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Disassembly Sequence Planning Considering Fuzzy Component Quality and Varying Operational Cost

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***Abstract*— Disassembly planning aims to search the best disassembly sequences of a given obsolete/used product in terms of economic and environmental performances. A practical disassembly process may face great uncertainty owing to various unpredictable factors. To handle it, researchers have addressed the stochastic cost and time problems of product disassembly. In reality, the uncertain environment of product disassembly is associated with both randomness and fuzziness. Besides uncertain disassembly cost and time, the quality of disassembled components/parts in a process has uncertainty and thus needs to be assessed via expert opinions/subjects. To do so, this paper presents a new AND/OR-graph-based disassembly sequence planning problem by considering uncertain component quality and varying disassembly operational cost. Important disassembly planning models are built on the basis of different disassembly criteria. A novel hybrid intelligent algorithm integrating fuzzy simulation and artificial bee colony is proposed to solve them. Its effectiveness is well illustrated through several numerical cases and comparison with a prior method, i.e., fuzzy-simulation-based genetic algorithm.**

***Note to Practitioners*—This paper deals with the uncertainty management problem of product disassembly. It builds some fuzzy programming models for product disassembly and proposes a hybrid intelligent algorithm integrating fuzzy simulation and artificial bee colony to solve them. Previously, such a problem was handled through a methodology based on stochastic planning, which was ineffective without considering the fuzzy characteristic of completing a disassembly task. The goal of this paper is to analyze the disassembly uncertainty feature from the perspective of fuzzy programming. Both theoretical and simulation results demonstrate that the proposed approach is highly effective. The obtained results can help decision-makers better determine a disassembly process of a used/returned/obsolete product.**

***Index Terms*— Disassembly, disassembly planning, fuzzy simulation, modeling and simulation.**

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I. Introduction

PRODUCT recovery aims to obtain valuable materials and useful components/units from used or obsolete products to minimize the amount of waste sent to landfills as well as to maximize their reuse/recycle value. The most important step of such recovery is disassembly. The disassembly of used products is required owing to its significant role in sustaining economic development [1]. It is essential for the remanufacturing, reuse, as well as recycle of used products [2], [3].

The disassembly modeling and planning problem is an important problem to resolve for sustainable economic development. Disassembly modeling approaches mainly include undirected graphs, directed graphs, AND/OR graphs, and Petri nets [4]–[9]. Disassembly planning determines an optimal disassembly sequence and has been well recognized as an NP-hard issue. Various solution methods have been formed in this field [1], [4], e.g., two-commodity network flow method, [10] and rule-based recursive approach [11]. Several intelligent algorithms are adopted by aiming to obtain the best disassembly sequence, e.g., rapidly growing random tree-based algorithm [12], genetic algorithm [13], improved max–min ant system [14], self-adaptive simplified swarm optimization method [15], heuristic method [16], and neural networks [17], [18].

The existing work [10]–[18] has well addressed deterministic disassembly evaluation and planning issues. Unfortunately, used/obsolete products to be disassembled are often ones used for a certain period of time, and thus can suffer from great uncertainty. Uncertain management problems of product disassembly are therefore raised. For instance, Tian *et al.* [19] present an energy management method for a product disassembly process integrating the maximum entropy principle and stochastic simulation. Gao *et al.* [20] give a disassembly planning and demanufacturing scheduling approach to an integrated flexible demanufacturing system. Ilgin and Gupta [21] and Brennan *et al*. [22] propose a disassembly sequence planning method by dealing with defective parts. Tian *et al.* [23]–[25] form a chance constrained programming approach to determine the optimal product disassembly sequence. They analyze main uncertainty factors for a disassembly process, e.g., disassembly time and tools [26], [27]. Ding *et al.* [28] present a multiobjective ant colony algorithm for solving the disassembly line balancing problem. Tang and Zhou [29] analyze the expected disassembly cost and net profit of used product disassembly subject to uncertain disassembly time. They present a machine learning method to do so [30], [31]. Reveliotis [32] provides effective learning-based strategies to disassembly uncertainty management. Teunter [33] presents a stochastic dynamic programming algorithm for determining the optimal disassembly and recovery strategy. Gungor and Gupta [34] describe the uncertainty related difficulties in a disassembly sequence planning. They present a methodology for disassembly sequence planning for products with defective parts in product recovery. Galantucci *et al.* [35] analyze a disassembly planning by using fuzzy logic and genetic algorithms. Ullerich and Buscher [36] present a flexible disassembly planning considering product conditions.

The existing studies [19]–[36] have mainly focused on disassembly time or cost uncertainty. However, a disassembly process of end-of-life products has multiple uncertain variables and different types of uncertainty. In addition to uncertain disassembly cost or time due to some unpredictable factors, e.g., disassembly tools and methods [24], disassembled component quality is uncertain owing to the influence of usage conditions and disassembly methods. Sometimes obtaining such data by means of experiments is a difficult task when assessing the disassembled component quality. Instead, expert opinions are often adopted to provide their assessment results. Consequently, disassembled component quality can be characterized as a fuzzy/imprecise value. In summary, it is necessary to introduce an assessment methodology for a disassembly process by integrating multiple uncertain variables of different types. To do so, this paper for the first time proposes a new disassembly sequence planning problem by considering the uncertainty of component quality and operational cost, where disassembled component quality is described as a fuzzy member function and disassembly (operation) cost is a random variable following a uniform distribution. This paper aims to find a new way to determine the optimal disassembly sequence by taking multiple uncertainty variables and mixed uncertainty features into full account. It formulates a hybrid method integrating fuzzy simulation and artificial bee colony (ABC) to solve the problem. Compared with the existing work, we make three contributions:

1) In order to better describe the actual condition of a product process, we establish new disassembly optimization models subject to component quality uncertainty and varying operational cost, which successfully integrate multiple uncertain variables of different types.
2) To well solve the proposed problem, we formulate a hybrid optimization method that innovatively integrates fuzzy simulation and ABC, i.e., in ABC, the objective function value and fitness of all chromosomes are evaluated via fuzzy simulation.
3) By comparing with the prior method, i.e., fuzzy-simulation-based genetic algorithm, we validate the effectiveness and feasibility of the proposed methodology in solving a fuzzy disassembly optimization problem.

The rest of this paper is organized as follows. Section II describes a disassembly problem and establishes its mathematical model. Section III describes the solution method. Section IV presents the solutions to several cases and comparison results. Finally, Section V concludes our work and describes some future research issues.

II. Problem Statement

In order to conveniently establish our models, we present the following preliminaries.

A. Concept of Fuzzy Variables

Zadeh proposed the fuzzy set theory [37] in 1965. It is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a membership value between zero and one. It has been well developed and applied to resolve many practical issues. In this field, three important types of measures are introduced: possibility, necessity, and credibility [37], [38].

Let ξ be a fuzzy variable with membership function μ, and let u and r be real numbers. The possibility, necessity, and credibility of a fuzzy event $\{\xi \geq r\}$ are defined, respectively, by

$$\text{Pos}\{\xi \geq r\} = \sup_{u \geq r} \mu\ (u) \tag{1}$$

$$\text{Nec}\{\xi \geq r\} = 1 - \text{Pos}\{\xi < r\} = 1 - \sup_{u<r} \mu(u) \tag{2}$$

$$\text{Cr}\{\xi \geq r\} = \frac{1}{2}(\text{Pos}\{\xi \geq r\} + \text{Nec}\{\xi \geq r\}). \tag{3}$$

With the definition of credibility, we express the concept of the expected value of a fuzzy variable ξ as follows [34]:

$$E(\xi) = \int_0^{+\infty} \text{Cr}\{\xi \geq r\}dr - \int_{-\infty}^0 \text{Cr}\{\xi \leq r\}dr. \tag{4}$$

B. Uncertainty Description of Product Disassembly

In the prior work, disassembly process parameters, i.e., time and cost, are assumed to be random variable and their detailed description can be found in [22] and [23]. In reality, the uncertain environment of product disassembly is frequently associated with both randomness and fuzziness. Disassembly cost or time is often described as a random viable. On the other hand, a disassembled component's quality condition is well described as a fuzzy one. A triangular fuzzy variable is most commonly used due to its intuitive and high computational efficiency. Thus, this paper adopts such a triangular fuzzy member to represent the quality level of a disassembled component. For instance, a triangular fuzzy member $\xi = (a, b, c), a < b < c$ is shown in Fig. 1.

According to (1)–(3), the possibility, necessity, and credibility of a fuzzy event $\{\xi \geq r\}$ are given as follows, respectively:

$$\text{Pos}\{\xi \geq r\} = \begin{cases} 1, & r \leq b \\ \dfrac{c-r}{c-b}, & b \leq r \leq c \\ 0, & r \geq c \end{cases} \tag{5}$$

$$\text{Nec}\{\xi \geq r\} = \begin{cases} 1, & r \geq a \\ \dfrac{b-r}{b-a}, & a \leq r \leq b \\ 0, & r \geq b \end{cases} \tag{6}$$

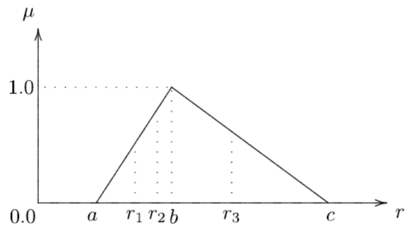

Fig. 1. Triangular fuzzy member $\xi = (a, b, c)$.

TABLE I

QUALITY LEVELS FOR COMPONENTS

Quality level	linguistic variable ξ
Excellent	(0.75, 0.825, 1)
Fine	(0.5, 0.625, 0.75)
Medium	(0.25, 0.375, 0.5)
Poor	(0, 0.125, 0.25)

$$\mathrm{Cr}\{\xi \geq r\} = \begin{cases} 1, & r \leq a \\ \dfrac{2b-a-r}{2(b-a)}, & a \leq r \leq c \\ \dfrac{c-r}{2(c-b)}, & b \leq r \leq c \\ 0, & r \geq c. \end{cases} \tag{7}$$

Based on this example, let ξ represent the fuzzy quality level of a disassembled component. It is seen that $\mathrm{Cr}\{\xi \geq r_1\} > \mathrm{Cr}\{\xi \geq r_2\}$, and $\mathrm{Cr}\{\xi \geq r_2\} > \mathrm{Cr}\{\xi \geq r_3\}$. The credibility of quality not less than c is 0, which simply means that the event of quality not less than c cannot happen.

In this paper, we propose four levels of scale, which are defined with linguistic variables to represent different quality levels ξ of disassembled components. They are excellent, fine, medium, and poor as listed in Table I.

Based on the above discussions, fuzzy set theory can be well used to describe disassembled component quality under uncertainty. Also, disassembly operational cost to disassembly components from the product is uncertainty due to some unpredictable factors, e.g., disassembly tools and methods. It is set to follow a uniform distribution [22], [23]. Based on them, this paper for the first time addresses disassembly sequence planning issues involving both fuzziness of disassembled component quality and randomness of disassembly operational cost. It is noted that random and fuzzy variables are both called as uncertain variables in this paper.

C. Problem Statement of Disassembly Sequence Optimization

This paper proposes a new disassembly problem for an end-of-life product by considering uncertainty of both disassembled component quality and disassembly operational cost, where component quality level is demarcated via a fuzzy variable while disassembly operational cost is represented by a uniformly distributed random variable. Our main aim is to maximize its profit.

The disassembly AND/OR graph describes the connection and precedence relations among components/subassemblies as well as their disassembly operations [35]. In the rest of this paper, subassemblies also refer to components or parts that require no further disassembly. However, they do not include fasteners, e.g., bolts, screws, and wires.

A disassembly AND/OR graph is represented by $G = (V, E)$. $V = \{v_1, v_2, \ldots, v_N\}$ is the set of nodes, in which each element has one-to-one correspondence to a subassembly of a product. N is the number of the elements in V, i.e., the number of subassemblies of a product.

$E = \{e_{ij}\}$ is the set of directed edges, e_{ij} is a directed edge in an AND/OR graph and represents a disassembly operation from node v_i to node v_j.

A disassembly AND/OR graph of a radio set is shown in Fig. 2. Each node's alphabetical combination represents a subassembly, which is numbered in integer with parentheses, i.e., (1), (2), ..., and (N). Each edge represents a disassembly operation as numbered by $1, 2, \ldots,$ and J [39]. Additionally, this paper introduces the concept of in-degree and out-degree. The former is the number of a subassembly's parents, and the latter is the number of child subassemblies disassembled from a parent. Note that subassembly i is called the parent of j if j is obtained by disassembling i, and j is called a child of i. For instance, subassembly (2) is a parent of (6) and (8), while (6) is a child of (1) in Fig. 2. Also, a rectangle node represents a subassembly. A feasible disassembly sequence must satisfy the below requirements:

1) Precedence relationship constraints among subassemblies. For example, in Fig. 2, via operation 1, (1) is disassembled into (2) and (23). Additionally, via operation 3, (4) and (19) can be obtained from the disassembly of (2). Note that this paper adopts precedence matrix $P = [p_{jk}]$ to represent the precedence relationship among operations and operations in an AND/OR graph [1], [40]

$$p_{jk} = \begin{cases} 1, & \text{if operation } j \text{ can be} \\ & \text{performed before operation } k \\ 0, & \text{otherwise.} \end{cases}$$

Thus, precedence matrix P of a product shown in Fig. 2 is expressed as in Fig. 5.

2) In an AND/OR graph, a disassembly operation is represented by multiple linked arcs directed from a parent to its child subassemblies, i.e., AND arcs. For example, in Fig. 2, via operation 11, (3) is disassembled into (5) and (26). Note that although a child subassembly can be obtained from different operations, each can only be produced by one operation, e.g., (26) can be obtained via one of operations 7 and 4 only, given a product to be disassembled.
3) Derived from the same parent subassembly, different disassembly operations lead to different children subassemblies and thus result in an "OR" relationship. For example, the parent subassembly (3) can be disassembled into (5) and (26) via operation 11 or (4) and (23) via operation 10. Thus, operations 11 and 10 establish a logical "OR" relationship.

Note that the "OR" relationship in a practical disassembly process differs from a regular logical "OR" one in mathematics. It means an exclusive OR one since operations, which are able to form a logical "OR" one for a subassembly, conflict

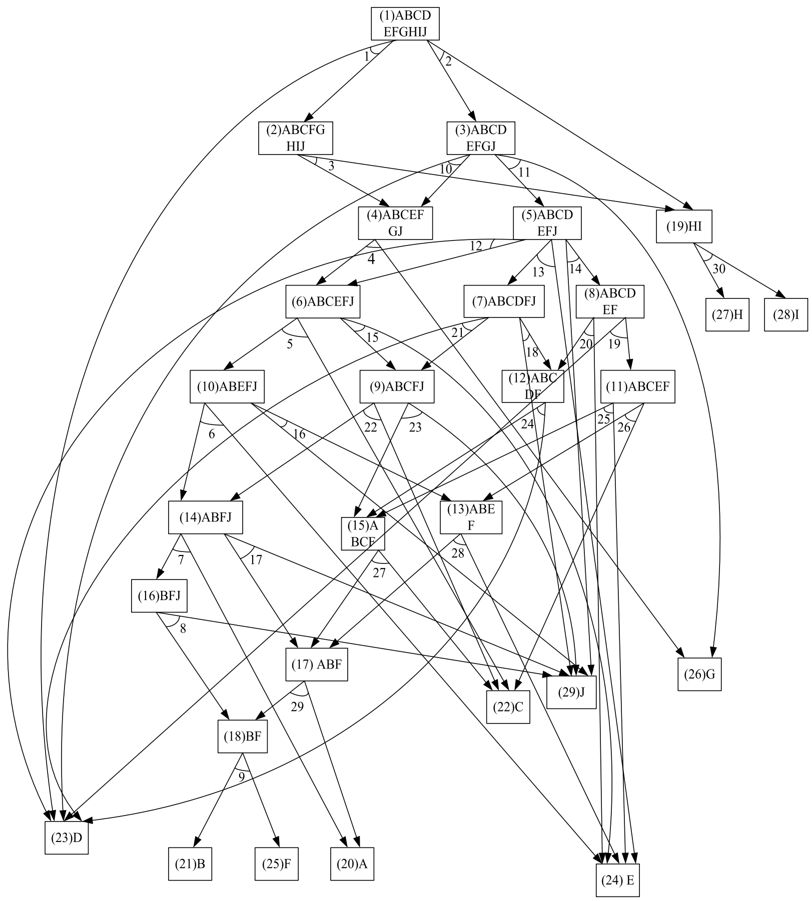

Fig. 2. AND/OR graph of the radio set.

with each other, i.e., only one of them can be performed in a feasible disassembly sequence. For example, operations 1 and 2 constitute an exclusive OR relationship, i.e., either 1 or 2 can be executed in a feasible disassembly sequence but not both. Due to such OR relationship, we can create a set of disassembly paths when a product is disassembled. We introduce a conflict matrix $C = [c_{jk}]$ to represent the conflict relationship (exclusive OR relationship) among operations in an AND/OR graph

$$c_{jk} = \begin{cases} -1, & \text{if operations } j \text{ and } k \text{ conflict with each other} \\ 0, & \text{otherwise.} \end{cases}$$

Thus, conflict matrix C of a product shown in Fig. 2 is expressed as in Fig. 6.

For example, since $c_{12} = -1$, operations 1 and 2 are in conflict, and either of them can be performed but not both. Note that C is a symmetric matrix that differs from P.

4) For convenience of description and calculation, this paper adopts a succession matrix $S = [s_{jk}]$ to represent the succession relationship between operations j and k [41]

$$s_{jk} = \begin{cases} 1, & \text{only if operation } k \text{ can be performed next to} \\ & \text{operation } j \\ 0, & \text{otherwise.} \end{cases}$$

Thus, succession matrix S of a product shown in Fig. 2 is expressed as in Fig. 7.

It should be noted that succession relations differ from precedence relations in a disassembly process. For instance, $p_{8,10}$ and $p_{10,8}$ in P are set as 0, while $s_{8,10}$ and $s_{10,8}$ in S are shown as 1, i.e., operation 8 in S can be performed next to operation 10, and the reverse order is also possible. However, p_{jk} and s_{jk} exactly have a relationship with each other that both of them are the same if: 1) p_{jk} is equal to 1 and 2) operations j and k are adjacent, e.g., p_{13} and s_{13} both equal 1, while $s_{31} = 0$ owing to their precedence relationship shown in P. Further we can find that succession matrix S is related to conflict matrix C since a succession relationship is subjected to conflict matrix C, i.e., operations which can form succession relationship cannot conflict with each other.

An incidence matrix G is used to depict the relationship between subassemblies and operations in an AND/OR graph

$$g_{ij} = \begin{cases} 1, & \text{if subassebmly } i \text{ is obtained by operation} j \\ -1, & \text{if subassebmly } i \text{ is disassembled via} \\ & \text{operation } j \\ 0, & \text{otherwise.} \end{cases}$$

Thus, incidence matrix G of a product shown in Fig. 2 is expressed as in Fig. 8.

For example, as shown in G, parent (1) (ABCDEF) is disassembled via operation 2, thus $g_{12} = -1$. Since this operation generates two child subassemblies (3) (ABCDF) and (14) (E), $g_{32} = 1$ and $g_{14,2} = 1$.

D. Mathematical Model

1) Notations:

1) i—The index of a subassembly, $i \in \{1, 2, \ldots, N\}$, where N is the number of all nodes in a given AND/OR graph.
2) j, k, m—The index of an operation, $j, k, m \in \{1, 2, \ldots, J\}$, where J represents the number of operations. Note that operation 0 refers to the initial operation and has to be preformed because this operation creates a product to be disassembled.
3) ζ_j—Cost of performing operation j, and it is a stochastic variable.
4) R_i—Recycling/reuse value of subassembly i.
5) ξ_i—The quality level of subassembly i, and it is a fuzzy variable and it is the scale from 0 to 1.
6) S—Succession matrix.
7) G—Disassembly-incidence matrix.

2) Decision Variables:

1) x_j: $x_j = 1$, if operation j is performed; otherwise, $x_j = 0$;
2) y_{jk}: $y_{jk} = 1$, if operation k is performed after operation j performed; otherwise, $y_{jk} = 0$.

3) Constraints: Given an AND/OR graph, a feasible disassembly sequence should satisfy the following constraints:

$$\sum_{j=1}^{J} x_j \geq 1 \tag{8}$$

$$x_k = \sum_{j=1}^{J} y_{jk}, \quad k = 1, 2, \ldots, J \tag{9}$$

$$s_{jk} - y_{jk} \geq 0, \quad j, k = 1, 2, \ldots, J \tag{10}$$

$$0 \leq \sum_{j=0}^{J} g_{ij} x_j \leq 1, \quad i = 1, 2, \ldots, N \tag{11}$$

$$\sum_{j=1}^{J} y_{jm} \geq \sum_{k=1}^{J} y_{mk}, \quad m = 1, 2, \ldots, J \tag{12}$$

$$\sum_{m=1}^{J} y_{jm} \leq 1, \quad j = 1, 2, \ldots, J \tag{13}$$

$$x_j, y_{kj} \in \{0, 1\}, \quad j, k = 1, 2, \ldots, J. \tag{14}$$

Constraint 8 guarantees that at least one operation excluding operation 0 is performed for a product. Constraint 9 guarantees that each operation can be performed at most once. Constraint 10 represents the feasibility between operations, i.e., it ensures that a disassembly path/sequence satisfies precedence and conflict relationships. Constraint 11 represents the relationship between subassemblies and operations, and guarantees that: 1) A subassembly cannot be disassembled if it is not previously created, e.g., subassembly (2) ABCDE can be first obtained via operation 1, i.e., $g_{21} = 1$, then subassembly (2) ABCDE can be disassembled via operation 12, i.e., $g_{2,12} = -1$ and 2) A subassembly cannot be obtained or disassembled by multiple operations simultaneously, e.g., subassembly (4) ABCD can be created via one of operations 3 and 4, and operations 5 and 13 are both departing from subassembly (4) ABCD, but these are subjected to an exclusive OR relation, i.e., either operation 5 or 13 is executed in a disassembly process but not both. Constraint 12 represents the equilibrium relationship of in-degree and out-degree of a subassembly, where $\sum_{j=1}^{J} y_{jm}$ and $\sum_{k.=1}^{J} y_{mk}$ are in-degree and out-degree of operation m, respectively, while enabling the disassembly sequence to stop at this point. Constraint 13 represents that a subassembly can be disassembled via one operation at most. Constraint 14 represents that decision variables can take 0 or 1.

4) Mathematics Models: Based on the above description, the disassembly profit is expressed as

$$f = \sum_{j=1}^{J} \sum_{i=1}^{N} g_{ij} \xi_i R_i x_j - \sum_{j=1}^{J} \zeta_j x_j \tag{15}$$

where the first item is the total revenue to disassemble a product and it is the multiplication of the quality (between 0 and 1) and product revenue; and the second one is disassembly operational cost.

It should be noted that revenue is the original value of a component. After its usage, its value is lower in general. To compute the value of each used component, a depreciation coefficient is introduced, namely, the value of each used component is regarded as the multiplication of this depreciation coefficient and revenue. In this paper, the quality with the scale from 0 to 1 is considered as this depreciation coefficient, denoting the quality level of a used component. If this component is a new one with the original value, its quality is 1 and otherwise if the component has no value, its quality is 0.

To maximize the disassembly profit, we build two useful disassembly models subject to uncertain component quality and varying operational cost, i.e., the expected value programming model for fuzzy disassembly optimization and the chance constrained programming model for fuzzy disassembly optimization, which are presented next in detail.

a) Expected value programming model: In a real disassembly process, one expects to obtain the largest average net profit of accomplishing a specific disassembly task via using limited resources. In order to determine the best disassembly sequence, this paper builds a fuzzy expected value programming model for disassembly revenue. Its objective function is written as

$$\max \ E(f) \tag{16}$$

$$\text{Subject to:} \qquad \text{Constraints (8)–(14).} \tag{17}$$

b) Chance constrained programming model: In an actual disassembly process, one expects to maximize the disassembly profit of accomplishing a disassembly task under limited resources with at least some given confidence levels. To handle it, a fuzzy chance constrained programming model for disassembly revenue is built with its following objective function:

$$\max \ \bar{f} \tag{18}$$

$$\text{Subject to: } \mathrm{Cr}\left\{\left(\sum_{j=1}^{J}\sum_{i=1}^{N} g_{ij}\xi_i R_i x_j - \sum_{j=1}^{J}\zeta_j x_j\right) \geq \bar{f}\right\} \geq \alpha \tag{19}$$

$$\text{Constraints (8)–(14)} \tag{20}$$

where $\bar{f}$ is a given disassembly profit, α is a predetermined confidence level, and (19) is a credibility constraint. Note that α is determined according to the risk degree of an event. In this paper, it denotes the credibility degree of the given disassembly profit.

III. Solution Algorithm

Fuzzy function is generally assessed via fuzzy simulation, which is effectively verified to deal with many fuzzy planning issues [41]–[46]. ABC, as one of the intelligent algorithms, has successfully handled many complicated optimization problems [47]–[52]. To make the full use of uncertain evaluation ability of fuzzy simulation, and very good convergence and optimization capability of ABC, this paper proposes a hybrid intelligent algorithm integrating fuzzy simulation and ABC to solve two newly proposed disassembly optimization problems.

A. Fuzzy Simulation

Let $\xi = (\xi_1, \xi_2, \ldots, \xi_m)$, μ be the membership function of ξ and μ_i be the membership function of ξ_i, $i = 1, 2, \ldots, m$. To solve the proposed disassembly optimization models, the following three types of uncertainty functions must be handled [38]:

$$U_1 : (x, y) \rightarrow E(f(x, y, \xi)) \tag{21}$$

$$U_2 : (x, y) \rightarrow \mathrm{Cr}\{f(x, y, \xi) \geq \bar{f}\} \tag{22}$$

$$U_3 : (x, y) \rightarrow \min\{\bar{f} | \mathrm{Cr}\{f(x, y, \xi) \leq \bar{f}\} \geq \alpha\}. \tag{23}$$

To compute U_1, we present the following procedure.

Step 1: $E = 0$.
Step 2: Randomly generate real numbers u_i of the ε-levels sets of fuzzy variables ξ_i such that $u_j = (u_{ij})$, $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, N$.
Step 3: Set $a = f(x, y, u_1) \wedge f(x, y, u_2) \wedge \cdots \wedge f(x, y, u_N)$ $b = f(x, y, u_1) \vee f(x, y, u_2) \vee \cdots \vee f(x, y, u_N)$.
Step 4: Randomly generate r from $[a, b]$.
Step 5: If $r \geq 0$, then $E = E + \mathrm{Cr}\{f(x, y, \xi) \geq r\}$.
Step 6: If $r \geq 0$, then $E = E + \mathrm{Cr}\{f(x, y, \xi) \geq r\}$.
Step 7: Repeat the fourth to sixth steps for N times.
Step 8: $E[C(x, y, \xi)] = a + E \cdot (b - a)/N$.

Similarly, to compute U_2, on the basis of (3), we adopt the following equation to calculate approximately the credibility:

$$J = \frac{1}{2}(\max_{1 \leq k \leq N}\{\mu \ (u_k) | f(x, y, u_k) \geq \bar{f}\} + \min_{1 \leq k \leq N}\{1 - \mu(u_k) | f(x, y, u_k) > \bar{f}\}). \tag{24}$$

Thus, the following procedure is used to compute the fuzzy function U_2:

Step 1: $k = 0$.
Step 2: Randomly generate real numbers u_i of the ε- level sets of fuzzy variables ξ_i.
Step 3: Set $u_k = (u_1, u_2, \ldots, u_m)$ and $\mu(u_k) = \mu_1(u_{11}) \wedge \mu_2(u_2) \wedge \cdots \wedge \mu_m(\mu_m)$.
Step 4: $k = k + 1$, if $i \leq N$, go to Step 2; otherwise go to Step 5.
Step 5: Return J.

Similarly, to compute U_3, the following formula is adopted:

$$J(r) = \frac{1}{2}(\max_{1 \leq k \leq N}\{\mu \ (u_k) | f(x, y, u_k) \geq r\} + \min_{1 \leq k \leq N}\{1 - \mu(u_k) | f(x, y, u_k) < r\}). \tag{25}$$

Thence, the following procedure is used to compute the fuzzy function U_3:

Step 1: $k = 0$.
Step 2: Randomly generate real numbers u_i of the ε- level sets of fuzzy variables ξ_i.
Step 3: Set $u_k = (u_1, u_2, \ldots, u_m)$ and $\mu(\mu_k) = \mu_1(u_1) \wedge \mu_2(u_2) \wedge \cdots \wedge \mu_m(\mu_m)$.
Step 4: $k = k + 1$, if $k \leq N$, go to Step 2; otherwise go to Step 5.
Step 5: Seek the minimal r meeting $L(r) > \alpha$.
Step 6: Return r.

B. ABC

ABC is composed of several tasks, i.e., encoding and decoding of solutions, employed bee phase, onlooker bee phase, scout bee phase, local search, and termination criterion.

1) Encoding and Decoding of Solutions: The encoding of a solution directly affects the efficiency of the proposed ABC algorithm. According to the characteristics of the proposed problems, the double-linked list structure is adopted as our encoding form. It is composed of two parts. An individual is expressed by $\upsilon = (\nu^1, \nu^2)$ where $\nu^1 = (\nu_1, \nu_2, \ldots, \nu_J)$ represents a disassembly operation sequence and $\nu^2 = (x_1, x_2, \ldots, x_J)$ indicates which operations are performed or not. In ν^2, $x_j \in \{0, 1\}$, $x_j = 1$ if operation j is done; otherwise, $x_j = 0$, $1 \leq j \leq J$. Note that this form is similar to that in [40].

2) Generation Method of the Initial Feasible Solution Set: Based on the above requirements 1–3, i.e., precedence and contradictory constraints, a feasible solution should guarantee precedence relationships and avoid conflicting operations. Thus, we use a method to check and adjust an initial random solution as follows, which has two phases:

Phase 1 is to adjust an initial disassembly sequence such that υ^1 guarantees the precedence relationship according to precedence matrix P. In other words, determine the operations that are performed in υ, i.e., $x_j = 1$, $j = 1, 2, \ldots, J$, and υ_j is recorded. According to P, the operations prior to the operations performed can be obtained. If the corresponding elements of prior operations of each operation performed in υ^2 are 0, they are adjusted to be 1.

Phase 2 is to eliminate the exclusive OR relationship and meet the succession relationship through matrices C and S. If the corresponding elements of contradictory operations of each operation performed in υ^2 are 1, they are adjusted to 0. If the corresponding elements of succession operations of each operation performed in υ^2 are 1, they are kept.

3) Employed Bee Phase: Differing from the regular ABC, initially, the crossover operation of employed bees is executed by sharing information and aims to create a new feasible food source. The new food source is then assessed and compared with the old one. The better food source is kept in the population and a greedy selection procedure is performed. Note that a food source is a disassembly sequence in this paper.

Then, local search is applied to select a new neighboring food source around a given food source and is able to improve exploitation search of the proposed algorithm. Additionally, to choose the better food source, a greedy selection procedure explained before is again performed.

4) Onlooker Bee Phase: In ABC, onlooker bees are used to screen the food sources according to each selection probability which is computed by the percentage of nectar amount of each food source in the total nectar amount. Hence, some food sources which have more nectar amount have higher probability to be found in this phase. The above approach may spend more computational time to calculate selection probability of each food source. Therefore, we adopt tournament selection which computes selection probability of few food sources. In this process, two of total food sources are randomly taken and tournament selection between these two randomly selected food sources is performed and their selection probability can be easily worked out. Then, the greedy selection is used to find the better one.

5) Scout Bee Phase: In our algorithm, when no improvement in the final nectar amount of food source occurs, a tournament selection process is performed to find new food sources by using scout bees, which is different from the basic scout bee phase in which only some random and feasible food sources are simply produced to replace the old ones.

In this phase, a parameter, i.e., a predetermined number of food sources *limit*, is used to balance between exploitation and exploration of the proposed method, and initially it is set as 0 for each food source. If the number of food sources created by this phase exceeds its predetermined limit, the food source abandoned by the scout bee is replaced with a new food source which is produced by the above tournament selection and *limit* is set to be 0.

6) Local Search Operator: The proposed ABC can deal with both feasible and infeasible solutions via a local search operator. Note that all the offspring individuals are improved by the operator. The improvement process is described in Algorithm 1.

By Algorithm 1, we can know that a new individual is accepted only if it is feasible and its corresponding objective function value is improved over the current best one. To ensure the efficiency of the local search operator, the algorithm is terminated if the current solution is not improved when a given maximum iteration count is reached.

7) Termination Criterion: ABC adopts the maximum iteration count as a termination criterion, i.e., when it is reached, output the solution and terminate the algorithm.

Algorithm 1: Solution Improvement Method via Local Search Operator

Input $I_1 = (\nu_1^1, \nu_1^2)$, $I_2 = (\nu_2^1, \nu_2^2)$
Output $I_c = (\nu_c^1, \nu_c^2)$
Procedure local search ($I_1 = (\nu_1^1, \nu_1^2)$, $I_2 = (\nu_2^1, \nu_2^2)$, $I_c = (\nu_c^1, \nu_c^2)$)
While($\mu < \lambda$) Do
    For $i = 1$ To J
        For $j = 1$ To J
            Select ν_1^1 from the initial solution $I_1 = (\nu_1^1, \nu_1^2)$,
            Select ν_2^1 from guiding solution $I_2 = (\nu_2^1, \nu_2^2)$;
                If ($\nu_1^1(i) = \nu_2^1(i)$) Then
                    $i++$;
                Else
                    If($\nu_1^1(i) = \nu_2^1(j)$) Then
                        $\nu_1^1(i) = \nu_1^1(j)$;
                        $\nu_c^1(i) = \nu_1^1(i)$;
                            If($\nu_1^2(i) = 0$) Then
                                $\nu_1^2(i) = 1$;
                            Else $\nu_1^2(i) = 0$;
                        $\nu_c^2(i) = \nu_1^2(i)$;
                        $i{++}, j{++}$;
        End For;
    End For;
    If($f(I_c) > f(I_1)$) Then
        $I_1 = I_c$;
    Else $\mu{++}$;
End While

C. Hybrid Intelligent Optimization Algorithm

We propose a hybrid algorithm that integrates fuzzy simulation and ABC as follows:

Step 1: Initialize the corresponding parameters of ABC and the number of simulation cycles.
Step 2: Update the food source through the employed bee and onlooker bee phases.
Step 3: Compute the objective function value and fitness of all chromosomes via fuzzy simulation.
Step 4: Search new food source through the scout bee phase.
Step 5: Repeat steps 2–4 for a predefined number of iterations.
Step 6: Report the best individual as the optimal solution.

In addition, the flowchart of the hybrid intelligent optimization algorithm is presented in Fig. 3.

IV. Experimental Results and Analysis

An actual case, i.e., the disassembly of a radio set derived from [39], is presented to testify the feasibility and effectiveness of the proposed methodology in this section. Its AND/OR graph is shown in Fig. 2, which has 29 subassemblies and 30 operations. Also, the proposed methodology is implemented in MATLAB 2010 and runs on an Intel(R) Core(TM) i3 CPU (2.53GHz/4.00G RAM) PC with a Windows 7 Operating System.

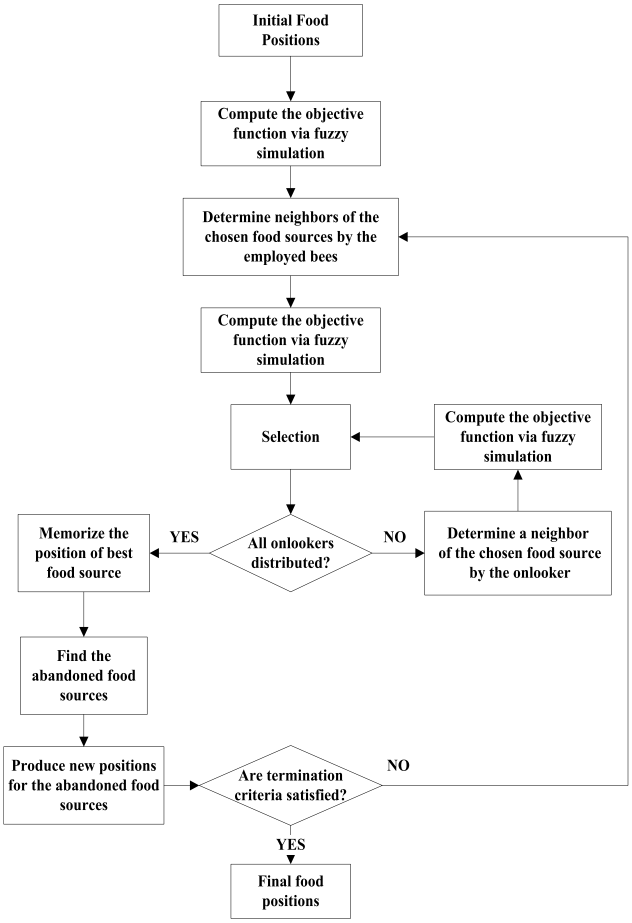

Fig. 3. Flowchart of the hybrid intelligent optimization algorithm.

The parameters of the hybrid algorithm are set as follows.

1) The population size *PopSize* is equivalent to the number of employed and onlooker bees, which is set to be 60.
2) The maximum iteration count is set as $\lambda = 50$.
3) *Limit* is set to be *PopSize*.
4) The number of simulation cycles of fuzzy simulation H is set to be 3000. Note that the number of simulation cycles H should be infinite in theory. If H is too small, the precision of the obtained solution tends to be low. If H is too large, the calculation time is too much. Thus, a proper value of H should be determined by considering the tradeoff between solution accuracy and computational efficiency. Usually, it is set to be 3000 according to [38] and [41].

The quality level $\xi_i = (a, b, c)$ and recycling/reuse value R_i of each subassembly are listed in Table II. They are determined by some system evaluation method and expert evaluation results [24]. Additionally, the disassembly cost of each operation is randomly generated from $\zeta_j \sim U(0.1, 0.3)$, where $U(0.1,\ 0.3)$ stands for a uniform distribution over [0.1, 0.3].

Example 1: One expects to obtain the largest average net profit of accomplishing a disassembly task. With the proposed model presented in Section II and methodology in Section III, the solution for this problem is obtained in Table III. The optimal disassembly sequence is $1 \to 3 \to 4 \to 5 \to 16 \to 28 \to 29 \to 9$, i.e., the corresponding disassembly subassembly sequence is (1)ABCDEFGHIJ → (2)ABCFGHIJ → (4)ABCEFGJ → (6)ABCEFJ → (10)ABEFJ → (13)ABEF → (17)ABF → (18)BF, and the obtained average/expected net profit is \$0.23.

Example 2: One expects to obtain the largest average net profit given a confidence level. Set $\alpha = 0.9$. The result is obtained and listed in Table IV. The optimal sequence is $1 \to 3 \to 4 \to 5 \to 6 \to 7 \to 8 \to 30$ with the obtained profit U.S. \$3.23, i.e., the corresponding disassembly subassembly sequence is (1)ABCDEFGHIJ → (2)ABCFGHIJ → (4)ABCEFGJ → (6)ABCEFJ → (10)ABEFJ → (14)ABFJ → (16)BFJ → (18)BF → (19)HI.

To test the efficiency of the proposed methodology, we compare its results and those of the existing fuzzy-simulation-based GA algorithm [41] as shown in Table V. Note that crossover probability p_c and mutation probability p_m in GA are set as follows [38], [41]: 1) $p_c = 0.8$ and $p_m = 0.2$ and 2) $p_c = 0.6$ and $p_m = 0.3$; each value is the average one of 20-time execution results to rid the randomness involved. Furthermore, the same encoding method, decoding rules, local search process and maximum iteration count are adopted when running the simulations. Also, when running the simulations, the same parameter's settings are executed via an orthogonal experiment method, namely, the *Pop_size* is set by three levels, i.e., 40, 60, and 80, λ is set by three levels, i.e., 50, 60, and 70, and H is demarcated by three levels, i.e., 2000, 3000, and 4000.

TABLE II

QUALITY LEVEL AND RECYCLING/REUSE VALUE OF EACH SUBASSEMBLY

Subassembly i	Quality level	ξ_i	R_i (\$)
1	Excellent	(0.75, 0.825, 1)	15.831
2	Excellent	(0.75, 0.825, 1)	10.963
3	Fine	(0.5, 0.625, 0.75)	11.704
4	Excellent	(0.75, 0.825, 1)	12.156
5	Excellent	(0.75, 0.825, 1)	8.687
6	Fine	(0.5, 0.625, 0.75)	7.781
7	Fine	(0.5, 0.625, 0.75)	11.272
8	Fine	(0.5, 0.625, 0.75)	12.019
9	Medium	(0.25, 0.375, 0.5)	4.896
10	Fine	(0.5, 0.625, 0.75)	6.671
11	Medium	(0.25, 0.375, 0.5)	4.378
12	Medium	(0.25, 0.375, 0.5)	9.378
13	Medium	(0.25, 0.375, 0.5)	10.122
14	Fine	(0.5, 0.625, 0.75)	8.701
15	Fine	(0.5, 0.625, 0.75)	4.027
16	Medium	(0.25, 0.375, 0.5)	10.409
17	Fine	(0.5, 0.625, 0.75)	5.547
18	Medium	(0.25, 0.375, 0.5)	12.664
19	Medium	(0.25, 0.375, 0.5)	3.005
20	Medium	(0.25, 0.375, 0.5)	6.85
21	Poor	(0, 0.125, 0.25)	7.697
22	Poor	(0, 0.125, 0.25)	8.844
23	Medium	(0.25, 0.375, 0.5)	11.081
24	Medium	(0.25, 0.375, 0.5)	5.29
25	Poor	(0, 0.125, 0.25)	9.139
26	Poor	(0, 0.125, 0.25)	7.885
27	Poor	(0, 0.125, 0.25)	3.143
28	Poor	(0, 0.125, 0.25)	4.703
29	Poor	(0, 0.125, 0.25)	8.887

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TABLE III
RUNNING RESULTS OF EXAMPLE 1

v^1	1	2	11	13	3	10	4	12	5	14	19	15	16	6	21	18	22	20	7	23	30	17	8	24	25	26	28	27	29	9
v^2	1	0	0	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
f																0.23														

TABLE IV
RUNNING RESULTS OF EXAMPLE 2

v^1	1	2	3	10	4	5	11	13	12	14	6	15	16	7	8	19	18	20	26	21	30	22	25	23	17	24	28	27	29	9
v^2	1	0	1	0	1	1	0	0	0	0	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
f																3.23														

TABLE V
COMPARISON OF RESULTS FOR ABC AND FUZZY-SIMULATION-BASED GA ALGORITHM

Cases	*Pop_size*	λ	H	Objective value ($) for the proposed method	Objective value ($)	
					Fuzzy-simulation-based GA algorithm (i)	Fuzzy-simulation-based GA algorithm (ii)
1	40	50	2000	3.15	2.87	2.76
2	40	60	3000	3.11	2.95	2.87
3	40	70	4000	3.28	2.91	2.74
4	60	50	3000	3.23	2.97	2.83
5	60	60	4000	3.08	2.96	3.10
6	60	70	2000	3.28	2.84	2.87
7	80	50	4000	3.20	2.75	2.99
8	80	60	2000	3.26	3.07	3.01
9	80	70	3000	3.22	2.93	2.92
	Mean value			3.20	2.91	2.90
	Variance			0.0053	0.0084	0.0136

From Table V, we can obtain the following conclusions.

1) Quasi-optimal solutions of both approaches are consistent and close. This shows that the proposed approach is reasonable and feasible when it is used to handle the proposed fuzzy disassembly model.
2) After both algorithms are run under different parameters, the average value of quasi-optimal solutions of the proposed algorithm is U.S. $3.20, while that of fuzzy-simulation-based GA algorithm is U.S. $2.90 and U.S. $2.89, respectively. This demonstrates that the proposed approach can perform more effectively the optimization of the proposed disassembly model than the previous approach.
3) After both algorithms are run under different parameters, the variance of quasi-optimal solutions of the proposed algorithm is 0.0053, while the variance of quasi-optimal solutions of fuzzy-simulation-based GA algorithm is 0.0084 and 0.0136, respectively. This demonstrates that the proposed approach is less sensitive to the parameters than the previous approach.

To further test the proposed approach, we compare the convergence of the proposed approach and fuzzy-simulation-based GA algorithm for the second case, the convergence curve is obtained by running two experiments as shown in Fig. 4. Note that Fig. 4 illustrates the tendency of the total objective function value. It is obtained based on function evaluations (FEs), i.e., $Pop\_size \times \lambda \times F_\lambda$, where F_λ is the number of FE at each iteration cycle for an algorithm, which is 2 in this paper. From Fig. 4, it is clear that the proposed approach performs better in convergence rate and solution optimality that the previous one does.

TABLE VI
IMPACT OF THE PRODUCT QUALITY ON DISASSEMBLY NET PROFIT AND SEQUENCE

Excellent quality part ratio	The optimal sequence	R_i ($)
5/29	1→3→4→5→6→17→29	0.25
10/29	1→3→4→5→6→17→29→9	0.28
15/29	1→3→4→5→6→7→8	0.24
20/29	1→3→4→5→16→28→29	0.30

In addition, to analyze the impact of uncertain product quality and disassembly operation cost on disassembly net profit and the optimal sequence, we show their results for Example 1 in Tables VI and VII.

From Tables VI and VII, we can see that different excellent quality part ratio and disassembly operation cost lead to different optimal disassembly sequences with different end

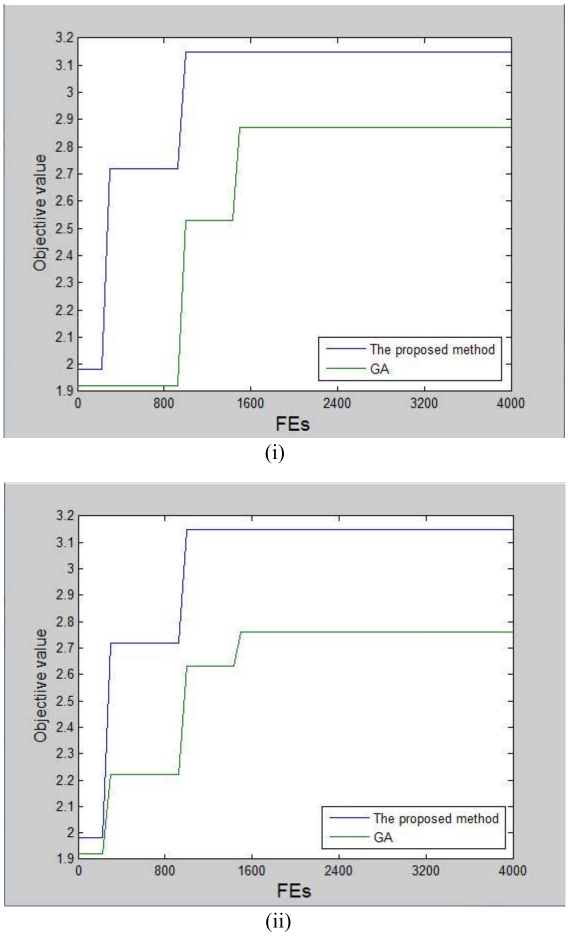

Fig. 4. Convergence curve.

TABLE VII
IMPACT OF THE DISASSEMBLY OPERATION COST ON DISASSEMBLY NET PROFIT AND SEQUENCE

Disassembly operation cost ζ_j	The optimal sequence	R_i (\$)
U(0.1, 0.3)	1→3→4→5→16→28→29→9	0.23
U(0.05, 0.35)	1→3→4→5→6→7→8→9	0.17
U(0.15, 0.45)	1→3→4→15→22→30→17→29→9	0.21
U(0.2, 0.4)	13→4→5→6→30→7→8	0.26

points and disassembly net profit. In other words, uncertain product quality and disassembly operation cost have a large impact on them.

In summary, the proposed approach is feasible and effective to handle the proposed fuzzy disassembly sequence planning problem by considering both uncertain component quality and varying disassembly operational cost.

V. CONCLUSION

This paper for the first time addresses a disassembly sequence planning problem by considering both uncertain component quality and varying disassembly operational cost. Its goal is to maximize the disassembly profit. A hybrid optimization algorithm integrating fuzzy simulation and ABC is designed to solve the proposed problem. It can perform well, and generate the "optimal" solution for the proposed fuzzy disassembly sequence optimization problem. The results can be adopted to guide decision makers in making informed decisions when disassembling an end-of-life product, and provide a new analysis approach to determine its best disassembly sequence.

Although the efficacy of the proposed method has been tested, this paper has some limitations. 1) It does not to use actual disassembly data to validate this method to provide the best decision support for disassembly practice and 2) It just focuses on the economical problem of product disassembly and the future research should make use of multiobjective optimization tools to achieve the comprehensive optimization by considering economical as well as environmental impact. Therefore, we need to develop more advanced disassembly planning models and approaches in the future by using some recently developed modeling and optimization methods [53]–[67].

APPENDIX

See Figs. 5–8.

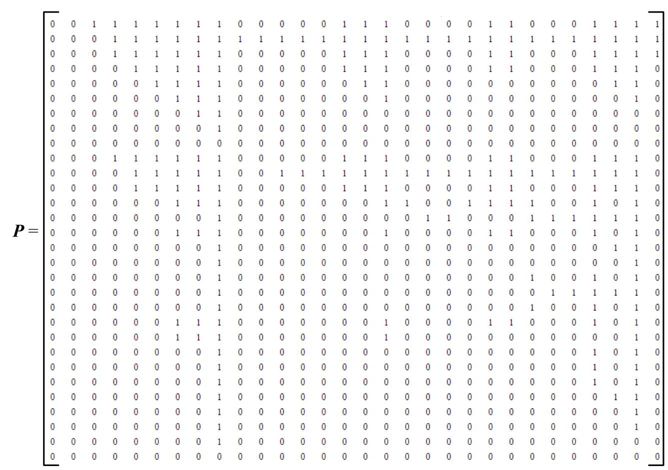

Fig. 5. Precedence matrix C of the radio set.

Fig. 6. Conflict matrix G of the radio set.

$$
\boldsymbol{S}=\begin{bmatrix}
0&0&1&1&1&1&1&1&1&0&0&0&0&0&1&1&1&0&0&0&0&1&1&0&0&0&1&1&1&1\\
0&0&0&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1\\
0&0&0&1&1&1&1&1&1&0&0&0&0&0&1&1&1&0&0&0&0&1&1&0&0&0&1&1&1&1\\
0&0&0&0&1&1&1&1&1&0&0&0&0&0&1&1&1&0&0&0&0&1&1&0&0&0&1&1&1&0\\
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0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0
\end{bmatrix}
$$

Fig. 7. Succession matrix S of the radio set.

$$
\boldsymbol{G}=\begin{bmatrix}
-1&-1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
1&0&-1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&1&0&0&0&0&0&0&0&-1&-1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
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0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&1&0&-1&0&0\\
0&0&0&0&0&1&-1&0&0&0&0&0&0&0&0&0&-1&0&0&0&0&1&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&0&-1&0&0&0\\
0&0&0&0&0&0&1&-1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&1&1&-1&0\\
0&0&0&0&0&0&0&1&-1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0\\
0&1&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&-1\\
0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0\\
0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
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1&0&0&0&0&0&0&0&0&1&0&1&0&0&0&0&0&0&1&0&1&0&0&1&0&0&0&0&0&0\\
0&0&0&0&0&1&0&0&0&0&0&0&1&0&1&0&0&0&0&1&0&0&0&0&1&0&0&1&0&0\\
0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1\\
0&0&0&0&0&0&0&1&0&0&0&0&0&1&0&1&1&1&0&0&0&0&1&0&0&0&0&0&0&0
\end{bmatrix}
$$

Fig. 8. Incidence matrix G of the radio set.

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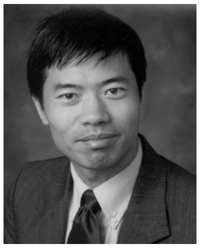

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