffs Under Uncertainty for Product Maintenance

Sara Behdad
Graduate Research Assistant
e-mail: behdad1@illinois.edu

Deborah Thurston
Professor
Fellow ASME
e-mail: thurston@illinois.edu

Industrial and Enterprise Systems
Engineering Department,
University of Illinois at Urbana-Champaign,
Urbana, IL, 61801

The problem addressed in this paper is disassembly sequence planning for the purposes of maintenance or component upgrading, which is an integral part of the remanufacturing process. This involves disassembly, component repair or replacement, and reassembly. Each of these steps incurs cost as well as the probability of damage during the process. This paper presents a method for addressing these tradeoffs, as well as the uncertainty associated with them. A procedure for identifying the best sequence of disassembly operations for maintenance and/or component upgrade is presented. It considers both disassembly and reassembly costs and uncertainties. Graph-based integer linear programming combined with multi-attribute utility analysis is employed to identify the best set of tradeoffs among (a) disassembly time (and resulting cost) under uncertainty, (b) the probability of not incurring damage during disassembly, (c) reassembly time (and resulting cost), and (d) the probability of not incurring damage during reassembly. An example of a solar heating system is used to illustrate the method. [DOI: 10.1115/1.4006262]

1 Introduction

Design for lifecycle requires consideration of disassembly for maintenance for two reasons. The first is easy access to remove components for repair, maintenance, or replacement by either the customer or the manufacturer if the product is under warranty. The second is disassembly by the manufacturer at the end of a product lifecycle for the purposes of recycling, reuse, or remanufacturing. The distinction between these two stages (customer use and product takeback) is becoming blurred as manufacturers adopt a leasing business model. The leasing model has been proposed as part of the solution to the e-waste problem [1–3]. Takeback operations often involve the extraction of specific, high-value components, such as personal computer hard drives and memory, and automotive radiators.

Many products are designed to operate with some sort of maintenance or upgrade during their life cycle. Maintenance is defined here as the activities carried out to alleviate depreciated performance of a system, equipment, or product to a level close to "as good as new" condition [4].

According to Kang and Xirouchakis [5], maintenance comprises the following steps:

- identifying the target component
- dismantling it from the assembly
- repairing or replacing it
- assembling the repaired component
- restoring the assembly to its functional state

The dismantling of target components often requires maintenance experts to identify a feasible and efficient disassembly sequence before carrying out the disassembly operations. In addition, one must avoid damage to components during disassembly. A final consideration is the reversibility of the disassembly sequence. There are often avoidable tradeoffs among disassembly time (and the resulting cost), the probability of damage, and reassembly considerations.

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While different algorithms and optimization approaches have been extensively applied to tackle the disassembly sequence problem, no methods have employed a decision analytic approach for dealing with these tradeoff issues. The aim of this research is to optimize the disassembly sequence while simultaneously considering tradeoffs among attributes; disassembly time (and resulting cost), the probability of no part damage, and the reversibility of disassembly sequence (both time and the probability of not incurring damage during reassembly). The paper also models decision maker preferences regarding the probability of not incurring damage during disassembly and reassembly, in addition to operation times by employing utility functions.

The remainder of this paper is organized as follows. Section 2 gives a brief review of related literature. Problem definition and selected attributes are introduced in Sec. 3. Section 4 presents a mixed integer programming model of disassembly sequence selection. The results of the model are presented in Sec. 5 for an example of a solar heating system, and, Sec. 6 concludes the paper.

2 Background

Determining the best disassembly sequence is the main task of disassembly process planning. Disassembly sequences are studied for a variety of purposes including:

— Remote construction and repair in hazardous or inaccessible environments such as nuclear equipment and spacecraft [6];
— Service performance: e.g., maintenance and component replacement to repair or upgrade [7];
— Assembly optimization [8];
— Material recovery at the end of life of a product [9–11].

Specifying the best disassembly sequence comprises two main steps: (1) generating a set of feasible disassembly sequences and (2) evaluating those sequences to find the most efficient one [10]. Many graph-based models can be applied to represent various disassembly sequences including undirected graph, digraph, AND/OR graph, Petri net, and so on [11], and several researchers have concentrated on the second step to specify the best disassembly sequence among all feasible options. Lambert [6] provides an extensive review of disassembly sequencing. Some of the methods are graph methods, mathematical programming including linear programming, mixed integer programming based models, the shortest path method, modified travelling salesman problems, heuristic methods including fuzzy logic, neural networks, and genetic algorithms.

According to Kang and Xirouchakis [5], most disassembly planning research has been aimed at end-of-life (EOL) products, which is incomplete disassembly planning. Kara et al. [12] suggested a methodology to reduce disassembly time by providing a disassembly sequence for the selected components with reuse potential. Behdad et al. [9] also focused on incomplete disassembly for the purpose of deriving value from end-of-life products. They employed a mathematical model to derive the best disassembly sequence for the multiple products which share disassembly operations.

Yi et al. [13] concentrated on selective disassembly. They applied an algorithm for the purpose of selective disassembly of mechanical parts based on a general Computer-aided Design (CAD) product model. The main purpose of their algorithm was to minimize the number of component removals using a wave propagation concept. They regarded the number of removals as a representative of disassembly cost or time. Chung and Peng [14] mentioned that the wave propagation concept only focuses on topological disassemblability of parts and misses consideration of tool accessibility to a fastener and batch removability to directly access a part for separation or replacement. They proposed an approach which combines topological disassemblability of parts and fastener accessibility to generate a feasible selective-disassembly sequence, not necessarily an optimal sequence.

The current work focuses on selective, rather than incomplete, disassembly and provides an approach for seeking an optimal disassembly sequence, not just a feasible disassembly considering multiple objectives.

Also, most of the previous work has considered disassembly planning as a deterministic problem. However, the disassembly process poses many uncertainties, particularly in the realm of disassembly for remanufacturing, and partial disassembly for maintenance, which limits the usefulness of deterministic methods. The sources of uncertainties vary. For example, in the disassembly of end-of-life products, the widely varying feedstock of take-back product types, ages and designs both from qualitative and quantitative points of view is the main source of uncertainty. However, in the disassembly for maintenance, dimensional instability or warping is a primary source of uncertainty. Uncertainty in time required for disassembly operations is common between all disassembly processes regardless of their purpose.

To deal with uncertainties, several approaches have been suggested in the literature. Zussman and Zhou [15] introduced a modified Petri net method for adaptive planning of disassembly processes with uncertainty caused by different product conditions and performance of external resources. In this method, probability values are assigned to transitions, which represent the success rates of the corresponding operations. Probabilities can be updated during process execution, and if a disassembly transition fails, a transition with the next largest decision value will be selected. Gungor and Gupta also used the same approach and developed a methodology to resolve uncertainty interactively during disassembly [16].

Martinez et al. suggested a control system based on a multi-agent technology, which achieves dynamic decision-making in real time. In that method, the disassembly sequence is generated step by step based on the actual state and failures during the process [17]. Some of the literature applied sensitivity analysis as a reactive approach to cope with the uncertainties [5,18].

The method proposed in this paper is categorized among proactive approaches for dealing with uncertainty. The proactive approach includes consideration of the degree of subjective risk aversion exhibited by the decision maker in deciding how much risk to assume. The method here takes all uncertainty estimation into account at the beginning of planning process to maximize the expected utility.

In addition, this method considers multiple criteria, including the cost and probability of damage during both disassembly and reassembly processes to derive an optimum disassembly sequence. Multicriteria disassembly planning has been considered in several studies. Lu et al. [19] applied an ant colony algorithm to derive a feasible disassembly sequence with minimal disassembly cost. They included three objectives in their model: disassembly orientation changes, tool changes, and changes in disassembly operation types.

Duta et al. [20] also applied a multi-objective optimization method to determine a disassembly sequence taking into account both the revenue from the end-of-life options for each subassembly and the operational time of disassembly tasks.

Hula et al. [21] utilized a multi-objective genetic algorithm to specify the Pareto set for the optimization of product disassembly under different scenarios of cost and environmentally conscious actions.

Lee et al. [22] also presented a multi-objective methodology to determine the appropriate end-of-life options based on the objectives of minimizing environmental effects and cost. They introduced two end-of-life disassembly charts illustrating the impact on the environment and cumulative costs incurred as a product is disassembled. They used the charts to assist in product design and to specify the optimal stage of end-of-life disassembly of the product.

Although multi-objective optimization of disassembly planning has been considered in several studies, the uncertainty associated with the disassembly process still needs to be taken into account. Multi-attribute utility analysis helps to overcome this limitation and facilitates consideration of the uncertainties that inherent in the disassembly process. While many multi-objective optimization models handle uncertainty through sensitivity analysis, multi-attribute utility directly includes the effect of uncertainty on the desirability of each feasible alternative, reflecting the decision maker's attitude toward risk.

3 Problem Definition

There are three types of disassembly: complete, incomplete, and selective disassembly. In complete disassembly, all components or subassemblies are separated from each other [5]. In contrast, during incomplete disassembly only some components are removed. Incomplete disassembly is usually employed for EOL products, and its main objective is to determine the level at which a product should be disassembled to recover the value added still embedded in the product. Selective disassembly requires the disassembly of selected components and the final desired status of the product or the target components is known, in contrast to incomplete disassembly in which the extent to which a product should be disassembled is not known and should be specified. In general, disassembly for the purpose of maintenance or upgrade is called selective disassembly. According to Kang and Xirouchakis [5], most disassembly planning research has been aimed at EOL products, which is incomplete disassembly planning. Therefore, a comprehensive approach is needed for selective disassembly for maintenance. Another issue is that much of the literature has considered disassembly as deterministic sequencing with a single criterion, rather than as a multiple criterion problem. Multi-attribute utility theory is an appropriate method to address those issues. Several attributes are defined and five steps are followed to identify the best disassembly sequence.

- Identify different disassembly alternatives
- Identify attributes (tradeoff criteria for comparing alternatives)
- Determine attribute utility functions
- Construct multi-attribute utility function
- Rank the alternatives based on overall utility

3.1 Disassembly Alternatives. One of the main issues in specifying the optimal disassembly sequence is to represent the feasible disassembly operations and related subassemblies in an appropriate way [9]. Different methods have been developed

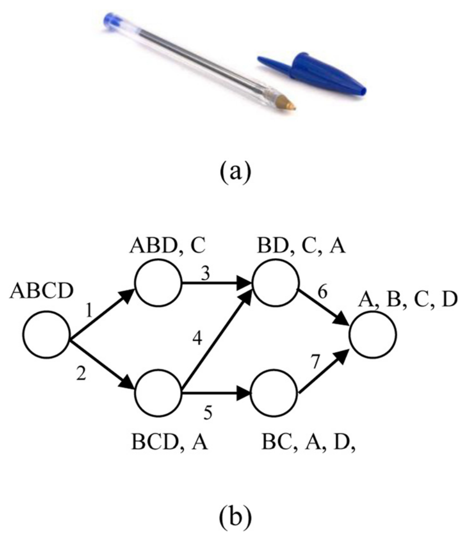

Fig. 1 Simple assembly (*a*) and its disassembly graph (*b*)

including AND/OR graph, Petri net, undirected, and digraph. The disassembly graph of a product can be shown in the form of a matrix called a transition matrix [23]. Figure 1 illustrates the structure of a simple ballpoint pen and its disassembly graph. Nodes and arcs of the graph correspond to the subassemblies and the disassembly transitions, respectively. In this example, the pen's plastic body (component B) is the target component, and the disassembly graph shows several alternative paths to reach that component. Table 1 shows the related transition matrix. Each cell of the matrix is defined with element t_{ij}, that is, -1 if transition j destroys subassembly i, and is 1 if it creates subassembly i. Otherwise, it is 0.

To find an optimal or near optimal disassembly sequence, all feasible disassembly sequences generated by the user for a given product can be represented with a systematic tool such as a graph or transition matrix. See Behdad et al. [9] for different methods of disassembly sequence representation.

3.2 Attributes. After identification of disassembly alternatives, the next step is to define the relevant criteria or objectives for identifying the preferred alternative. The term "attribute" is employed here instead of "objective" or "criteria," because once a problem is identified as a tradeoff problem, maximizing or minimizing any one objective is no longer the goal. Instead, the goal is to maximize some measure (utility) of a *combination* of attributes [24,25]. The relevant attributes in the disassembly process for the purpose of maintenance or upgrade are disassembly cost, the probability of not incurring damage during disassembly, reassembly cost, and the probability of not incurring damage during reassembly.

Table 1 Transition matrix of the pen with four major components

		Disassembly transitions						
		1	2	3	4	5	6	7
Subassemblies	ABCD	-1	-1	0	0	0	0	0
	ABD	1	0	-1	0	0	0	0
	BCD	0	1	0	-1	-1	0	0
	BD	0	0	1	1	0	-1	0
	BC	0	0	0	0	1	0	-1
	A	0	1	1	0	0	0	0
	B	0	0	0	0	0	1	1
	C	1	0	0	1	0	0	1
	D	0	0	0	0	1	1	0

Note: A: cap, B: plastic body, C: end-cap, D: internal ink reservoir and the sphere.

3.2.1 Disassembly Cost. Disassembly cost, c_j, of each transition (action) is estimated based on the labor cost and the disassembly time, as shown in following equation:

$$c_j = c_L * t_j \tag{1}$$

where c_j is the disassembly cost of transition j, c_L is the labor cost, and t_j is the time of transition j.

In practice, disassembly time can vary considerably because of corrosion of connections or other contaminations. These factors can be significant, particularly for those products that have been operated in aggressive environments. Corrosion not only degrades the quality of the products but also contributes to more difficult and unsafe disassembly operations. In addition to corrosion, disassembly time is influenced by other factors including operator skills, material properties, disassembly tools, and fixtures. Moreover, product deformation during the usage stage and possible changes in the original product structure due to the repair, replacement, and manipulation efforts also influence the disassembly time.

3.2.2 Probability of not Incurring Damage During Disassembly. The probability that the dismantled components do not become damaged during the disassembly process is another attribute. This probability is related to all of the components involved in disassembly.

3.2.3 Reassembly. In selective disassembly for the purpose of maintenance or upgrade, reassembly is as important process as disassembly. To include consideration of the reversibility of the disassembly process, the same attributes used for disassembly are employed: the cost of reassembly and the probability that components do not become damaged during reassembly.

4 Problem Modeling

In this section, a mathematical model for determining the optimal selective-disassembly sequence is presented. The aim of the model is to identify a sequence of the disassembly transitions that results in the best combination of conflicting attributes under uncertainty. As mentioned earlier, in selective disassembly the target component and the final state of the disassembly plan is given. Therefore, an approach similar to the shortest path method can be employed. The constraints of the model are formulated in the same way as a single-source, single-destination shortest path problem. The purpose is to find a path with maximum utility from a whole product (as an initial node) to a target component as a given node, in contrast to the shortest path which is looking for a path with minimum cost. Applying the shortest path formulation to identify the disassembly sequence with the highest utility is particularly useful in the case of complicated subassemblies with large complex disassembly graphs in which determining and counting all disassembly alternatives and their associated transitions time and damage cannot be conducted manually.

The index set, decision variables, and model parameters are defined as follows:

Index set

i: attribute
j: feasible disassembly transition (action)
l: node of disassembly graph (assembly states)
t: target node
I: the set of all attributes
n: the total number of attributes
J: the set of all feasible disassembly transitions
I_l: the set of disassembly transitions (arcs) coming to node l
O_l: the set of disassembly transitions outgoing from node l

Decision Variables

x_j: The binary (0, 1) variable that indicates whether disassembly transition j is performed ($x_j = 1$) or not ($x_j = 0$).

Parameters

y_i: the performance level of attribute i
$y_{i,j}$: the performance level of attribute i for disassembly transition j
$U(y_{i,j})$: the single attribute utility of attribute i for disassembly transition j
k_i: the single attribute scaling constant, which scales each attribute from 0 to 1
K: the multi-attribute scaling constant, which scales the overall utility from 0 to 1

The problem can then be formulated as a binary integer linear program that maximizes multi-attribute utility. The background and justification for engineering design applications of the multiplicative form for the objective function developed in Eqs. (2)–(5) has been presented fully elsewhere [24–26], and will not be repeated here. In practice, the design decision maker's utility function is assessed directly through the use of lottery questions. The single attribute utility functions $U(y_{i,j})$ reflect the value the decision maker derives over the tolerable (and feasible) range of each attribute, while the scaling constants k_i reflect the tradeoffs the designer is willing to make among the attributes. The scaling constant K simply normalizes the multi-attribute utility to range between 0 and 1. Again, implementation details for engineering design can be found in Refs. [24–27]

$$1 + KU(y_1, y_2, \ldots, y_n) = \prod_{i=1}^{n}[Kk_iU_i(y_i) + 1] \tag{2}$$

where K is a nonzero solution to the equation

$$1 + K = \prod_{i=1}^{n}[1 + Kk_i] \tag{3}$$

After rearrangement, this multiplicative utility function, the objective function of the model, would be:

Objective Function:

$$\mathrm{Max}U = \sum_{j\in J}\left\{\frac{1}{K}\left(\prod_{i\in I}[Kk_iU(y_{i,j}) + 1] - 1\right)\right\}x_j \tag{4}$$

In the case of uncertain attribute outcomes, the utility function $U(y_{i,j})$ can be replaced by expected utility, applying the probability density function $f(y)$

Subject to:

$$EU(y) = \int f(y)U(y)dy \tag{5}$$

The disassembly network has been described by a set of node equations. A binary decision variable is assigned to each disassembly transition or arc of the graph. The summation of the arcs leaving the first node should be equal to 1. The summation of the arcs entering destination node (node correspond to target part) should be equal to 1. For the remaining nodes (transit nodes), the number of arcs entering must be equal to the number of arcs leaving a node. These constraints are shown in Eqs. (6)–(8)

$$\sum_{j\in o_1} x_j = 1 \quad \text{(initial node)} \tag{6}$$

$$\sum_{j\in I_l} x_j = \sum_{j\in O_l} x_j \quad \text{(transit nodes)} \tag{7}$$

$$\sum_{j\in I_t} x_j = 1 \quad \text{(target node)} \tag{8}$$

x_j is a flow variable assigned to each link of the graph representing the execution of disassembly transition j. The formulation of the constraints is the same as the linear programming suggested by Lambert for incomplete disassembly planning based on the transition matrix structure [28].

Assumptions and Conditions:

- Each subset of attributes exhibits utility independence of the remaining attributes.
- The disassembly process is reversible.
- The target component(s) is given.

5 Example

A solar heating system illustrates the proposed methodology. Suppose a manufacturer that is responsible for after sale service has received a report of malfunctioning of the auxiliary heater. The question is: What is the best method for disassembly of the system to reach the heater? Before answering this question, some insights about components, scale, and geometry of the whole system are provided.

Figure 2 is a simplified version of a solar thermal heater that shows the geometric information of the system and Fig. 3 shows a part of the plumbing system of the solar heating system.

Different components of the system are listed in Table 2. There are several reasons for choosing this system as an example. This system is designed for durable use, has a long expected life, and high initial cost, making it a good candidate for repair and reuse rather than replacement with an entirely new system [29].

There are several fundamental components in most solar water heating systems, including collector, storage tank, and interconnecting plumbing. The system is powered by the sun. The collector catches solar rays and heats a fluid such as water or antifreeze, then transfers the heat to the storage tank. Expansion tanks are installed to accommodate the expansion of the heated fluid.

The size of the heater depends on the collector area and storage volume required to provide 100% of a household's hot water needs during the summer.

Storage tanks are usually 50-, 60-, 80-, or 120-gal capacity. A 50- to 60-gal system is sufficient for 1–3 people. Collector size can be estimated based on the number of members in a household. A collector area of 20 square feet for each of the first two family members, plus 8 square feet for each additional family member is sufficient [30].

Different disassembly sequences to access the auxiliary heater are shown in a network illustrated in Fig. 4. The disassembly

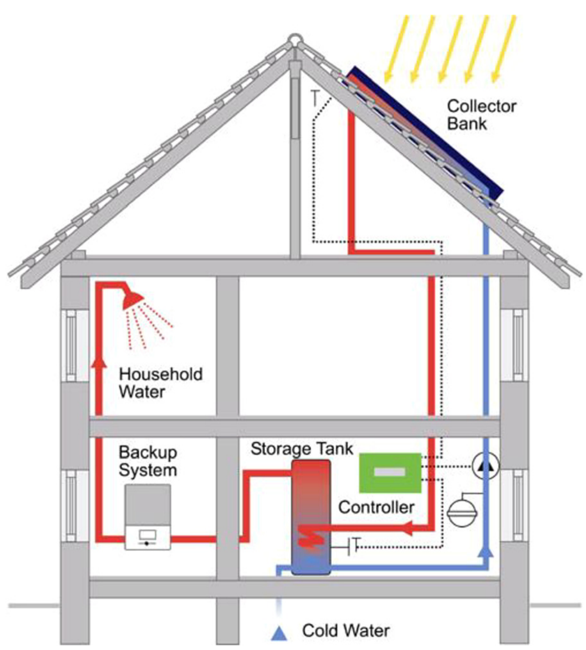

Fig. 2 Solar heating system structure [31]

Fig. 3 A portion of the plumbing system

Table 2 Major components of a solar heating system

Parts	Label
Insulation plate 1	A
Insulation plate 2	Q
Thermal storage	B
Auxiliary heater	F
Fan	E
Valves 1, 2	S, T
Collector	H
Expansion tank 1	C
Expansion tank 2	D
Pipes 1–10	G, P, O, L, M, K, J, R, N, I
Pumps 1, 2	V, U

transactions are mainly related to dismantling the pipes tied into the auxiliary heater. Each arc of the graph shows a single disassembly operation. Each road from node 1 to node 11 shows a specific disassembly alternative. Two labels are shown in each node: the label(s) associated with dismantled part(s) and the disassembly transition. For simplicity, the notation introduced in Fig. 1 has not been applied here and the resulting subassemblies are not listed in each node of the graph. In addition, since the focus of this example is on selective disassembly in which the target component is given, the last node of the graph represents all different disassembly states (nodes) in which the auxiliary heater is accessible, rather than the fully disassembled product. For the case of more complicated products, a transition matrix is a better tool for representing the feasible disassembly alternatives. In this situation, the problem formulation can be adjusted based on the matrix representation.

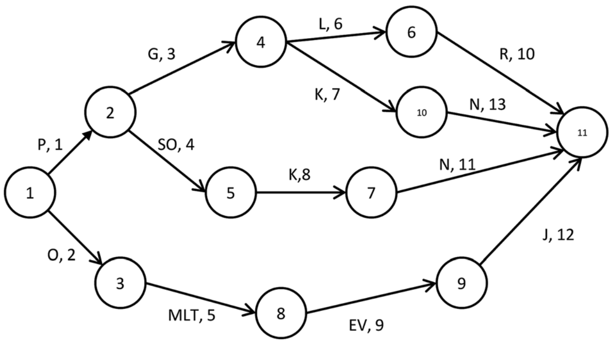

Fig. 4 The network of possible disassembly alternatives

5.1 Results for the Case With Deterministic Disassembly and Reassembly Times. This section presents results when a deterministic point estimate (no uncertainty) of disassembly and reassembly times is considered.

For the purpose of this example, the following notation has been used to reflect the performance levels of attributes:

t_j: the performance level of first attribute: disassembly time ($y_{1,j}$) for disassembly transition j

p_j: the performance level of second attribute: probability of not incurring damage during disassembly ($y_{2,j}$) for disassembly transition j

t_{aj}: the performance level of third attribute: reassembly time: ($y_{3,j}$) for transition j

p_{aj}: the performance level of fourth attribute: probability of not incurring damage during reassembly ($y_{4,j}$) for transition j.

An exponential single attribute utility function is employed for disassembly time in Eqs. (9)–(13). In many cases, an exponential form as shown in Eq. (9) is revealed during the decision maker's lottery assessment process, reflecting decreasing marginal gains in utility as one moves from "worst" to "best" over the range. The lottery assessment procedure is fully described in Ref. [24]. The magnitude of constant c reflects the degree of nonlinearity, if any, as well as the degree of risk aversion exhibited by the design decision maker [24]. Larger values of c reflect a utility function that is more concave and more risk averse, while smaller values reflect a flatter, less risk averse (more risk tolerant) utility function. For the current example, $c = 0.01$.

The single attribute utility function $U(t_j)$ can be normalized between zero (worst tolerable) and one (best feasible) by calculating the constants a and b using Eqs. (10)–(12), so that $U(t_{\min}) = 1$ and $U(t_{\max}) = 0$, where the disassembly time ranges over the interval $0 \le t \le 100$.

c: The risk aversion coefficient

t_j: Time of transition j(min)

a, b, and c are constant

$$U(t_j) = a - be^{ct_j} \tag{9}$$

$$a - be^{ct_{\min}} = 1 \quad \text{and} \quad a - be^{ct_{\max}} = 0 \tag{10}$$

$$a = \frac{e^{ct_{\max}}}{e^{ct_{\max}} - e^{ct_{\min}}} \tag{11}$$

$$b = \frac{1}{e^{ct_{\max}} - e^{ct_{\min}}} \tag{12}$$

$$U(t_j) = 1.58 - 0.58e^{0.01t_j} \tag{13}$$

The second attribute is the probability of not having damaged parts. The probability of an outcome (in this case, damage) can be defined as an attribute (rather than the magnitude of the outcome itself) if the magnitude of the outcome is the same across the range of probabilities, which is the case here [32]. If p_j is defined as the probability of not incurring damage during transition j, then by applying the proportional score method (Eq. (14)) the utility of this attribute would be its value (Eq. (15)). Thus, this single attribute utility is linear with probability and scaled from 0 to 1 over the range of worst to best estimated probabilities.

$$U(p_j) = \frac{p_j - \text{Worst value}}{\text{Best value} - \text{Worst value}} \tag{14}$$

where $\text{Worst value} = 0, \quad \text{Best value} = 1$

$$U(p_j) = p_j \tag{15}$$

The same procedure is followed for estimating the single attribute utilities of reassembly cost and the probability of not incurring damage during reassembly.

Expert opinions, historical data, and/or analytic estimation can be used for estimating the probabilities of damage. Another method is to employ Immersive Computer Technology to carry out virtual experiments in order to simulate a large number of disassembly process steps, and better estimate the probability of damage associated with each possible step. For the purpose of this paper, the assumed probabilities listed in Tables 3 and 4 can be taken as reasonable estimates, considering the difficulty of disassembly.

Single attribute and overall utilities for each feasible disassembly transition are calculated and shown in Table 5.

The scaling constants k_i for disassembly time, probability of damage during disassembly, reassembly time, and probability of damage during reassembly are considered as 0.17, 0.30, 0.15, and 0.35, respectively. Applying Eq. (3), normalizing constant K would be 0.09.

Using the overall utilities as coefficient factors and solving the integer linear programming model gives the optimal route from node 1 to node 11, with highest utility. Route 1-3-8-9-11 shown in Fig. 5 with dashed line is the optimal disassembly sequence for the solar heater. Therefore, for disassembly of solar heating system for the purpose of auxiliary heater maintenance, transitions 2, 5, 9, and 12 should be executed. The optimal disassembly process starts by removing the pipe 3. Then, the combined module of valve 2 and pipes 4 and 5 is removed, and finally, fan, pump 1, and pipe 7 are disassembled.

5.2 Results for the Case With Uncertain Disassembly and Reassembly Times.

This section presents results when a probabilistic estimate (including uncertainty) of disassembly and reassembly times is considered. The results of the model can vary depending on whether the input values for disassembly and reassembly time are treated as being deterministic or probabilistic. There is often a large degree of uncertainty associated with these inputs, so including consideration of that uncertainty will yield more accurate results.

Table 3 Disassembly time and probability of not incurring damage during disassembly

Operation j	t_j	p_j
1	38	0.94
2	21	0.97
3	11	0.99
4	4	0.93
5	17	0.99
6	18	0.93
7	34	0.85
8	13	0.85
9	12	0.95
10	10	0.96
11	11	0.99
12	4	0.95
13	11	0.99

Table 4 Reassembly time and probability of not incurring damage during reassembly

Operation j	t_{aj}	p_{aj}
1	43	0.90
2	27	0.92
3	18	0.95
4	4	0.95
5	22	0.91
6	14	0.87
7	24	0.90
8	10	0.90
9	11	0.93
10	7	0.92
11	16	0.93
12	5	0.85
13	16	0.93

Table 5 Single attribute utilities and overall utility for each transition

Operation j	$U(t_j)$	$U(p_j)$	$U(t_{aj})$	$U(p_{aj})$	Overall utility
1	0.73	0.94	0.69	0.90	0.84
2	0.85	0.97	0.81	0.92	0.90
3	0.92	0.99	0.88	0.95	0.94
4	0.97	0.93	0.97	0.95	0.94
5	0.89	0.99	0.85	0.91	0.92
6	0.89	0.93	0.91	0.87	0.89
7	0.76	0.85	0.84	0.90	0.84
8	0.91	0.85	0.93	0.90	0.88
9	0.92	0.95	0.93	0.93	0.93
10	0.94	0.96	0.96	0.92	0.94
11	0.93	0.99	0.90	0.93	0.94
12	0.97	0.95	0.97	0.85	0.91
13	0.93	0.99	0.90	0.93	0.94

Note: Assumed scaling constants: $k_t = 0.17$, $k_p = 0.30$, $k_{ta} = 0.15$, $k_{pa} = 0.35$, and $K = 0.09$.

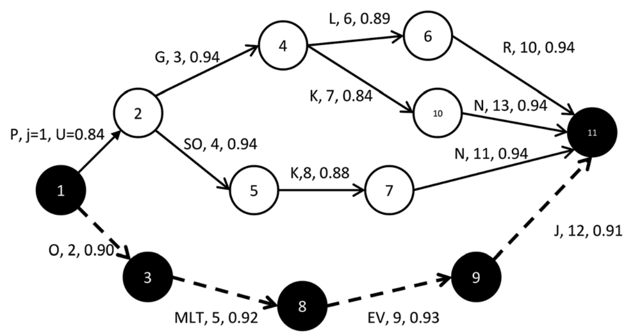

Fig. 5 The network of disassembly transitions and related utilities and optimal path

The same exponential single attribute utility function in Eq. (9) is employed, but this time the effect of the uncertainty on the desirability of each alternative is reflected using expected utility as calculated in Eq. (5).

If the decision maker's degree of risk aversion as reflected by the coefficient c in Eq. (9) is high, he or she would prefer to have a longer (less desirable) disassembly time than to be exposed to the possibility of risking a significantly longer time, even when there is some possibility of a shorter time.

Fischer et al. [33] showed that the beta distribution is well suited for modeling uncertainty in disassembly and reassembly execution times. The maximum likelihood estimator for the beta distribution was determined by Carnahan [34], and the distribution is relatively straightforward to obtain since it can be characterized by only three input parameters: the optimistic, the pessimistic, and the most common values.

If the disassembly or reassembly time of the jth transition has a beta distribution with the probability density function

$$\begin{cases} f(t) = \dfrac{\Gamma(p+q)}{r\Gamma(p)\Gamma(q)}\left(\dfrac{t-t_L}{r}\right)^{p-1}\left(\dfrac{t_U-t}{r}\right)^{q-1} & t_L \le t \le t_U \\ = 0 & \text{Otherwise} \end{cases} \tag{16}$$

where

Table 6 Disassembly time range and probability distribution

Operation j	$[t_L, t_U]$	Distribution
1	[31,39]	$\beta(2,5)$
2	[20,42]	$\beta(2,5)$
3	[5,15]	$\beta(2,3)$
4	[2,7]	$\beta(2,3)$
5	[14,36]	$\beta(2,3)$
6	[5,19]	$\beta(3,3)$
7	[30,41]	$\beta(2,3)$
8	[11,16]	$\beta(2,3)$
9	[10,25]	$\beta(3,5)$
10	[2,11]	$\beta(3,3)$
11	[8,16]	$\beta(3,5)$
12	[2,17]	$\beta(2,3)$
13	[8,16]	$\beta(3,5)$

$$r = t_L - t_U$$

p and q are shape parameters.

Then, the expected utility based on Eqs. (5), (9) and the probability density function of a beta distribution can be calculated by the following equation [35]:

$$E\left[U(t_j)\right] = \frac{\Gamma(p+q)}{r\Gamma(p)\Gamma(q)} \int_{t_L}^{t_U} a - be^{ct_j} \left(\frac{t-t_L}{r}\right)^{p-1} \left(\frac{t_U - t}{r}\right)^{q-1} dt \tag{17}$$

The range of disassembly and reassembly times and their probability distributions are listed in Tables 6 and 7, respectively. Single attribute and overall utilities for each feasible transition are calculated and shown in Table 8. The overall utilities in Table 8 are calculated with all four utilities.

Using the overall utilities, the model gives route 1-2-4-6-11 as the optimal route. The route is shown in Fig. 6 with dashed line. As can be seen, the optimal sequence changes when uncertainty is present.

Therefore, considering uncertainty is an essential point that is handled via utility theory. The same reasoning procedure can be followed for the results shown in Fig. 5 that is the case in which uncertainty in disassembly/reassembly time has been resulted into a different disassembly sequence. As Fig. 5 illustrates, the subassemblies P, G, L, and R need to be dismantled so the designer can concentrate on ease of disassembly of these modules.

A sensitivity analysis can be performed to show how the optimal sequence changes when the scaling constants k_i are changed. These scaling constants reflect the tradeoffs that the decision maker is willing to make among the conflicting attributes i. Rather than a sensitivity analysis on the time and probability of damage occurring during disassembly and reassembly, this sensitivity analysis can be conducted on the scaling constants themselves. As one example, the scaling constant for disassembly time was increased from 0.17 to 0.27, and the scaling constant of the probability of disassembly damage was decreased from 0.30 to 0.19, changes which reflect a greater willingness to increase the probability of damage in order to decrease disassembly time. The resulting overall utility was 3.58 and the route 1-2-4-6-11 remained as the optimal route. This example shows that the results of the model are not significantly influenced by the scaling constants over this range. When the sensitivity is not high, then it will not be difficult for the approach to be used in practice.

Table 7 Reassembly time range and probability distribution

Operation j	$[t_{aL}, t_{aU}]$	Distribution
1	[28,44]	$\beta(3,3)$
2	[23,45]	$\beta(2,3)$
3	[10,19]	$\beta(2,3)$
4	[2,6]	$\beta(3,4)$
5	[21,37]	$\beta(2,5)$
6	[6,13]	$\beta(2,3)$
7	[22,27]	$\beta(3,4)$
8	[8,15]	$\beta(2,5)$
9	[9,23]	$\beta(2,3)$
10	[3,8]	$\beta(2,3)$
11	[14,18]	$\beta(2,3)$
12	[3,20]	$\beta(3,5)$
13	[14,18]	$\beta(2,3)$

Table 8 Single attribute utilities and overall utility for each transition

Operation j	$U(t_j)$	$U(t_{aj})$	Overall utility
1	0.77	0.74	0.86
2	0.82	0.79	0.89
3	0.94	0.91	0.95
4	0.97	0.97	0.94
5	0.84	0.81	0.90
6	0.92	0.94	0.90
7	0.76	0.84	0.84
8	0.91	0.93	0.88
9	0.90	0.90	0.92
10	0.96	0.96	0.94
11	0.93	0.90	0.94
12	0.95	0.93	0.90
13	0.93	0.90	0.94

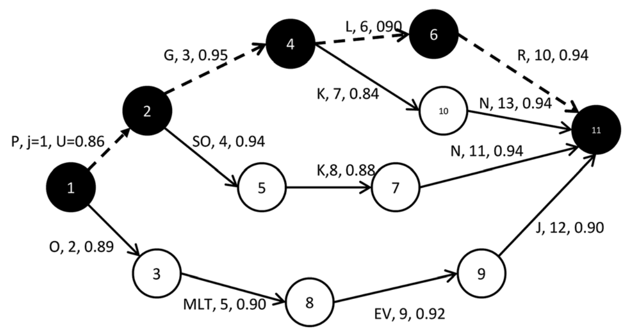

Fig. 6 The network of disassembly transitions and optimal path for the case of uncertain attributes

The results of the model can not only help the manufacturer to plan the disassembly process, but also help the designer to modify the product in order to improve disassembly.

For example, the result in Fig. 5 indicates that the subassemblies O, MLT, EV, and J should be disassembled, so the designer can focus efforts on the number and type of fasteners that connect these modules to the main body of the system.

Furthermore, the model provides some design insights that previously eluded the designer. For example, many designers do not consider disassembly damage and its effects on reparability during development of the original design concept. One important aspect of the proposed model is that it quantifies the effects of those probabilities in terms of utility. Lower probability of incurring damage results in higher utility, and can be achieved by applying some design guidelines such as reducing the complexity of the product or the number of parts. The model reveals the importance of considering design properties such as product architecture and materials type, which influence the probability of incurring damage and eventually utility of different disassembly sequences. Various design modifications with different assembly and disassembly times and also probability of damage could be studied by employing the model. The results of the model answer this question: How much does a design change influence the performance

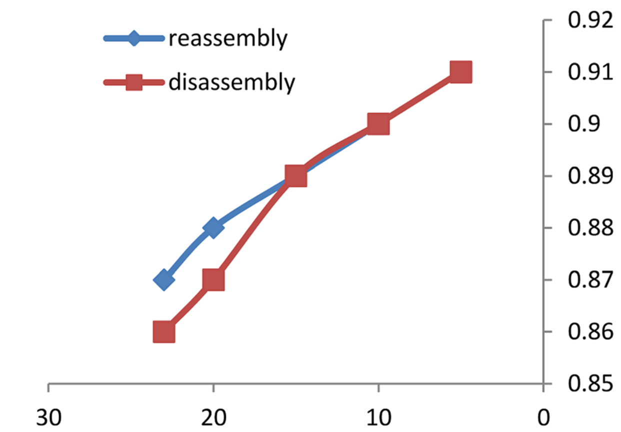

Fig. 7 The influence of decreasing the disassembly and reassembly time on overall utility of operation 5

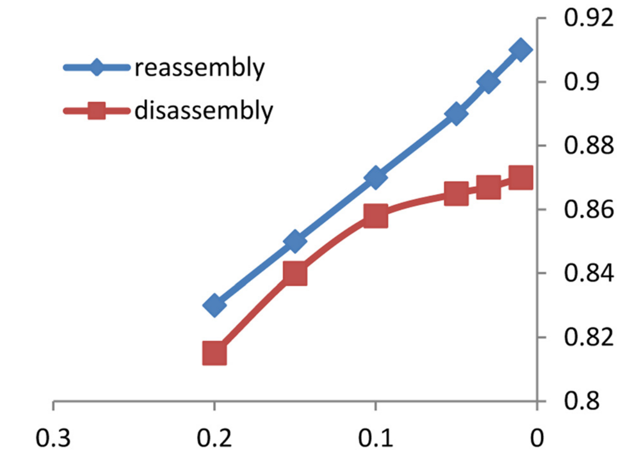

Fig. 8 The influence of decreasing the probability of incurring damage during disassembly and reassembly on the overall utility of operation 5

(utility) of disassembly alternatives? Figures 7 and 8, respectively, depict the influence of disassembly and reassembly time, and the probability of disassembly/reassembly damages on the utility of operation 5 while the other attributes levels are equal.

To clarify the discussion, consider the optimal sequence in the current example and see how the model aids in evaluating the suggested design modifications.

Sequences 1, 3, 6, and 10 has the highest utility (0.91), but the probability of incurring damage during reassembly for this sequence is high (0.31). Operation 6 is one step of this sequence that has a high probability of incurring damage during reassembly. On the other hand, the probability of damage during disassembly (0.07) is not as high as the probability of damage during reassembly. Therefore, the probability of damage for disassembly (0.07) is an accurate estimate.

Investigating the design of the heating system reveals that in the current design four hexagonal socket head cap screws have been used for attaching pipe 4 to pipe 8. The design team suggests using another type of screw. A hexalobular socket head cap screw whose cylindrical head has a hexalobular socket formed at its center. These two different types of screw are shown in Fig. 9.

The new design increases the fastening force and results in decreasing the probability of incurring damage during reassembly by 0.06 for operation 6 since the hexalobular head hole is shaped to withstand high tightening torque. However, with a hexalobular wrench, the rotation angle cannot be visually checked with ease,

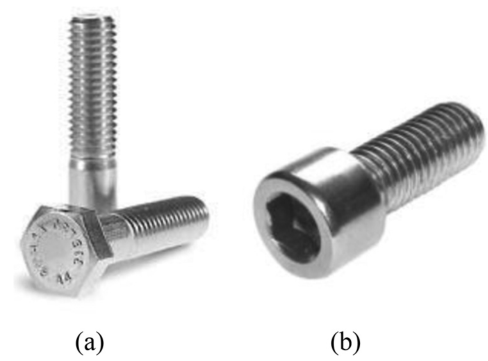

Fig. 9 Hexagonal (*a*) and hexalobular (*b*) socket head cap screws

Table 9 The utility comparison of two different types of screw

	Operation 6				
	t_{Dis}	p_{Dis}	t_{Re}	p_{Re}	Overall utility
Current design	[5,19]	0.93	[6,13]	0.87	0.90
New design	[10,24]	0.93	[13,20]	0.93	0.88

so using the new screw will shift the reassembly and disassembly time ranges of all four screws by 7 and 5 min, respectively.

The manufacturer seeks to determine whether using the new type of screws will increase overall utility or not. The corresponding utilities were calculated for each design, and are listed in Table 9.

Although by employing the new design, the parts are less likely to be damaged during reassembly, the disassembly and reassembly times are increased, so that the overall utility is decreased. To conclude, using the new type of screws for attaching pipe 4 to pipe 8 will not improve the decision maker's utility.

6 Conclusion

Disassembly sequence optimization has a direct impact on the effectiveness of a maintenance plan as well as on product upgrade efforts. As with assembly, components can often be disassembled in several different orders. Overall effort can be reduced by careful planning of the disassembly and reassembly sequence.

This paper presented a procedure for identifying the best sequence of disassembly operations for maintenance and/or component upgrade. It considers both disassembly and reassembly operations. Binary integer linear programming is combined with multi-attribute utility analysis to select the most appropriate disassembly sequence when the target component is given (e.g., disassembly for the purpose of maintenance/upgrade). The multi-attribute utility optimization maximized tradeoffs under uncertainty. Utility functions which incorporate a design decision maker's attitude toward risk were constructed. Four attributes were considered: (1) disassembly time as a measure of disassembly cost, (2) the probability of not incurring damage during disassembly transitions, (3) reassembly cost, and (4) the probability of not incurring damage to components during reassembly. A simple example regarding replacement of an auxiliary heater inside a solar heating system illustrated the method. The results of the model were presented for two cases: a case in which disassembly and reassembly times are deterministic and a case with uncertainty. The different results obtained from the two cases illustrated the usefulness of utility theory in handling uncertainty. Moreover, sensitivity analyses illustrated the influence of disassembly/reassembly time and the probability of damage on the optimal solution.

The proposed method was initially motivated by the need to select the best disassembly sequence for the purpose of maintenance and upgrade, but the results also provided some insights for designers. The designer can apply the results obtained about the disassembly sequence to modify the product design based on transitions and disassembled modules. In this paper, two different designs of a screw have been evaluated, as an example.

The proposed method can be extended by considering more attributes such as "knowledge of disassembly/operator experience," "capacity of the disassembly operations," and the "environmental effects" of the operations. In addition, constructing a procedure for determining different disassembly alternatives and enumeration of the feasible disassembly sequence can be automated to facilitate the analysis of complex products.

In the current study, cost and the probability of damage have been considered as two utility-independent attributes. Future work could consider the combined effect probability of damage and cost of resulting repair and rework, in the form of total expected cost.

Furthermore, statistical analyses and simulation tools can be applied to better estimate the uncertain parameters of the model (e.g., disassembly time and probability of damage). More investigation is needed to determine the disassembly time of an operation depending on the parts having been disassembled so far, and their effect on the risk of damage.

The selection of precedence relations and feasible subassemblies is another possible area of future inquiry.

Finally, investigating the specific redesign guidelines according to the model results can be a focus point for future studies.

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