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Disassembly Sequence Planning: Recent Developments and Future Trends

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Abstract

Remanufacturing has gained increasing attention due to its economic, environmental and societal benefits as well as its contribution to the sustainability of natural resources. Disassembly is the first and usually the most difficult process in remanufacturing a product. Disassembly sequence planning, which aims to find the optimal disassembly sequence, is required to improve efficiency and reduce cost. There have been many investigations in this field and several disassembly sequence planning methods have been developed. This paper reviews the main existing disassembly sequence planning methods from the perspectives of disassembly mode, disassembly modelling and planning method. The characteristics of different methods are analysed and summarised from those perspectives. Future trends in disassembly sequence planning are also discussed to reveal gaps in existing research.

Keywords: Remanufacturing, disassembly model, optimisation algorithm, disassembly sequence planning, disassembly sequence optimisation

1. Introduction

Traditionally, many manufacturing companies have tended to be driven by profits without due regard to energy consumption, pollutant emission and material conservation.

This paradigm is no longer viable and modern manufacturing industry must focus on environmental friendliness and sustainable energy and material usage. Remanufacturing provides an economically and environmentally sound way to achieve this by closing the materials use cycle and forming a closed-loop manufacturing system.[1] The essence of remanufacturing is to renew an End-of-Life (EoL) product through appropriate recovery techniques instead of disposing of it through recycling, landfill or incineration.[2] Landfill and incineration can do harm to the environment, causing air pollution and soil contamination. Recycling of EoL products promotes resource sustainability and can be more environmentally friendly. However, energy consumption could be high for some recycling processes. On the other hand, remanufacturing can save energy, production cost and raw materials as well as providing high-value components quickly for production.[3] Remanufacturing of an EoL product invariably starts with taking it apart to recover its components. As the condition of the product is not known after years of usage,[4] traditional disassembly processes have to rely on human operators, which can lead to high costs.

Research efforts have been spent on introducing robots to replace manual labour in disassembly. When dealing with complex disassembly work, humans are more flexible than robots, because machines do not have the knowledge humans use to perform tasks, nor the same capabilities for sensing, perception, reasoning and manipulation. To enable robots to see the product to be disassembled, machine vision has been applied to extract structural information about a product such as its geometrical and locating features.[5,6,7,8] To give robots knowledge about how to disassemble a product, researchers have used knowledge bases for storing historical disassembly information and the robots can flexibly deal with their current disassembly tasks using the stored data.[9,10] To optimise the disassembly plan,[11] intelligent optimisation algorithms including Particle Swarm Optimisation (PSO),[12] Bees Algorithm,[13] Artificial Bee Colony (ABC)[14] and Ant Colony Optimisation (ACO)[15,16,17] can be employed.

A well-designed disassembly sequence helps to improve disassembly efficiency and reduce disassembly cost. The method of finding this well-designed disassembly sequence is called “disassembly sequence planning” (DSP) which is a non-deterministic polynomial (NP) problem[18,19]. DSP[20,21,22,23] is to determine the optimal disassembly sequences for given EoL products with considering disassembly precedence relationships. As shown in Figure 1, three steps are involved in DSP, namely, deciding the disassembly mode, building a disassembly model and applying a selected planning method. Of all the steps in DSP, the primary task is to determine suitable disassembly mode for EoL products. After the disassembly mode is determined, disassembly modelling for the EoL product needs to be performed to describe the disassembly precedence relationships between parts or subassemblies. Finally, planning methods should be used to find the optimal solution from various alternatives.

The disassembly mode should be chosen according to the particular situation (such as complete[24,25] or partial disassembly[26]). After that, the disassembly model, which describes the disassembly precedence relationship of products,[27] should be built to avoid generating unfeasible disassembly sequences. The hybrid disassembly graph was employed to model the contact and non-contact constraints between different parts.[26] Petri net which includes markings, places, transitions and arcs is an efficient method to generate feasible disassembly sequences.[28] The component-fastener graph was adopted to describe the precedence relationship of EoL products.[29] After the disassembly model is built, a suitable planning method is selected to produce the optimal disassembly sequence plan. Planning methods can be differentiated according to the disassembly objective and the optimisation technique used. In terms of disassembly objectives, Shimizu et al.[30] combined the time deviation ratio and cost deviation ratio to calculate the fitness function. Kongar et al.[31] proposed fitness functions based on disassembly time, time penalty of method change and time penalty of direction change. Zhang et al.[32] considered the following factors in calculating fitness: disassembly methods, disassembly types, disassembly directions and corresponding weight. The total disassembly time consisting of standard time, tool changing time and direction changing time was used as the optimisation objective.[33] For optimisation method, intelligent algorithms are the most widely used methods to solve this combinational optimisation problem[34,35], ACO,[26] genetic programming[30], PSO,[32] Scatter Search[33] and Genetic Algorithm (GA)[36] have been used to find optimal disassembly sequence.

Although there have been many publications on DSP,[37] no recent works are presented to systematically discuss these methods. This paper conducts a detailed review of DSP techniques from the perspectives of disassembly mode, disassembly modelling and planning methods. The objective of this review is to discuss the characteristics of the different techniques and identify future research trends.

2. Disassembly mode

Table 1. Complete/partial disassembly.

Disassembly mode	References
Complete disassembly	Yeh et al.,[38,39,40] Chen et al.,[41] Xia et al.,[42,43,44,45] Pornsing et al,[46] Xing et al.,[47] Lu et al.,[48] ElSayed et al.,[49,50,51] Go et al.,[52] Chen et al.,[53] Zhang et al.,[54,55,56] Li et al.,[57] Xu et al.,[58] Azab et al.,[59] Kheder et al.,[60] Jin et al.,[61] Tian et al.,[62,63,64] Deng et al.,[65] Kuo,[66,67] Guo et al.,[68] Hsu,[69] Zhang et al.,[70] Huang et al.,[71] Wang et al.,[72] Jue et al.,[73] Zhang,[74] Wang et al.,[75,76,77]

	Dong et al.,[78] Wei,[79] Agrawal et al.,[80] Zhao et al.,[81] Zhang et al.,[82] Yang et al.,[83] Alshibli et al.,[84] Song et al.,[85] Gungor et al.,[86,87] Shan et al.,[88] Kang et al.,[89] Moore et al.,[90] Lambert,[91,92] Rai et al.,[93] Adenso-Diaz et al.,[94] Gonnuru,[95] Tang et al.,[96] Wu et al.,[97] Kongar et al.,[98] Fang et al.[99] and Lu et al.[100]
Partial disassembly	Luo et al.,[101,102] Smith et al.,[103,104,105,106,107,108] Xia et al.,[109] Guo et al.,[110] Li et al.,[111,112] Rickli et al.,[113,114] Jin et al.,[115] ElSayed et al.,[116] Han et al.,[117] Song et al.,[118,119] Percoco et al.,[120] Liu et al.,[121] Wang et al.,[122] Mitrouchev et al.,[123] Wang et al.,[124] Ullerich et al.,[125] Wang et al.,[126] Chung et al.,[127,128,129] Kara et al.,[130] Fang et al.,[131] Li et al.,[132,133,134] Lu et al.,[135,136] Lambert,[137,138] Tripathi et al.[139] Ma et al.,[140] Wu et al.,[141] Xue et al.,[142] Giudice et al.,[143] Kang et al.,[144] Zhang et al.,[145] Kheder et al.[146] and Deng et al.[147]

Of all the steps of DSP, choosing suitable disassembly mode is the first procedure we need to consider. From the literature reviewed, existing disassembly modes can be grouped in two ways: 1. complete/partial disassembly; 2. sequential/parallel disassembly, as shown in Table 1 and Table 2.

Table 2. Sequential/parallel disassembly.

Disassembly mode	References
Sequential disassembly	Yeh et al.,[38,39,40] Chen et al.,[41] Xia et al.,[42,43,44,45,109], Pornsing et al.,[46] Xing et al.,[47] Lu et al.,[48] ElSayed et al.,[49,50,51,116] Go et al.,[52] Chen et al.,[53] Li et al.,[57] Xu et al.,[58] Azab et al.,[59] Kheder et al.,[60,146] Jin et al.,[61,115] Tian et al.,[62,63,64] Deng et al.,[65] Kuo,[66,67] Guo et al., [68,110] Hsu,[69] Huang et al.,[71] Wang et al.,[72] Jue et al.,[73] Zhang,[74] Wang et al.,[75,76,77] Dong et al.,[78] Wei et al.,[79] Agrawal et

	al.,[80] Zhao et al.,[81] Yang et al.,[83] Alshibli et al.,[84] Gungor et al.,[86,87] Shan et al.,[88] Moore et al.,[90] Lambert,[91,92,137,138] Rai et al.,[93] Adenso-Diaz et al.,[94] Gonnuru,[95] Tang et al.,[96] Wu et al.[97,141] Kongar et al.,[98] Fang et al.,[99] Lu et al.,[100] Luo et al.,[101,102] Smith et al.,[103,104,105,108] Li et al.,[111,112] Rickli et al.,[113,114] Han et al.,[117] Song et al.,[118,119,148] Percoco et al.,[120] Liu et al.,[121] Wang et al.,[122] Mitrouchev et al.,[123] Wang et al.,[124] Ullerich et al.,[125] Wang et al.,[126] Chung et al.,[127,128,129] Kara et al.,[130]Fang et al.,[131] Li et al.,[132,133,134] Lu et al.,[135,136] Tripathi et al.,[139] Xue et al.,[142] Giudice et al.,[143]Zhang et al.[145] and Deng et al.[147]
Parallel disassembly	Zhang et al.,[54,55,56] Zhang et al.,[70] Zhang et al.,[82] Kang et al.[89,144] Smith et al.,[106,107] and Ma et al.[140]

Complete disassembly involves dismantling an EoL product into individual components while partial disassembly does not entail the complete breakdown of the product. From Table 1, it is obvious that complete disassembly is the more frequently investigated disassembly mode compared with the partial disassembly mode. Complete disassembly takes longer and costs more, partial disassembly which is to recover high-value components or parts that are difficult to obtain by other means should be considered whenever appropriate.

Table 2 shows references to publications discussing sequential and parallel disassembly. With sequential disassembly, which is the most frequently studied mode, parts are removed from the product one at a time (or in pairs, as in the case of disassembling a nut and a bolt). Parallel disassembly, which involves removing several components simultaneously, can be more efficient. For large complex EoL products, this method should be considered as it can reduce disassembly time compared with the sequential disassembly mode.

Regarding disassembly mode, the numbers of reviewed papers of complete and partial disassembly are respectively 63 and 47, the numbers of reviewed papers of sequential and parallel disassembly are respectively 100 and 10. It is apparent that the focus of research so far has been on complete disassembly. However, there are many cases where only partial disassembly is needed. For example, when the aim of disassembly is to retrieve a particular component located in the middle of disassembly process, this component is used for repair, replacement or recycling. Until now, much attention has been paid to sequential disassembly than parallel disassembly. Future work might concentrate on the parallel disassembly due to its potential for high efficiency. To date, the only research group invested both partial and parallel disassembly has been conducted by Smith et al.[107] It is expected that this area will expand in the future when high disassembly efficiency is considered.

3. Disassembly modelling

After the disassembly mode is determined, disassembly modelling for the EoL product needs to be performed to describe the disassembly precedence relationships between parts or subassemblies. It ensures that unfeasible disassembly sequences are eliminated. Disassembly modelling consists of a pre-processing stage and a model construction stage as shown in Figure 2.

3.1 Pre-processing

The pre-processing method extracts the precedence relationships between different parts from known information about the product such as its computer-aided design (CAD) model. From the literature reviewed, pre-processing tends to be performed manually, as shown in Table 3.

Table 3. Pre-processing methods.

Methods	References
Manual work	Yeh et al.,[38,39,40] Xia et al.,[42,43,44,45,109] Pornsing et al.,[46] Xing et al.,[47] Lu et al.,[48] ElSayed et al.,[50,116] Go et al.,[52] Chen et al.,[53] Zhang et al.,[54,55,56] Li et al.,[57] Xu et al.,[58] Azab et al.,[59] Kheder et al.,[60,146] Jin et al.,[61,85,115] Tian et al.,[62,63,64] Deng et al.,[65] Kuo,[66,67] Guo et al.,[68,110] Hsu,[69] Huang et al.,[71] Wang et al.,[72] Jue et al.,[73] Zhang et al.,[74] Wang et al.,[75,76,77] Dong et al.,[78] Wei,[79] Zhao et al.,[81] Zhang et al.,[82] Yang et al.,[83] Alshibli et al.,[84] Gungor et al.,[86,87] Shan et al.,[88] Kang et al.,[89,144] Moore et al.,[90] Lambert,[91,92,137,138] Rai et al.,[93] Adenso-Diaz et al.,[94] Gonnuru,[95] Tang et al.,[96,149] Wu et al.,[97,141] Kongar et al.,[98] Fang et al.,[99] Lu et al.,[100] Luo et al.,[101,102] Smith et al.,[103,104,105,106,107,108] Li et al.,[111,112] Rickli et al.,[113,114] Han et al.,[117] Song et al.,[118,119,148]

	Percoco et al.,[120] Wang et al.,[122] Wang et al.,[124] Ullerich et al.,[125] Wang et al.,[126] Chung et al.,[127,128,129] Kara et al.,[130] Fang et al.,[131] Li et al.,[132,133,134] Lu et al.,[135,136] Tripathi et al.,[139] Ma et al.,[140] Xue et al.,[142] Giudice et al.,[143] Zhang et al.[145] and Deng et al.[147]
Visual processing & matching	ElSayed et al.[49,51] and Alshibli et al.[84]
Module of SolidWorks	Agrawal et al.[80]
WFlow	Liu et al.[121]

There are 105 papers using manual work to finish pre-processing (NB: if the pre-processing method is not clearly explained in a paper, here, it is taken by default as manually carried out). Due to the powerful recognition and reasoning ability of humans, manual pre-processing is suitable for almost all cases; however, it can be a cumbersome task to extract precedence relationships and generate the disassembly model manually. When the product is complex, manual pre-processing is also an error-prone task which easily leads to the generation of inaccurate models. Thus, automatic pre-processing should be considered to avoid these disadvantages. ElSayed et al.[49] employed visual processing and pattern recognition for pre-processing. They used visual processing to identify specific components and convolution/correlation-based 2D template matching to compare the extracted component with the given templates. Their technique was not fully automatic pre-processing because the template had to be provided manually in advance. Apart from the methods just mentioned, Solidworks[80] and WFlow[121] have also been employed to perform pre-processing, but the details were not clear from these publications.

Regarding pre-processing methods, it is obvious that most pre-processing methods require manual work. This is because humans are much more flexible and can deal with much more complicated tasks than machines. However, it is time-consuming and error-prone for humans to finish complex tasks when the number of components is large. In addition, most pre-processing methods can be finished only if CAD models are provided. However, after years of usage, EoL products can rarely be described accurately by original CAD model. Thus, manual work is necessary to adjust existing CAD models or create new representations of actual components. Some researches try to use visual information to exact the precedence relationships between different parts,[8,9] but that simply is not enough. For example, contact forces between different components in disassembly process could also yield useful information on the condition of disassembly process which helps to build accurate disassembly model. However, no research has been conducted on this.

3.2 Disassembly model building

Disassembly model building method is used to produce a model representing the disassembly precedence relationships through specific methods like graphs and matrices. Table 4 shows that disassembly models can be divided into four categories: graphs, Petri nets, matrix-based and other model types.

3.2.1 Graphs

The use of disassembly trees was proposed by Bourjault et al.[150] The tree starts from the root node which indicates the original EoL product. The branch nodes represent subassemblies or parts of the product.[38] As shown in Figure 3, *R* indicates the original product while ***S*** represents a subassembly. Through disassembly (directed edges in Figure 3), different subassemblies are generated.

$$G = \{V, E, Ra\} \tag{1}$$

Disassembly network graphs are used to describe the structural relationships between parts. According to different descriptions of the constraint relationships, a disassembly network graph as shown in Figure 4 can be a three-element, four-element or five-element graph. The minimal part in a disassembly network graph is a component or a connection. A three-element disassembly network graph is described by Equation (1),[53] where G is the disassembly network graph, $\boldsymbol{V}$ represents the minimum part, E_{ij} is the directed edge from i to j indicating that component i should be disassembled before component j, $\boldsymbol{Ra}$ is a set of arcs (an actual arc stands for an “AND” relationship and a virtual arc means an “OR” relationship between different parts). Using this method, the structural relationship between different parts can be clearly described. However, the relationships between different parts cannot be simply represented as “AND” or “OR” relationships, the precedence relationship between contact components and non-contact components should also be considered. Thus, in addition to elements $\boldsymbol{V}$ and $\boldsymbol{E}$, a four-element disassembly network graph includes the relationship sets $\boldsymbol{E_{fc}}$ and $\boldsymbol{E_c}$ which are respectively described as directed solid edge and directed dotted edge.[54,55,82] $\boldsymbol{E_{fc}}$ and $\boldsymbol{E_c}$ respectively give the disassembly precedence relationship between contact parts and that between non-contact parts. Song et al. added a selective constraint set to the four-element disassembly network graph to provide further structural relationship information and give a five-element disassembly network graph.[118,119] A part belongs to the selective constraint set if it has constraint relationships with many other parts and can be disassembled once one of those parts is removed.

Table 4. Disassembly model building methods.

Methods		Description	References
Graph-based method	Disassembly tree	The tree starts from the root node which indicates the original EoL product; the branch nodes represent subassemblies or parts of the product.	Yeh et al.,[38,39,40] Xia et al.,[42,45] ElSayed et al.,[49,50,51,116] Go et al.,[52] Azab et al.,[59] Kuo,[67] Wang et al.,[76,77] Alshibli et al.,[84] Lambert et al.,[91,92,137,138] Gonnuru,[95] Kongar et al.,[98] Guo et al.,[110] Han et al.,[117] Lu et al.,[135] Tripathi et al.,[139] Ma et al.[140] and Xue[142]
	Disassembly network graph	Three-element graph: This includes the minimal disassembled part, directed edges and the relationship between pairs of parts.	Chen et al.,[53] Tian et al.,[63,64] Wang et al.,[72] Wu et al.[97] Fang et al.,[131] Li et al.[132,133,134] and Deng et al.[147]
		Four-element graph: This includes the minimal disassembled part, undirected/directed edges and directed dotted edges.	Zhang et al.,[54,55,56] Zhang et al.[82] and Wu et al.[141]
		Five-element graph: This includes the minimal disassembled part, one undirected edge and three directed edges which indicate different constraint relationships.	Song et al.[118,119,148]

	State representation based disassembly graph	This describes the structure of the EoL product at several disassembly levels.	Tian et al.,[62] Jue et al.,[73] Wei,[79] Wang et al.,[122] Mitrouchev et al.[123] and Kara et al.[130]
	Directed flow disassembly network	This graph-based method starts from one node and ends in another node.	Huang et al.,[71] Kang et al.[89,144] Rickli et al.,[113,114] Liu et al.,[121] and Ullerich et al.[125]
Petri net method	Simplified Disassembly Petri net	This includes the number of places and transitions, places, transitions, place-transition matrix and transition-place matrix.	Rai et al.,[93] Xia et al.[109]and Zhang et al.[145]
	Extended disassembly Petri net	This Petri net includes only one non-leaf output place exists in each transition.	Tang et al.[149]
	Extended stochastic disassembly Petri net	This is a high level Petri net with arbitrary distribution.	Deng et al.[65]
	Disassembly tree Petri net	This comprises four steps: identification, determination of the disassembly rate, construction and evaluation.	Kuo[66]
	Disassembly Petri net	This includes an 8-tuple: places, transitions, input and output	Guo et al.[68] and Moore et al.[90]

		functions, marking, disassembly cost, recycling value and weight function.	
	Fuzzy attributed Petri net	Fuzzy sets theory is combined with Petri net to handle the uncertainties in the disassembly process.	Hsu[69] and Tang et al.[96]
	Synchronous net	This employs reduction principles which include S-Combination, T-Combination and place combination.	Dong et al.[78]
	Fuzzy reasoning Petri net	This is derived from the basic Petri net and its objective is knowledge representation and logic reasoning.	Zhao et al.[81]
Matrix-based method	Disassembly interference matrix	Simple case: the element a_{ij} is set to nonzero if disassembly operation *i* precedes operation *j*, and 0 otherwise.sss	Zhang[74] and Yang et al.[83]
		6-direction matrix: This describes the relative position (±x, ±y, ±z) between different components.	Xia et al.,[43,44] Xing et al.,[47] Xu et al.,[58] Jin et al.,[61,85,115] Wei,[79] Agrawal et al.,[80] Gungor et al.,[86,87] Shan et al.,[88] Adenso-Diaz,[94] Fang et al.,[99] Lu et al.[100] Percoco et al.,[120] Wang et al.,[126] Lu et al.,[135,136] Giudice et al.[143] and Kheder et al.[146]

		Multi-direction matrix: this includes the global precedence matrix and local precedence matrix.	Li et al.[57] and Luo et al.[102]
	Multi-layer representation method	This method includes several levels and the corresponding representation matrix to reduce storage space and search time, compared with the traditional matrix representation method.	Wang,[75] Luo et al.[101] and Wang et al.[124]
	Disassembly sequence structure method	Four-matrix method: This includes disassembly matrices for fasteners and components and motion constraint matrices for fasteners and components	Smith et al.[103,107,108]
		Five-matrix method: Besides the description matrices used in the four-matrix method, there is also a projection matrix for components.	Smith et al.[104,105,106]
	Dynamic disassembly precedence matrix	The precedence matrix is generated iteratively according to the dynamic disassembly of the product.	Pornsing et al.[46] and Luo et al.[102]
	Disassembly transition	In this matrix, each row and column respectively represent	Huang et al.[71]

	matrix	the resulting subassembly and disassembly operation.	
	Enhanced support matrix	The fasteners are regarded as separate parts and added into a support matrix which describes the support relationship among parts for stability analysis.	Lu et al.[48]
	Hybrid disassembly matrix	This method includes connectivity matrix, topological disassemblability matrix and rating matrix of disassemblability level.	Chung et al.[127]
	Two disassembly matrices	This method includes subassembly division precedence matrix and part disassembly route matrix.	Chung et al.[128,129]
Other method	Generic constraint handling algorithm	The disassembly operation is divided into disassembly operations with and without constraints. Each disassembly operation with constraints should be gradually handled, and then, disassembly operations without any constraints should be inserted.	Li et al.[111,112]

A state-representation-based disassembly graph describes the structural relationships of a product at different levels or disassembly stages.[62] With this method, several parts are disassembled during each disassembly stage (in Figure 5(a)) or disassembly level (in Figure 5(b)). The method provides good visualisation of the disassembly process and can also be applied to complex products. Tian et al.[62] used disassembly models similar to that depicted in Figure 5(b), but ignored details such as disassembly direction. As mentioned previously, to remedy this, Mitrouchev et al.[123] used sets of disassembly of removal (SDR) to obtain the possible removal directions for each component. From the SDR, the detachability of each component can be determined.

Unlike a disassembly network graph, a directed flow disassembly network[113] starts from one node which stands for the assembled product and ends at another node which represents the complete disassembly of all parts,[114] as shown in Figure 6. However, disassembly details (such as disassembly time, tool and direction) are usually ignored in this method. To address this, Liu et al. included a feasibility graph which not only describes the constraint and adjacency relationships between different parts or subassemblies but also contains other disassembly information (disassembly tool, time etc.).[121] The optimal disassembly sequence (bold arrows in Figure 6) can be chosen from the available solutions.

3.2.2 Petri net methods

Xia et al. used the simplified disassembly Petri net method which was defined as a five-tuple as shown in Equation (2).[109]

$$DPN = (P, T, I_{n*m}, O_{m*n}, M) \quad (2)$$

where $\boldsymbol{P}$ and $\boldsymbol{T}$ respectively represent the sets of EoL products (named places) and disassembly operators (named transitions), n and m are respectively the number of places and transitions, matrix **I** and matrix **O** respectively indicate the places-transitions matrix and transitions-places matrix, **M** represents the disassembly state of the product. Similarly, a simplified representation of the disassembly Petri net approach was presented, which included places $\boldsymbol{P}$, transitions $\boldsymbol{T}$ and arcs.[66] An eight-tuple disassembly Petri net was also used to describe the geometric constraint relationships, removal states and AND/OR logical relationships of all the components.[68] In addition, to provide rich descriptions of the disassembly structure, as shown in Figure 7, the five elements of the simplified disassembly Petri net method[109] were supplemented with the removal cost c and reuse value of components and the set of weight functions w related to the transition. Based on the standard Petri net, a higher level Petri net, the “Extended stochastic disassembly Petri net” was proposed.[65] In this method, parameters related to the disassembly process such as the disassembly time probability density functions of the transition, the quality condition function and the probability value of the transition were included.

Traditional disassembly Petri net methods have disadvantages of complex reachability graph generation and heavy computational burden. When EoL products have complex structures, it is difficult and can take long time to generate the reachability graph. Dong et al.[78] proposed a disassembly model based on a synchronous net to simplify the Petri nets. Through reduction principles, the complex reachability graph problem is solved. In addition, the traditional disassembly Petri net method is not robust enough to handle uncertainties during disassembly process. Compared with traditional Petri net models, the predicate/transition net which is a high-level Petri net was developed to have a compact size and powerful modelling capability. A novel high-level Petri net, the "Fuzzy attributed and timed predicate/transition net" (FATP/T), was developed to deal with uncertainty problems.[69] The Fuzzy Reasoning Petri net (FRPN) proposed by Zhao et al. handles uncertainty problems in a different way from FATP/T.[81] Apart from the basic elements of a disassembly Petri net, FRPN also incorporates rules with associated confidence levels to enable knowledge-based reasoning and decision making to address the problem of combinational explosion. Petri net was also combined with Bayesian learning to deal with the uncertainties in the disassembly process to reduce the impact of inaccuracy of decision making.[149]

3.2.3 Matrix-based methods

The matrix-based methods use several matrices to describe the disassembly precedence relationships between different parts. The disassembly interference matrix method is the most common matrix-based method. The simplest way of constructing a disassembly interference matrix was described in publications.[74,83] With this method, regardless of details such as disassembly directions and disassembly operations, if component i should be disassembled before component j, element b_{ij} of the disassembly interference matrix is nonzero. Otherwise, it is '0'. However, actual disassembly process is more complex due to non-ignorable factors such as disassembly directions and disassembly tools. Based on the CAD model of the product, disassembly interference matrices ($\mathbf{C}_{X+}$, $\mathbf{C}_{X-}$, $\mathbf{C}_{Y+}$, $\mathbf{C}_{Y-}$, $\mathbf{C}_{Z+}$, $\mathbf{C}_{Z-}$) can be generated in six directions (X+, X-, Y+, Y-, Z+, Z-) according to the spatial interference relationship between different parts.[47] If there is spatial interference between parts i and j along a specific direction, element b_{ij} of the disassembly interference matrix is '1' in that direction. Otherwise, it is '0'. After the disassembly interference matrices of all the directions are obtained, the feasible disassembly sequence can be generated. However, connections are different from components in the actual disassembly process. Therefore, according to the same interference rules mentioned above,[43,44,120] the disassembly interference matrices of components and connections were respectively introduced as independent matrices which are row-column matrices and disassembly interference matrices.[42,43,44] However, the actual disassembly directions of parts are not always the simple 6 directions (X+, X-, Y+, Y-, Z+, Z-) but could be complex directions. They may change with different structures of components, which results in the previously mentioned methods not meeting the requirements of actual disassembly situations. The extended interference matrix method was proposed to handle those situations.[57,102] With this method, a global coordinate system and a local coordinate system were simultaneously used to increase the diversity of disassembly directions. The global coordinate system was employed to describe interference relationships between components viewed from a common frame of reference while the local coordinate system was adopted to describe the disassembly interference from the perspective of individual components. The translating and rotating relationships between the global coordinate system and local coordinate system were used to establish the extended interference matrix method.

As with the methods used in publications,[43,44,120] the connections and components were considered separately by different description methods. Smith proposed the disassembly sequence structure method to represent the spatial relationships between components and connections.[103,107] With this method, the disassembly matrices for components and connections (2 matrices) and the disassembly motion matrices for components and connections (2 matrices) were simultaneously built. The disassembly matrices were used to record the disassembly direction of each part, and the disassembly motion matrices, to record touching parts that constrain the disassembly of target components in specific directions. This method helps to reduce model complexity compared with other matrix-based methods. By adding the projection matrix for the components, Smith et al. proposed the five-matrix disassembly sequence structure method.[104,105,106] Besides the four-matrix method,[103,107] the projection matrix for the components was used to record the number of blocking components for each component. Compared with the four-matrix disassembly sequence structure method, this method further decreases the time to search for feasible sequence solutions. An obvious disadvantage of these method is that the matrices should be generated manually which may be a cumbersome task.

The disassembly interference matrix method needs to record all the relationships of parts even if there are no precedence relationships between them, which naturally results in data redundancy. To reduce processing time and data size, the multi-layer representation method was proposed.[75,101] The Bill-of-Materials (BoM) represented by a list of elements from the product all the way down to basic components was used to generate the natural structure of the product which comprises different layers and nodes. For every subassembly of each layer, a matrix was used to describe the constraints between different components of the subassembly. Compared with the disassembly interference matrix, this method needs a smaller space to store the product model.[101]

The above-mentioned methods are static description methods because they cannot be altered dynamically according to the actual disassembly situation. To deal with changing conditions, the dynamic disassembly precedence matrix was proposed.[46,102] Based on the same rules,[74] the disassembly interference matrix was iteratively updated through the following rule: if all elements in column i are 0, then component i will be disassembled, after which, all the elements in row i of the disassembly interference matrix will be set to 0.[46] Slightly different from the method of publication,[46] component i should be disassembled if there is only a non-zero element in column (or row) i, after which, the corresponding row i and column i are deleted dynamically.[102]

In terms of disassembly operations and support relationships, there also exists matrix-based methods that are different from the above. The disassembly transition matrix considered the disassembly operation to form a disassembly transition matrix of which the column and row respectively represent the disassembly operation and resulting subassembly.[71] An obvious disadvantage of this method is that all the feasible subassemblies and disassembly operations should be enumerated, which is a time-consuming process. Because actual disassembly operations are affected by gravity, to be closer to real situations, the enhanced support matrix was proposed.[48] The base component supporting other parts or fasteners was determined first and then the support relationships between different components were considered. Furthermore, the hybrid disassembly matrix[127] and two disassembly matrices[128,129] were also studied.

3.2.4 Other methods

To propose a universal method to handle various disassembly models, the generic constraint handling algorithm was proposed by Li et al.[111,112] Disassembly operations are divided into two parts: those with, and those without, constraints. First, the positions of disassembly operations without any constraints should be kept unchanged. Then, the element positions of disassembly operations with constraints should be adjusted according to the disassembly precedence relationships. A feasible disassembly sequence will be obtained after all the positions of disassembly operations with constraints have been adjusted. To be a generic constraints description method, the algorithm ignores many details such as the tools used and the disassembly directions which are important for disassembly.

Regarding the disassembly model building methods, graphs (58 papers) are the most common methods to build the disassembly model, followed by matrix-based method (40 papers). Graphs give an intuitive way to describe precedence and contact information among the parts of an EoL product. Matrix-based methods provide a more convenient means for the computer to handle disassembly constraint relationships. For matrix-based methods, redundant data is a common problem faced by existing description methods, as most of the methods need to record the relationships between all parts even when no such relationships exist. On the other hand, Petri net (12 papers) gives detailed geometrical and topological information on the components of the EoL product. Generally, it has been noted that the actual disassembly process is full of uncertainties and randomness. At the end of its service life, a product may not have a structure consistent with its original structure, which leads to deviations from the disassembly model. Moreover, most disassembly model building methods are static methods. To handle uncertainties caused by unplanned problems such as damaged or missing parts, disassembly models must be capable of dynamic adjustment.

4. Planning methods

After the disassembly mode and disassembly model have been determined for a given EoL product, planning methods should be used to find the optimal solution from various alternatives. This section covers existing planning methods from two points of view: disassembly objectives (Section 4.1) and optimisation methods (Section 4.2).

4.1 Disassembly objective

The disassembly objective deals with the criteria for the optimal disassembly plan (low cost, environmental impact or high revenue). After the disassembly models are created, specific disassembly objectives are described to make the optimisation process move in specific directions. In the reviewed articles, disassembly objectives are summarized as shown in Table 5. From Table 5, it can be seen that the disassembly objectives are divided into four approaches: disassembly cost, disassembly revenue, environmental indices and other indices.

Table 5. Disassembly objectives.

Disassembly objectives			Description	References
Disassembly cost objectives	Disassembly time	Basic disassembly time	Time required for disassembling a regular component	Yeh,[38,39] Chen et al.,[41] Xia et al.,[42] Pornsing et al.,[46] ElSayed et al.,[49,50,116] Go et al.,[52] Zhang et al.,[54,55,56] Azab et al.,[59] Hsu,[69] Zhang,[74] Wang,[75] Tang et al.,[96] Luo et al.,[101,102] Smith et al.,[108] Li et al.,[111,112] Jin et al.,[115] Song et al.,[118,119] Percoco et al.,[120] Wang et al.,[124] Giudice et al.[143] and Kang et al.[144]
		Additional disassembly time	Extra time caused by issues such as geometric complexity and process complexity	Wang,[75] and Luo et al.[101,102]
		Direction-change disassembly time	Extra time required to change directions of movement during disassembly	Yeh et al.,[38,39,40] Chen et al.,[41] Xia et al.,[42,43,44] Pornsing et al.,[46] Xing et al.,[47] Lu et al.,[48] Go et al.,[52] Chen et al.,[53] Li et al.,[57] Xu et al.,[58] Azab et al.,[59] Kheder et al.,[60,88] Jue et al.,[73] Wang,[75] Dong et al.,[78] Agrawal et al.,[80] Zhang et al.,[82] Yang et al.,[83] Gungor et al.,[86,87] Shan et al.,[88] Moore et al.,[90] Adenso-Diaz et al.,[94] Wu et al.,[97,141] Kongar et al.,[98] Fang et al.,[99] Lu et al.,[100] Smith et al.,[103,104,105,107,108] Guo et al.,[110]

			Jin et al.,[115] Percoco et al.,[120] Wang et al.,[126] Li et al.,[132,134] Xue,[142] Giudice et al.,[143] Zhang et al.[145] Deng et al.[147] and Mi et al.[151]
	Tools-change disassembly time	Time required for changing tools	Yeh et al.,[38,39,40] Chen et al.,[41] Xia et al.,[42,43,44] Lu et al.,[48] ElSayed et al.,[49,50,51,116] Go et al.,[52] Chen et al.,[53] Zhang et al.,[55] Li et al.,[57] Xu et al.,[58] Azab et al.,[59] Kheder et al.,[60,146] Wang et al.,[72] Jue et al.,[73] Zhang et al.,[74] Dong et al.,[78] Agrawal et al.,[80] Zhang et al.,[82] Yang et al.,[83] Alshibli et al.,[84] Gungor et al.,[86,87] Shan et al.,[88] Moore et al.,[90] Adenso-Diaz et al.,[94] Wu et al.,[97,141] Kongar et al.,[98] Fang et al.,[99] Lu et al.,[100] Smith et al.,[108] Guo et al.,[110] Li et al.,[132,134] Lu et al.,[135,136] Xue et al.,[142] Zhang et al.,[145] Deng et al.[147] and Mi et al.[151]
	Travelling time between different disassembly points	Time for moving between different disassembly points	ElSayed et al.,[49,50,51,116] Azab et al.[59] and Alshibli et al.[84]
	Stochastic time	Disassembly times are stochastically distributed	Yeh et al.[40] Chen et al.,[53] Tian et al.,[62,63,64] Deng et al.,[65] and Kuo[66]

	Fuzzy time	Disassembly times are represented as triangular fuzzy numbers	Zhang et al.[70]
	Disassembly tooling cost	Cost of tooling for disassembly operation	Xia et al.,[43] Kuo,[66] Guo et al.,[68,110] Zhang et al.,[70] Wang et al.,[72] Wang et al.,[76,77] Kang et al.,[89] Lambert,[91,137,138] Gonnuru,[95] Smith et al.,[108] Rickli et al.,[113,114] Han et al.,[117] Song et al.,[118,119] Ullerich et al.,[125] Chung et al.,[129] Lu et al.,[135] Tripathi et al.,[139] Ma et al.[140] and Giudice et al.[143]
	Labour cost	Cost of disassembling an EoL product per time unit	Pornsing et al.,[46] Tian et al.,[63,64] Deng et al.,[65] Kuo,[66] Hsu,[69] Tang et al.,[96] Smith et al.,[108] Jin et al.,[115] Song et al.,[118,119] Percoco et al.,[120] Ullerich et al.[125] and Kang et al.[144]
	Parts number	Total number of parts disassembled	Xing et al.,[47] Lu et al.,[48] Kheder et al.,[60] Agrawal et al.,[80] Gungor et al.,[86] Luo et al.,[101] Smith et al.,[103,107,108] Jin et al.,[115] Wang et al.[126] and Deng et al.[147]
	Operation number	The total number of operations in the disassembly process	Chung et al.[129]

	Disassembly distance		Distance moved in disassembling a component	Xing et al.[47]
	Maintenance degree		Type of maintenance required (no maintenance, corrective maintenance or preventive maintenance)	Kheder et al.[60,146]
	MTTR		Calculated by the summation of mean time to repair of each part.	Chung et al.[127]
Disassembly revenue objectives	Components revenue	Non-destructive disassembly revenue of a component	Revenue for a salvaged component undamaged by disassembly	Chen et al.,[53] Kuo,[66] Guo et al.,[68,110] Hsu,[69] Kang et al.,[89,144] Lambert et al.,[91,92,137,138] Gonnuru,[95] Tang et al.,[96] Smith et al.,[108] Rickli et al.,[114] Jin et al.,[115] Ullerich et al.,[125] Lu et al.[135] and Ma et al.[140]
		Destructive disassembly revenue of a component	Revenue for a component damaged by disassembly	Smith et al.[108] and Guo et al.[110]
	Recovered weight (or volume)		Weight (or volume) of each component	Xia et al.,[45,109] Pornsing et al.,[46] Chen et al.,[53] Kuo,[66] Li et al.,[111,112] Jin et al.,[115] Smith et al.,[108] Ullerich et al.,[125] Tripathi et al.,[139] Kang et al.[144] and Kheder et al.[147]
	Recovered value		A function of the reuse value of each reusable component and the recycling value	Xia et al., [45,109] Pornsing et al.,[46] Chen et

		of each recyclable component	al.,[53] Kuo,[66,67] Gungor et al.,[86,87] Kongar et al.,[98] Li et al.,[111,112] Jin et al.[115] and Tripathi et al.[139]
	Dynamic product value	Product value modelled as a negative exponential function of time	Rickli et al.[114]
	Profit probability	Profit probability of a disassembly sequence	Rickli et al.[114]
Environmental objectives	Environmental impact of a component	Effect of a component on the environment	Xia et al.,[45,109] Pornsing et al.,[46] Kuo,[67] Gungor et al.,[86,87] Moore et al.,[90] Gonnuru,[95] Smith et al.,[108] Li et al.,[111,112] Rickli et al.,[113] Jin et al.,[115] Percoco et al.,[120] Ullerich et al.,[125] Tripathi et al.,[139] Ma et al.[140] and Giudice et al.[143]
	Environmental impact of a disassembly operation	Effect of a disassembly operation on the environment	Rickli et al.[113]
Other objectives	Feasibility	Index relating to the feasibility of a disassembly sequence	Rickli et al.[113,114]
	Stability	Index relating to the stability of components connected in a particular way (soldering, welding, riveting, screwing)	Lu et al.,[48] Yang et al.[83] and Deng et al.[147]

From Table 5, it can be noted that the disassembly cost objective is sub-divided into disassembly time, disassembly tooling cost, labour cost, parts number, operation number, disassembly distance and maintenance degree. The basic disassembly time is the time required for disassembling a regular component. However, the actual disassembly time for removing a component is not a constant value because it is influenced by other factors. To distinguish the disassembly times for operations with different degrees of difficulty, the idea of additional disassembly time was proposed.[75,101,102] The additional disassembly time was combined with the basic disassembly time to be variable disassembly time. The additional disassembly time still does not take into account practical factors such as tool changes, direction changes and time for travelling between disassembly points. Researchers have supplemented the additional disassembly time with further allowances for tool changes, direction changes and movements between disassembly points. Tool changes incur time penalties for obvious reasons. In the case of direction changes, the larger the disassembly direction changes, the larger the penalty. In the reviewed papers, the time to travel between disassembly points is normally calculated using the Euclidean distance between different disassembly points and the speed of the transfer equipment (for example, a robot arm). However, in practice, the actual disassembly time for a component depends not only on the aforementioned deterministic time elements, but also on uncertainties in the disassembly process. Stochastic disassembly times[53] and fuzzy times[70] have been proposed to deal with those uncertainties. Depending on the problem, the randomly varying (stochastic) time for removing a component could be taken as normally distributed or Gaussian distributed, whereas triangular numbers have been adopted to represent imprecise (fuzzy) disassembly time. Apart from disassembly time, the cost of tooling should also be considered. Tooling cost means the cost of tooling for disassembly operations such as the cost of torches, wrenches screwdrivers *etc*. In cases where manual disassembly is adopted to deal with uncertainties in the disassembly process, labour costs become a consideration.[46] Other factors affecting disassembly costs are the parts number[36] the disassembly distance,[47] maintenance degree,[60] mean time to repair (MTTR)[127] and operation number.[129]

The disassembly revenue for a component is also a disassembly objective. Disassembly revenue can also be divided into nondestructive disassembly revenue[115] and destructive disassembly revenue[110] (again, if a paper does not specify the type of revenue, it is taken as nondestructive disassembly revenue by default). Table 5 shows that the existing literature mainly focuses on nondestructive disassembly revenue. Guo et al. considered the destructive disassembly revenue of a component.[110] However, different destructive disassembly methods will result in different disassembly revenues although no paper so far has discussed this point. With a view to recycling, some authors have considered the recovered weight and recovered value of a component.[109] The above mentioned objective description methods are static methods. However, in practice, the properties of EoL products can change, among other factors, according to the time they were in use. To account for this dynamic scenario, the product value curve was taken as a negative exponential function of time.[114] Apart from these, the profit probability was also studied.[114]

There has been less work on objectives connected to the environment than on those associated with costs and revenues. Environmental objectives are to reduce environmental impacts of components[109] and of operations.[113] The former concern potential harm by a component and the latter relate to that by a disassembly operation (such as wastage of cleaning fluid or energy). In addition, stability[48] and feasibility[113] have also been taken as disassembly objectives. Rickli and Camelio[113] used the ratio of feasible arcs over the total number of arcs in a disassembly graph as a feasibility index to be maximised. Other researchers also take into account how stably components are connected together (welding, riveting or press fitting, etc.).[48]

Based on the statistics of publications in Table 5, it can be seen that work related to economic factors (disassembly cost and revenue, 97 papers) has received the most attention. However, considering the importance of environmental factors (18 papers), it is expected that they will attract more research efforts in the future. For both economic factors and environmental factors, suitable dynamic descriptions are needed for the parts of which the conditions are uncertain or variable. As stated in section 1, researchers have paid increasing attention to robotic disassembly which helps to promote the automation of disassembly process. When robotic disassembly is considered,[49] as an important environmental factor, the energy consumption of robots in the disassembly process can also be optimised to promote sustainability.[152] In addition, for robotic disassembly, the moving path or trajectory of robot arm should avoid the obstacle caused by the contour of EoL products. When DSP for robotic disassembly is considered, it is meaningful to combines the obstacle-avoiding path planning or trajectory planning with DSP. However, there is no research focuses on this.

4.2 Optimisation methods

The optimisation methods deal with ways of efficiently finding the optimal disassembly sequences. Finding the optimal disassembly sequence under given objectives is an NP-complete problem requiring the use of heuristic algorithms. The main optimisation methods found in the reviewed literature on DSP are nature-inspired heuristic algorithms (NIHA), linear programming methods (LPM), rule-based methods (RBM), stochastic simulation (SSI) techniques and so on.

4.2.1 Nature-inspired heuristic algorithms

NIHA are derived from natural phenomena such as ants foraging and bees foraging. These algorithms can solve combinatorial optimisation problems. In the reviewed literature of DSP, they are the most common methods to find the optimal disassembly sequences.

In NIHA, GA which is derived from evolution and genetics, is the most widely used method to solve disassembly sequence optimisation problems. The disassembly sequences are first coded into chromosomes, and then, the selection, crossover and mutation operators are used to find new chromosomes.[52] In general, the new chromosomes may not meet the precedence relationship of EoL products. Therefore, GA was combined with precedence preserving crossover (PPX) in several studies to ensure the feasibility of new chromosomes.[49,60,116] In addition, feasibility (FE) was added to the fitness function of GA.[113,114] For GA, it is easy to be trap at local optimal solutions. To solve this problem, GA with adaptive crossover rate and mutation rate (ACRMR)[41] and GA with Gaussian mutation[70] were used to improve the quality of solutions. Moreover, simulated annealing (SA) based GA,[83] SA-binary tree (BTA) based GA,[97] Tabu search (TS) based GA[134] and Chaotic GA (CGA)[145] were also proposed to improve the quality of solutions.

The PSO which is derived from the flocking behaviour of birds, is also a common method used for disassembly sequence optimisation. With this method, the velocity and position of particles are updated in each iteration. Pornsing et al. used the discrete PSO to convert continuous velocity to discrete velocity through sigmoid and round functions.[46] Xu et al. employed adaptive PSO to avoid premature convergence by using the inertia weight and adaptive mutation rate.[58] To avoid local optima, Li et al. used the crossover operator, a shift operator and the escaping method to improve the quality of solutions.[111] In addition, simplified swarm optimisation (SSO) is regarded as a type of PSO because the difference between PSO and SSO is only the position update mechanism.[38] To ensure global convergence, a revised updating mechanism of SSO (RUM-SSO) was proposed by dividing the whole population into different groups.[40] Because the parameters of SSO play vital roles in determining the quality of solutions,[38] the self-adaptive parameter control (SPC) method integrated with PPX, feasible solution generator (FSG) and repetitive pair-wise exchange method was developed to automatically tune the parameters of SSO.[38,39]

Table 6. Optimisation methods.

Optimisation methods		Descriptions	References
GA	GA	This includes three main steps: selection, crossover and mutation.	Go et al.,[52] Zhang et al.,[54] Li et al.,[57] Zhang,[74] Wang,[75,77] Gonnuru,[95] Kongar et al.,[98] Chung et al.,[129] Li et al.,[132] Lu et al.,[136] Wu et al.[141] and Giudice et al.[143]
	GA-PPX	The genetic algorithm and precedence-preserving crossover are simultaneously used.	ElSayed et al.,[49,50,51,116] Kheder et al.[60] and Agrawal et al.[80]
	GA-FE	Feasibility is added into the disassembly objective functions of genetic algorithms.	Rickli et al.[113,114]
	GA-ACRMR-PPX	Adaptive crossover rate and mutation rate are used to ensure global convergence.	Chen et al.[41]
	GA-GM	Based on GA, Gaussian mutation operator is included to achieve a better solution.	Zhang et al.[70]
	GA-SA	SA is used after the mutation operation to achieve better performance.	Yang et al.[83]
	GA-SA-BTA	Binary tree and SA are combined with the genetic algorithm.	Wu et al.[97]
	GA-TS	Tabu search is integrated with genetic algorithm.	Li et al.[134]
	CGA	Chaotic theory is applied on initial populations and operators of genetic algorithm.	Zhang et al.[145]
PSO	PSO	Velocity and position of each particle are updated in the iteration.	Lu et al.[135]
	DPSO	Velocity and position of particles are obtained using the sigmoid function and normal distribution respectively.	Pornsing et al.[46]

	IPSO	Crossover, shift operators and escaping method are used to avoid local optimal solutions.	Jin et al.[61] and Li et al.[111,112]
	APSO	This dynamically adjusts inertia weight and adaptive mutation rate to avoid local convergence.	Xu et al.[58]
	SSO	RUM-SSO: A new updating mechanism is used.	Yeh et al.[40]
		PPX-SSO: This includes PPX, FSG, SPC and repetitive pair-wise exchange procedures.	Yeh[38]
		ISSO: Self-adaptive parameter control methods and the update mechanism are improved.	Yeh[39]
ACO	ACO	Ants choose a suitable path by detecting high concentration of pheromone.	Xing et al.,[47] Wang et al.,[76] Shan et al.,[88] Fang et al.,[99] Lu et al.,[100] Luo et al.,[101] Wang et al.,[126] Xue et al.,[142] Kheder et al.[146] and Mi et al.[151]
	IMMAS	The concentration of pheromone is limited to a certain range [τ_{min}, τ_{max}].	Liu et al.[121]
	TSACO	The first stage and second stage respectively correspond to operation selection and operation sequencing.	Wang et al.,[72]
	ASGA	This is used to tradeoff between speed and accuracy.	Tripathi et al.[139]
SS	SS-PPX	PPX is integrated with SS to preserve the precedence relationships of new solutions.	Guo et al.[68,110]
	SS-PR	The path-relink combination operator is added to SS.	Guo et al.[68]
ABC	DABC	This is inspired by the foraging behaviour of bees including onlookers, employed bees and scouts.	Percoco et al.[120] and Zhang et al.[82]
IA	AIA	Selection and single-parent mutation operators are used.	Lu et al.[48]
	SA	A hill-climbing search method suitable for solving combinatorial	Azab et al.[59]

		and continuous optimisation problems.	
	FFO	This is derived by the foraging behaviour of fruit flies.	Jue et al.[73]
LPM	BLPM	BLBP, of which the decision variables are 0 or 1, is a type of LPM.	Kang et al.[89,144] Lambert[91,92,137,138] Ullerich et al.,[125] and Ma et al.[140]
	BAB	This consists of setting the upper/lower bounds and branching operations.	Zhang et al.,[56] Gungor et al.[86] and Han et al.[117]
RBM	RCM	This reduces searching time and eliminates unrealistic solutions by employing rules.	Smith et al.[103,106,107,108]
	RBM-GA	RBM and GA are used to find optimal solutions of disassembly sequence.	Smith et al.[104,105]
SSI	MCS	This can handle the uncertainties in disassembly process.	Chen et al.[53] and Tian et al.[63]
	TPA	Numerical solutions are used to solve stochastic problems based on time and frequency domain methods.	Tian et al.[62]
	NN-SSI	Based on SSI, part of data is the training set and the remaining is the testing set of neural network.	Tian et al.[64] and Deng et al.[65]
	GA-NN-SSI	Based on SSI, GA is used to optimize weight and thresholds of neural network.	Tian et al.[64]
	STLBA	This comprises a feasible solution generator, a teaching phase operator and a learning phase operator.	Xia et al.[42,43,44,45]
	EM	This enumerates all possible solutions and find the best one .	Luo et al.,[102] Jin et al.,[115] Wang et al.[122] and Wang et al.[124]
	OIM	It is used to obtain the shortest disassembly path to the target object.	Song et al.[118,119]
	QL	This includes state and action, the disassembly state matrix is updated through actions.	Xia et al.[109]

FRS	This encapsulates the fuzzy sets and rough sets to solve DSP problem.	Zhang et al.[55]
TS	This consists of short and long-term memories, which are used respectively to prevent reversal and reinforce attractive components.	Alshibli et al.[84]
GRASP	The solution construction step and local search step are included in GRASP.	Adenso-Diaz[94]
DA	A typical algorithm to solve the shortest path problem.	Lu et al.[135]

The ACO algorithm inspired by the foraging behaviour of ants has also been used to find the optimal disassembly sequence. According to the concentration of pheromone, the ants move to the next permitted destination.[101] When the solution space is large enough, it is easy for ACO to converge to local optimal solutions. The max-min ant system was proposed to avoid premature convergence by limiting the concentration of pheromone to a certain range.[121] Execution efficiency of ACO was also studied through a two-stage ACO method.[72] The first stage ACO was employed to convert complex graph-based method into a simple weighted graph while the second stage ACO was used to find the optimal disassembly sequence. In addition, a self-guided ant algorithm (ASGA) was proposed to make tradeoff between efficiency and accuracy.[139]

Scatter search (SS) is a systematic integrated method which includes diversification generation, solution improvement, reference set updating, subset generation and solution combination. It can achieve a balance between quality and diversity of solutions by forming high quality solution sets and diverse solution sets. Guo et al. used the PPX to preserve disassembly precedence relationships from one generation to the next based on SS.[110] After that, Guo et al. continued to use the path-relink combination operator to disassemble large and complex products.[68]

The Immune algorithm (IA) and ABC have also been used to solve DSP. The selection operator and the single-parent mutation operator were adopted to ensure the diversity and quality of the antibodies.[48] A transition rule was added in the discrete artificial bee colony (DABC) algorithm to generate new candidate solutions which helps to find the optimal disassembly solution more quickly.[120] Other methods such as SA[59] and fruit fly optimisation (FFO)[73] have also been used. They are not so commonly used, and thus will not be discussed in detail.

4.2.2 Linear programming methods

LPM is popular method for solving constrained extremum problems. The binary linear programming method (BLPM) is a type of LPM with decision variable that is either 1 or 0.[89] Compared with the integer linear programming method, BLPM helps to improve efficiency by using a simplified representation.[91] However, it is difficult to employ BLPM to solve complicated DSP problems. The branch-and-bound algorithm (BAB) was also used to solve linear programming problems.[117] BAB finds the optimal disassembly sequence by setting the upper/lower bounds and branching operations. To improve the efficiency of BAB, Askiner et al. used two user-defined variables to reduce the search space and the number of nodes.[86]

4.2.3 Stochastic Simulation

SSI is an efficient method of finding the optimal disassembly sequence of a stochastic disassembly process. Monte Carlo simulation (MCS) was used to obtain the optimal disassembly sequence with stochastic disassembly time.[53,63] However, this method, which has the disadvantages of low accuracy and low efficiency, is easily influenced by the sample size. Tian et al. used a two-phase approach to address this problem. Disassembly probability density functions were generated by a time-domain or frequency-domain procedure.[62] Furthermore, neural network (NN)[64] and GA-NN based SSI[64] were also proposed to find optimal disassembly sequences with stochastic disassembly costs.

4.2.4 Rule-based methods

Smith et al.[103,106,107,108] used rules to eliminate unrealistic solutions and generate feasible disassembly sequences. With this method, five rules are iteratively checked until the target component is obtained to produce a feasible disassembly sequence under the partial disassembly mode. After that, Smith et al.[104,105] continued to combine RBM with GA to solve the DSP. Based on the disassembly sequence structure method (five-matrix method), Smith used RBM and GA to reduce the search time by narrowing the search space to find the optimal disassembly sequence. Compared with other methods, this reduces the search time by adding a projection matrix of components.[103]

4.2.5 Simplified Teaching-Learning Based Optimisation

Although NIHA performs well in disassembly sequence optimisation problems, it is essential to use suitable parameters under specific cases, which makes it insufficiently robust for different situations. Under this condition, a simplified teaching-learning based optimisation algorithm (STLBA) was applied in DSP.[42,43,44] Its obvious advantage is that there is no need to tune the input parameters of STLBA to achieve the optimisation goal. Together with FSG, STLBA includes the teaching phase operator, which is used to improve the mean of learners' results, and a learning phase operator, which is used to learn from each other. STLBA can solve complex combinatorial optimisation problems through fewer input parameters than NIHA.

4.2.6 Other methods

Apart from the optimisation methods mentioned before, a reinforcement value was added to the Q-learning method (QL) to achieve the optimisation goal with a smaller number of disassembly operations.[109] Enumerating methods (EM) were also used to solve small-to-medium-sized problems.[102,115,124] When a complicated model is used, the processing time increases exponentially, which makes EM incapable of dealing with complex situations. In addition, the object inverse-directed method (OIM) is mainly used in the partial disassembly mode to generate the optimal disassembly solution.[118]

Other methods such as fuzzy-rough set (FRS),[55] TS,[84] greed randomized adaptive search procedure (GRASP)[94] and Dijkstra's algorithm (DA)[135] were also used in DSP. They are not so commonly used, thus will not be discussed in detail.

Regarding the optimisation methods, there have been many publications on NIHA. GA (27 papers) is the most frequently used method in NIHA, followed by ACO (13 papers). Most NIHA research has focused on improving either solution quality or efficiency. Different from NIHA of which the performance relies on the input parameters, STLBA was proposed to solve DSP without parameter adjustment.[42] This makes STLBA easier to apply and it is expected to gain popularity in the future. However, most of the planning methods are static methods and the obtained results may not be usable in practice due to uncertainties in the disassembly process. To make optimisation results more suitable for practical processes, it is important to develop disassembly sequence re-planning methods to update the optimal disassembly sequence in response to the actual state of the disassembly. However, there is no research in this regard. In recent years, deep reinforcement learning, as a promising artificial intelligence method, has been paid increasing attention.[153,154] However, so far, there is no research using deep reinforcement learning to solve DSP problems involving uncertainties. This is an opportunity for researches in the area of disassembly planning.

Finally, as it is likely that, in the short to medium term, disassembly cannot economically be carried out entirely by robots. Human works are still required to perform difficult disassembly tasks involving high degrees of uncertainty. In addition, to flexibly finish complicated tasks, human-robot collaborative mode[155,156] realises the combination of robot efficiency and human flexibility.[157] The human-robot collaborative systems have successfully been applied in cellular manufacturing field.[158,159] More works would need to be done on how to find optimal disassembly sequences for situations when humans and robots work together.

5. Conclusion and future trends

This paper has reviewed the state-of-art of DSP from the perspectives that encompass the disassembly process for remanufacturing: disassembly mode, disassembly modelling and planning methods. This section concludes the results of this review and summarises the future trends of this field.

Based on the analyses aforementioned, it affirms that: 1. most researches have focused on complete and sequential disassembly; 2. most of the pre-processing methods are manually finished only if CAD models of EoL products are provided; 3. most disassembly model building methods are static methods and can not be dynamically adjusted by the uncertainties in disassembly process; 4. most researches consider economic factors and a few researches focus on environmental factors; 5. deterministic objectives are more frequently studied compared with the stochastic and fuzzy objectives; 6. most optimisation methods focus on NIHA; 7. much attention has been paid to off-line optimisation methods.

Based on the findings, the following research potentials can be finished in the future: 1. more works can be finished on parallel and partial/parallel disassembly; 2. there a lack of completely automatic modelling methods to finish pre-process without CAD models; 3. dynamic disassembly model should be built to handle with uncertainties caused by unplanned problems in the future; 4. dynamic descriptions of economic and environmental factors should be needed for which the conditions are uncertain or variable for future studies; 5. when DSP is considered under robotic disassembly mode, energy consumption of robots in the whole disassembly process can be studied and optimised to promote sustainability in the future; 6. when robotic disassembly is considered, we cannot find any research that combines obstacle-avoiding path planning or trajectory planning of the robots with DSP; 7. limited research has been conducted on disassembly sequence re-planning to make optimisation results more suitable for practical disassembly process; 8. the researches are expected to pay more attention on applying deep reinforcement learning which is a promising artificial intelligence method to DSP in the future; 9. there is a lack of research on DSP under human-robot collaborative mode which takes both human flexibility and robot efficiency into consideration.

Appendix

Table 7. List of abbreviations.

Abbreviations	Full name
ABC	Artificial Bee Colony
ACO	Ant colony optimisation
ACRMR	Adaptive crossover rate and mutation rate
AIA	Advanced immune
APSO	Adaptive particle swarm optimisation
ASGA	Algorithm of self-guided ants
BAB	Branch and bound algorithm
BLPM	Binary linear programming method
BTA	Binary tree algorithm
CAD	Computer-aided design
CGA	Chaotic genetic algorithm
DA	Dijkstra's algorithm
DABC	Discrete Artificial Bee Colony
DMM	Disassembly mathematical model
DPSO	Discrete particle swarm optimisation
DSP	Disassembly sequence planning
EM	Enumerating method
EoL	End of Life
FFO	Fruit fly optimisation
FRS	Fuzzy-rough set
FSG	Feasible solution generator
FE	Feasibility
GA	Genetic algorithm
GA-NN	Genetic algorithm-Neural network
GM	Gaussian mutation
GRASP	Greedy randomized adaptive search procedure
IA	Immune algorithm
IMMAS	Improved max-min ant system
LPM	Linear programming method
IPSO	Improved particle swarm optimisation
ISSO	Improved simplified swarm optimisation
MCS	Monte Carlo simulation
MTTR	Mean time to repair
NIHA	Nature-inspired heuristic algorithm
NN	Neural network
OIM	Object inverse-directed method
PPX	Precedence preserving crossover
PPX-SSO	Precedence preserving crossover-simplified swarm optimisation

PSO	Particle swarm optimisation
QL	Q-Learning
RBM	Rule-based method
RCM	Rule-based recursive method
RUM-SSO	Revised updating mechanism-Simplified swarm optimisation
SA	Simulated Annealing
SDR	Set of direction of removal
SPC	Self-adaptive parameters control
SS	Scatter search
SSI	Stochastic simulation
SSO	Simplified swarm optimisation
SS-PPX	Scatter search precedence preserving crossover
SS-PR	Scatter search path relink
STLBA	Simplified teaching-learning-based optimisation algorithm
TS	Tabu search
TSACO	Two-stage ant colony optimisation
TPA	Two phase approach

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The authors declare that there is no conflict of interest with respect to this paper.

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References

1. Guide VDR. Production planning and control for remanufacturing: industry practice and research needs. *J Oper Manag* 2000; 18(4): 467-483.
2. Duflou JR, Seliger G, Kara S, et al. Efficiency and feasibility of product disassembly: A case-based study. *CIRP Ann-manuf Techn* 2008; 57(2): 583-600.

3. Soh SL, Ong SK and Nee AYC. Design for disassembly for remanufacturing: methodology and technology. *Proc CIRP* 2014; 15: 407-412.
4. Vongbunyong S, Kara S and Pagnucco M. A framework for using cognitive robotics in disassembly automation. *Leveraging technology for a sustainable world* 2012: 173-178.
5. Gil P, Pomares J, Diaz STPC, et al. Flexible multi-sensorial system for automatic disassembly using cooperative robots. *Int J Comp Integ M* 2007; 20(8): 757-772.
6. Knoth R, Brandstotter M, Kopacek B, et al. Automated disassembly of electronic equipment. In: *IEEE international symposium on electronics and the environment* San Francisco, USA, 6-9 May 2002, pp.290-294. New York: IEEE.
7. Merdan M, Lepuschitz W, Meurer T, et al. Towards ontology-based automated disassembly systems. In: *IEEE annual conference on industrial electronics society* Glendale, USA, 7-10 November 2010, pp.1392-1397. New York: IEEE.
8. Vongbunyong S, Kara S and Pagnucco M. Application of cognitive robotics in disassembly of products. *CIRP Ann-manuf Techn* 2013; 62(1): 31-34.
9. Vongbunyong S, Kara S and Pagnucco M. Basic behaviour control of the vision-based cognitive robotic disassembly automation. *Assembly Autom* 2013; 33(1): 38-56.
10. Vongbunyong S, Kara S and Pagnucco M. Learning and revision in cognitive robotics disassembly automation. *Robot Cim-int Manuf* 2015; 34: 79-94.
11. Ghoreishi N, Jakiela MJ and Nekouzadeh A. A nongraphical method to determine the optimum disassembly plan in remanufacturing. *J Mech Design* 2013; 135(2): 1-13.
12. Poli R, Kennedy J and Blackwell T. Particle swarm optimization. *Swarm Intell-us* 2007; 1(1): 33-57.

13. Pham DT and Ghanbarzadeh A. Multi-objective optimisation using the bees algorithm. In: *Proceedings of innovative production machines and systems* Cardiff, UK, 2-13 July 2007, pp.529-533. Cardiff: MEC
14. Karaboga D. An idea based on honey bee swarm for numerical optimization. Report, Erciyes University, Turkey, October 2005.
15. Dorigo M, Birattari M and Stutzle T. Ant colony optimization. *IEEE Comput Intell M* 2006; 1(4): 28-39.
16. Hu Q, Qiao L and Peng G. An ant colony approach to operation sequencing optimization in process planning. *Proc IMechE, Part B: J Engineering Manufacture* 2017; 231(3): 470-489.
17. Zhang X, Wang S, Yi L, et al. An integrated ant colony optimization algorithm to solve job allocating and tool scheduling problem. *Proc IMechE, Part B: J Engineering Manufacture* 2018; 232(1): 172-182.
18. Zhang Z, Yuan B and Zhang Z. A new discrete double-population firefly algorithm for assembly sequence planning. *Proc IMechE, Part B: J Engineering Manufacture* 2016; 230(12): 2229-2238.
19. Sanjeev KR, Padmanaban KP and Rajkumar M. Minimizing makespan and total flow time in permutation flow shop scheduling problems using modified gravitational emulation local search algorithm. *Proc IMechE, Part B: J Engineering Manufacture* 2016; 232(3): 534-545.
20. Kang JG and Xirouchakis P. Disassembly sequencing for maintenance: a survey. *Proc IMechE, Part B: J Engineering Manufacture* 2006; 220(10): 1697-1716.
21. Lee DH, Kang JG and Xirouchakis P. Disassembly planning and scheduling: review and further research. *Proc IMechE, Part B: J Engineering Manufacture* 2001; 215(5): 695-709.

22. Lee DH, Kim HJ, Choi G, et al. Disassembly scheduling: integer programming models. *Proc IMechE, Part B: J Engineering Manufacture* 2004; 218(10): 1357-1372.

23. Kim JG, Jeon HB, Kim HJ, et al. Disassembly scheduling with capacity constraints: minimizing the number of products disassembled. *Proc IMechE, Part B: J Engineering Manufacture* 2006 220(9): 1473-1481.

24. Gupta SM, Erbis E and McGovern SM. Disassembly sequencing problem: a case study of a cell phone. In: *Proceeding of the SPIE International conference on environmentally consious manufacturing IV*, Philadelphia, USA, 26-27 October 2004, pp.43-52. New York: SPIE.

25. Li JR, Khoo LP and Tor SB. A novel representation scheme for disassembly sequence planning. *Int J Adv Manuf Tech* 2002; 20(8): 621-630.

26. Zhang X, Li S, Wang J, et al. Single object selective disassembly sequence planning based on ant colony algorithm. *Comput Integr Manuf* 2007; 13(6): 1109-1114.

27. Tang Y, Zhou MC, Zussman E, et al. Disassembly modeling, planning and application: a review. In: *IEEE international conference on robotics and automation*, San Francisco, USA, 24-28 April 2000, pp.2197-2202. New York: IEEE.

28. Hsieh FS. Robustness analysis of Petri nets for assembly/disassembly processes with unreliable resources. *Automatica* 2006; 42(7): 1159-1166.

29. Kuo TC. Disassembly sequence and cost analysis for electromechanical products. *Robot Cim-int Manuf* 2000; 16(1): 43-54.

30. Shimizu Y, Tsuji K and Nomura M. Optimal disassembly sequence generation using a genetic programming. *Int J Prod Res* 2007; 45(19): 4537-4554.

31. Kongar E and Gupta S M. Disassembly sequencing using genetic algorithm. *Int J Adv Manuf Tech* 2006; 30(5): 497-506.

32. Zhang X and Zhang S. Product disassembly sequence planning based on particle swarm optimization algorithm. *Comput Integr Manuf* 2009; 15(3): 508-514.

33. González B and Adenso-Díaz B. A scatter search approach to the optimum disassembly sequence problem. *Comput Oper Res* 2006; 33(6): 1776-1793.

34. Laili Y, Tao F, Zhang L, et al. A ranking chaos algorithm for dual scheduling of cloud service and computing resource in private cloud. *Comput Ind* 2013; 64(4): 448-463.

35. Laili Y, Tao F, Zhang L, et al. A study of optimal allocation of computing resources in cloud manufacturing systems. *Int J Adv Manuf Tech* 2012; 63(5-8): 671-690.

36. Hui W, Dong X and Duan GH. A genetic algorithm for product disassembly sequence planning. *Neurocomputing* 2008; 71(13): 2720-2726.

37. Dong J and Arndt G. A review of current research on disassembly sequence generation and computer aided design for disassembly. *Proc IMechE, Part B: J Engineering Manufacture* 2003; 217(3): 299-312.

38. Yeh WC. Optimization of the disassembly sequencing problem on the basis of self-adaptive simplified swarm optimization. *IEEE T Syst Man Cyb* 2012; 42(1): 250-261.

39. Yeh WC. Simplified swarm optimization in disassembly sequencing problems with learning effects. *Comput Oper Res* 2012; 39(9): 2168-2177.

40. Yeh WC, Lin CM and Wei SC. Disassembly sequencing problems with stochastic processing time using simplified swarm optimization. *Int J Innov Manag Tech* 2012; 3(3): 226-231.

41. Chen JZ, Zhang YX and Liao HT. Disassembly sequence planning based on

improved genetic algorithm. *Adv Intel Soft Compu* 2011; 2: 471-476.

42. Xia K, Gao L, Li WD, et al. Disassembly sequence planning using a simplified teaching–learning-based optimization algorithm. *Adv Eng Inform* 2014; 28(4): 518-527.
43. Xia K, Gao L, Wang L, et al. A simplified teaching-learning-based optimization algorithm for disassembly sequence planning. In: *Proceeding of the 2013 IEEE 10th International Conference on. e-Business Engineering*, Coventry, UK, 11-13 September 2013, pp.393-398. New York: IEEE.
44. Xia K, Gao L, Chao KM, et al. A cloud-based disassembly planning approach towards sustainable management of WEEE. In: *Proceeding of the 2015 IEEE 12th International Conference on e-Business Engineering*, Beijing, China, 23-25 October 2015, pp.203-208. New York: IEEE.
45. Xia K, Gao L, Wang L, et al. Service-oriented disassembly sequence planning for electrical and electronic equipment waste. *Electron Commer R A* 2016; 20: 59-68.
46. Pornsing C and Watanasungsuit A. Discrete particle swarm optimization for disassembly sequence planning. In: *IEEE international conference on management of innovation and technology*, Singapore, 23-25 September 2014, pp.480-485. New York: IEEE.
47. Xing YF, Wang CE and Liu Q. Disassembly sequence planning based on Pareto ant colony algorithm. *J Mech Eng* 2012; 48(9): 186-192.
48. Lu C and Liu YC. A disassembly sequence planning approach with an advanced immune algorithm. *P I Mech Eng C-J Mec* 2012; 226(11): 2739-2749.
49. ElSayed A, Kongar E, Gupta SM, et al. An online genetic algorithm for automated disassembly sequence generation. In: *Proceedings of the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in*

Engineering, Washington, USA, 28-31 August, 2011, pp.657-664. New York: ASME.

50. ElSayed A, Kongar E and Gupta SM. A genetic algorithm approach to end-of-life disassembly sequencing for robotic disassembly. In *Proceeding of the 2010 Northeast decision sciences institute conference*, Alexandria, USA, 26-28 March 2010, pp.402-408. Boston: LRM
51. ElSayed A, Kongar E, Gupta SM, et al. A robotic-driven disassembly sequence generator for end-of-life electronic products. *J Intell Robot Syst* 2012; 68(1): 43-52.
52. Go TF, Wahab DA, Rahman MNA, et al. Genetically optimised disassembly sequence for automotive component reuse. *Expert Syst Appl* 2012; 39(5): 5409-5417.
53. Chen Y and Chen W. Product disassembly sequence optimization based on profit-probability under uncertain environment. *Comput Integr Manuf* 2014; 20(4): 793-798.
54. Zhang XF, Yu G, Wang L, et al. Parallel disassembly sequence planning for complex products based on genetic algorithm. *J Comp-Aided Des Comp Graph* 2015; 27(7): 1327-1333.
55. Zhang XF, Yu G, Hu ZY, et al. Parallel disassembly sequence planning for complex products based on fuzzy-rough sets. *Int J Adv Manuf Tech* 2014; 72(1): 231-239.
56. Zhang XF and Zhang SY. Product cooperative disassembly sequence planning based on branch-and-bound algorithm. *Int J Adv Manuf Tech* 2010; 51(9): 1139-1147.
57. Li HJ, Jiang J and Wang YF. Disassembly sequence planning based on extended

interference matrix and genetic algorithm. *Comp Eng Des* 2013; 34(3): 1064-1068.

58. Xu J, Zhang SY and Fei SM. Product remanufacture disassembly planning based on adaptive particle swarm optimization algorithm. *J Zhejiang Univ-Sc A* 2011; 45(10): 1746-1752.

59. Azab A, Ziout A and ElMaraghy W. Modeling and optimization for disassembly planning. *Jordan J Mech and Ind Eng* 2011; 5(1): 1-8.

60. Kheder M, Trigui M and Aifaoui N. Disassembly sequence planning based on a genetic algorithm. *P I Mech Eng C-J Mec* 2015; 229(12): 2281-2290.

61. Jin GQ, Li WD and Xia K. Disassembly matrix for liquid crystal displays televisions. *Proc CIRP* 2013; 11: 357-362.

62. Tian GD, Liu Y, Tian Q, et al. Evaluation model and algorithm of product disassembly process with stochastic feature. *Clean Technol Envir* 2012; 14(2): 345-356.

63. Tian GD, Zhou MC, Chu J, et al. Probability evaluation models of product disassembly cost subject to random removal time and different removal labor cost. *IEEE T Autom Sci Eng* 2012; 9(2): 288-295.

64. Tian GD, Zhou MC and Chu J. A chance constrained programming approach to determine the optimal disassembly sequence. *IEEE T Autom Sci Eng* 2013; 10(4): 1004-1013.

65. Deng H, Qiang T, Guo X, et al. Probability Evaluation Modeling and Planning of Product Disassembly Profit. *Int J u- e-Serv Sci Tech* 2015; 8(9): 327-340.

66. Kuo TC. Waste electronics and electrical equipment disassembly and recycling using Petri net analysis: Considering the economic value and environmental impacts. *Comput Ind Eng* 2013; 65(1): 54-64.

67. Kuo TC. Enhancing disassembly and recycling planning using life-cycle analysis.

Robot Cim-Int Manuf 2006; 22(5): 420-428.

68. Guo X, Liu S, Zhou MC, et al. Disassembly sequence optimization for large-scale products with multiresource constraints using scatter search and Petri nets. *IEEE T Cybernetics* 2016; 46(11): 2435-2446.
69. Hsu HP. A fuzzy knowledge-based disassembly process planning system based on fuzzy Attributed and timed predicate/transition net. *IEEE T Syst Man Cy-S* 2017; 47(8): 1800-1813.
70. Zhang Z, Feng Y, Tan J, et al. A novel approach for parallel disassembly design based on a hybrid fuzzy-time model. *J Zhejiang Univ-Sc A* 2015; 16(9): 724-736.
71. Huang J, Esmaeilian B and Behdad S. Multi-Purpose disassembly sequence planning. In: *Proceeding of ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Boston, USA, 2-5 August 2015, pp.1-9. New York: ASME.
72. Wang JF, Wu X and Fan X. A two-stage ant colony optimization approach based on a directed graph for process planning. *Int J Adv Manuf Tech* 2015; 80: 839-850.
73. Jue Q, Wei W, Kemeng B, et al. Guiding disassembly sequence planning based on improved fruit fly optimization algorithm. In: *Proceedings of 5th International Conference on Advanced Design and Manufacturing Engineering*, Valencia, Spain, 27-29 September 2013, pp.188-194. Valencia: ICADME
74. Zhang CM. Optimization for disassemble sequence planning of electromechanical products during recycling process based on genetic algorithms. *Int J Multim Ubiq Eng* 2016; 11(4): 107-114.
75. Wang H. Disassembly sequence planning for end-of-life products. Master Thesis, University of Manitoba, Canada, 2016.
76. Wang H, Niu Q, Xiang D, et al. Ant colony optimization for disassembly sequence

planning. In: *Proceeding of the ASME 2006 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Philadelphia, USA, 10-13 September 2006, pp.635-641. New York: ASME.

77. Wang H, Xiang D and Duan G. A genetic algorithm for product disassembly sequence planning. In: *Proceeding of the 2006 IEEE International Conference on Engineering of Intelligent Systems*, Islamabad, Pakistan, 22-23 April 2006 pp.1-5. New York: IEEE.
78. Dong B and Zhang R. Disassembly sequence planning based on synchronous net. In: *Proceeding of the 2013 Sixth International Symposium on Computational Intelligence and Design*, Nanjing, China, 28-29 October 2013, pp.297-300. New York: IEEE.
79. Wei Y. Research on modularization disassembly sequence planning based on interference matrix. In: *Proceeding of First International Conference on Information Sciences, Machinery, Materials and Energy*, Chongqing, China, 11-13 April 2015, pp.1073-1076.
80. Agrawal D, Nallamothu PT, Mandala SR, et al. Automated disassembly sequence planning and optimization. In: *Proceeding of the 2013 Industrial and Systems Engineering Research Conference*, San Juan, Puerto Rico, 18-22 May 2013, pp.122-131.
81. Zhao S, Li Y, Fu R, et al. Fuzzy reasoning Petri nets and its application to disassembly sequence decision-making for the end-of-life product recycling and remanufacturing. *Int J Comp Integ M* 2014; 27(5): 415-421.
82. Zhang L, Peng HW, Bian BY, et al. Parallel disassembly modelling and planning method of complex products. *China Mech Eng* 2014; 7: 937-943.

83. Yang SY, Li JJ, Wen ZJ, et al. Research on disassembly sequence planning for transfer case of concrete pump. *Mach Des Res* 2014; 30(5): 106-109.

84. Alshibli M, ElSayed A, Kongar E, et al. Disassembly sequencing using Tabu search. *J Intell Robot Syst* 2016; 82(1): 69-79.

85. Jin GQ, Li WD, Wang S, et al. Solution space generation for disassembly research on liquid crystal displays televisions. In: *Proceedings of the 2014 IEEE 18th International Conference on Computer Supported Cooperative Work in Design*, Hsinchu, China, 21-23 May 2014, pp.35-40. New York: IEEE.

86. GÜngÖr A and Gupta SM. Disassembly sequence plan generation using a branch-and-bound algorithm. *Int J Prod Res* 2001; 39(3): 481-509.

87. Gungor A and Gupta SM. Disassembly sequence planning for complete disassembly in product recovery. In: *Proceeding of the 1998 Northeast Decision Sciences Institute Conference*, Boston, USA, 250-252 March 1998, pp.25-27.

88. Shan H, Li S, Huang J, et al. Ant colony optimization algorithm-based disassembly sequence planning. In *Proceeding of the 2007 IEEE International Conference on Mechatronics and Automation*, Sanya, China, 15-18 December 2007, pp.867-872. New York: IEEE.

89. Kang JG, Lee DH, Xirouchakis P, et al. Parallel disassembly sequencing with sequence-dependent operation times. *CIRP Ann-Manuf Techn* 2001; 50(1): 343-346.

90. Moore KE, Güngör A and Gupta SM. Petri net approach to disassembly process planning for products with complex AND/OR precedence relationships. *Eur J Oper Res* 2001; 135(2): 428-449.

91. Lambert AJD. Optimizing disassembly processes subjected to sequence-dependent cost. *Comput Oper Res* 2007; 34(2): 536-551.

92. Lambert AJD and Gupta S M. Methods for optimum and near optimum disassembly sequencing. *Int J Prod Res* 2008; 46(11): 2845-2865.

93. Rai R, Rai V, Tiwari M K, et al. Disassembly sequence generation: a Petri net based heuristic approach. *Int J Prod Res* 2002; 40(13): 3183-3198.

94. Adenso-Díaz B, García-Carbajal S and Lozano S. An efficient GRASP algorithm for disassembly sequence planning. *OR Spectrum* 2007; 29(3): 535-549.

95. Gonnuru VK. Disassembly planning and sequencing for end-of-life products with RFID enriched information. *Robot Cim-Int Manuf* 2013; 29(3): 112-118.

96. Tang Y, Zhou MC and Gao M. Fuzzy-Petri-net-based disassembly planning considering human factors. *IEEE T Syst Man Cy A* 2006; 36(4): 718-726.

97. Wu H and Zuo HF. Using genetic annealing simulated annealing algorithm to solve disassembly sequence planning. *J Syst Eng Electron* 2009; 20(4): 906-912.

98. Kongar E and Gupta SM. A genetic algorithm for disassembly process planning. In: *Proceeding of SPIE international conference on Environmentally Conscious Manufacturing II*, Newton, UK, 28-29 October 2001, pp.54-62. New York: SPIE.

99. Fang XJ, Hua QS and Feng ZY. Disassembly sequence planning based on ant colony optimization algorithm. In: *Proceeding of the 2010 IEEE Fifth International Conference on Bio-Inspired Computing: Theories and Application*, Changsha, China, 23-26 September 2010, pp.1125-1129.

100. Lu C, Huang HZ, Fuh JYH, et al. A multi-objective disassembly planning approach with ant colony optimization algorithm. *Proc IMechE, Part B: J Engineering Manufacture* 2008; 222(11): 1465-1474.

101. Luo Y, Peng Q and Gu P. Integrated multi-layer representation and ant colony search for product selective disassembly planning. *Comput Ind* 2016; 75: 13-26.

102. Luo Y and Peng Q. Disassembly sequence planning for product maintenance. In

Proceeding of the ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Chicago, USA, 12-15 August 2012, pp.601-609. New York: ASME.

103. Smith SS and Chen WH. Rule-based recursive selective disassembly sequence planning for green design. *Adv Eng Inform* 2011; 25(1): 77-87.

104. Smith S, Smith G and Chen WH. Disassembly sequence structure graphs: An optimal approach for multiple-target selective disassembly sequence planning. *Adv Eng Inform* 2012; 26(2): 306-316.

105. Smith S and Chen WH. Multiple-target selective disassembly sequence planning with disassembly sequence structure graphs. In: *Proceedings of the ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering*, Chicago, USA, 12-15 August 2012, pp.12-15. New York: ASME

106. Smith S and Hung PY. A parallel disassembly method for green product design. In: *Proceeding of IEEE international conference on Electronics Goes Green*, Berlin, Germany, 9-12 September 2012, pp.1-6. New York: IEEE.

107. Smith S and Hung PY. A novel selective parallel disassembly planning method for green design. *J Eng Design* 2015; 26(10): 283-301.

108. Smith S, Hsu LY and Smith GC. Partial disassembly sequence planning based on cost-benefit analysis. *J Clean Prod* 2016; 139: 729-739.

109. Xia K, Gao L, Li WD, et al. A q-learning based selective disassembly planning service in the cloud based remanufacturing system for WEEE. In: *Proceeding of ASME 2014 International Manufacturing Science and Engineering Conference*, Detroit, USA, 9-13 June 2014, pp.1-8. New York: ASME.

110. Guo X and Liu S. A scatter search approach for multiobjective selective

disassembly sequence problem. *Discrete Dyn Nat Soc* 2014; 2014: 1-9.

111. Li WD, Xia K, Gao L, et al. Selective disassembly planning for waste electrical and electronic equipment with case studies on liquid crystal displays. *Robot Cim-Int Manuf* 2013; 29(4): 248-260.

112. Li WD, Xia K, Lu B, et al. A distributed service of selective disassembly planning for waste electrical and electronic equipment with case studies on liquid crystal display, In: Li WD and Mehnen J (eds) *Cloud Manufacturing Distributed Computing Technologies for Global and Sustainable Manufacturing*, London: Springer, 2013, pp.23-47.

113. Rickli JL and Camelio JA. Multi-objective partial disassembly optimization based on sequence feasibility. *J Manuf Syst* 2013; 32(1): 281-293.

114. Rickli JL and Camelio JA. Partial disassembly sequencing considering acquired end-of-life product age distributions. *Int J Prod Res* 2014; 52(24): 7496-7512.

115. Jin G, Li WD, Wang S, et al. A systematic selective disassembly approach for Waste Electrical and Electronic Equipment with case study on liquid crystal display televisions. *Proc IMechE, Part B: J Engineering Manufacture* 2015; Special issue: 1-18.

116. ElSayed A, Kongar E and Gupta SM. An evolutionary algorithm for selective disassembly of end-of-life products. *Int J Swarm Intell Evol Comput* 2012; 1: 1-7.

117. Han HJ, Yu JM and Lee DH. Mathematical model and solution algorithms for selective disassembly sequencing with multiple target components and sequence-dependent setups. *Int J Prod Res* 2013; 51(16): 4997-5010.

118. Song X, Zhou W, Pan X, et al. Disassembly sequence planning for electro-mechanical products under a partial destructive mode. *Assembly Autom* 2014; 34(1): 106-114.

119. Song X and Pan X. Electromechanical product disassembly sequence planning based on partial destruction mode. *Comput Integr Manuf* 2012; 18(5): 927-931.

120. Percoco G and Diella M. Preliminary evaluation of artificial bee colony algorithm when applied to multi objective partial disassembly planning. *Res J Appl Sci Eng Tech* 2013; 6(17): 3234-3243.

121. Liu X, Peng G, Liu X, et al. Disassembly sequence planning approach for product virtual maintenance based on improved max–min ant system. *Int J Adv Manuf Tech* 2012; 59(5): 829-839.

122. Wang C, Mitrouchev P, Li G, et al. Least levels disassembly graph method for selective disassembly planning. In: *Proceeding of the ASME 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Buffalo, USA, 17-20 August 2014, pp.1-10. New York: ASME.

123. Mitrouchev P, Wang CG, Lu LX, et al. Selective disassembly sequence generation based on lowest level disassembly graph method. *Int J Adv Manuf Tech* 2015; 80(1): 141-159.

124. Wang H, Peng Q, Zhang J, et al. Selective Disassembly Planning for the End-of-life Product. *Proc CIRP* 2017; 60: 512-517.

125. Ullerich C and Buscher U. Flexible disassembly planning considering product conditions. *Int J Prod Res* 2013; 51(20): 6209-6228.

126. Wang JF, Liu JH, Li SQ, et al. Intelligent selective disassembly using the ant colony algorithm. *Ai Edam* 2003; 17(4): 325-333.

127. Chung C and Peng Q. A hybrid approach to selective-disassembly sequence planning for de-manufacturing and its implementation on the Internet. *Int J Adv Manuf Tech* 2006; 30(5): 521-529.

128. Chung C and Peng Q. An integrated approach to selective-disassembly sequence planning. *Robot Cim-Int Manuf* 2005; 21(4): 475-485.
129. Chung C and Peng Q. Evolutionary sequence planning for selective disassembly in de-manufacturing. *Int J Comp Integ M* 2006; 19(3): 278-286.
130. Kara S, Pornprasitpol P and Kaebernick H. Selective disassembly sequencing: a methodology for the disassembly of end-of-life products. *CIRP Ann-Manuf Techn* 2006; 55(1): 37-40.
131. Fang HC, Ong SK and Nee AYC. An integrated approach for product remanufacturing assessment and planning. *Proc CIRP* 2016; 40: 262-267.
132. Li JR, Khoo LP and Tor SB. An object-oriented intelligent disassembly sequence planner for maintenance. *Comput Ind* 2005; 56(7): 699-718.
133. Li JR, Khoo LP and Tor SB. Generation of possible multiple components disassembly sequence for maintenance using a disassembly constraint graph. *Int J Prod Econ* 2006; 102(1): 51-65.
134. Li J R, Tor SB and Khoo LP. A hybrid disassembly sequence planning approach for maintenance. *J Comput Inf Sci Eng* 2002; 2(1): 28-37.
135. Lu Z, Sun YC, Okafor EG, et al. Disassembly sequence planning for maintenance based on metaheuristic method. *Aircr Eng Aerosp Tec* 2011; 83(3): 138-145.
136. Lu Z and Sun YC. Disassembly sequence planning of civil aircraft products for maintainability design. *Acta Aeronaut Astronaut Sin* 2010; 31(1): 143-150.
137. Lambert AJD. Linear programming in disassembly/clustering sequence generation. *Comput Ind Eng* 1999; 36(4): 723-738.
138. Lambert AJD. Optimum disassembly sequence with sequence-dependent disassembly costs. In: *the 2003 IEEE international symposium on Assembly and Task Planning*, Besancon, France, 11-11 July 2003, pp.151-156. New York: IEEE.

139.Tripathi M, Agrawal S, Pandey MK, et al. Real world disassembly modeling and sequencing problem: optimization by algorithm of self-guided ants. *Robot Cim-Int Manuf* 2009; 25(3): 483-496.

140.Ma YS, Jun HB, Kim HW, et al. Disassembly process planning algorithms for end-of-life product recovery and environmentally conscious disposal. *Int J Prod Res* 2011; 49(23): 7007-7027.

141.Wu H and Zuo HF. Selective-disassembly Sequence Planning Based on Improved Genetic Algorithm. *Acta Aeronaut Astronaut Sin* 2009; 30(5): 952-958.

142.Xue JF. Planning of selective disassembly sequence based on ant colony optimization algorithm. *J Comput Aided Des Comput Graph* 2007; 19(6): 742-747.

143.Giudice F and Fargione G. Disassembly planning of mechanical systems for service and recovery: a genetic algorithms based approach. *J Intell Manuf* 2007; 18(3): 313-329.

144.Kang JG, Lee DH, Xirouchakis P, et al. Optimal disassembly sequencing with sequence-dependent operation times based on the directed graph of assembly states. *J Korean Inst Eng* 2002; 28(3): 264-273.

145.Zhang W, Su Q and Liu P. Research on virtual maintenance disassembly sequence intelligent planning. *J Syst Simu* 2013; 25(8): 1912-1918.

146.Kheder M, Trigui M and Aifaoui N. Optimization of disassembly sequence planning for preventive maintenance. *Int J Adv Manuf Tech* 2017; 90(5): 1337-1349.

147.Deng MX, Wang JM, Tang QH, et al. Research on selective disassembly sequence planning for Repair. In: *Proceeding of 4th international conference on Sensors, Mechatronics and Automation*, Zhuhai, China, 12-13 November 2016, pp.685-671.

148.Song XW, Pan XX, Feng K, et al. Complex product disassembly sequence planning oriented to defective parts. *Comput Integr Manuf* 2013; 19(6): 1249-1255.

149.Tang Y and Zhou MC. Learning-embedded disassembly petri net for process planning. In: *Proceeding of the 2006 IEEE international conference on Systems, Man and Cybernetics*, Taipei, China, 08-11 October 2006, pp.80-84. New York: IEEE.

150.Bourjault A. Contribution to a methodological approach of automated assembly: automatic generation of assembly sequence PhD Thesis, University of France, France, 1984.

151.Mi X, Zhen X, Zhou S, et al. Research and implementation on visualization system of disassembly sequence planning based on Ant colony algorithm. In: *Proceeding of the 2011 IEEE international conference on computer supported cooperative work in design*, Laussane, Switzerland, 08-10 June 2011, pp.581-585. New York: IEEE.

152.Brossog M, Kohl J, Merhof J, et al. Energy consumption and dynamic behavior analysis of a six-axis industrial robot in an assembly system. *Proc CIRP* 2014; 23: 131-136.

153.Mnih V, Kavukcuoglu K, Silver D, et al. Human-level control through deep reinforcement learning. *Nature* 2015; 518(7540): 529-533.

154.Mnih V, Badia AP, Mirza M, et al. Asynchronous methods for deep reinforcement learning. In: *Proceeding of 33rd International Conference on Machine Learning*. New York, USA, 19-24 June 2016, pp. 1928-1937.

155.Green SA, Billinghurst M, Chen XQ, et al. Human-robot collaboration: A literature review and augmented reality approach in design. *Int J Adv Robot Syst*

2008; 5(1): 1-18.

156. Bauer A, Wollherr D and Buss M. Human–robot collaboration: a survey. *Int J Hum Robot* 2008; 5(1): 47-66.

157. Chen WH, Wegener K and Dietrich F. A robot assistant for unscrewing in hybrid human-robot disassembly. In: *Proceeding of the 2014 IEEE International Conference on Robotics and Biomimetics*, Bali, Indonesia, 5-10 December 2014, pp.536-541. New York: IEEE.

158. Tan JTC, Duan F, Zhang Y, et al. Human-robot collaboration in cellular manufacturing: design and development. In: *Proceeding of the 2009 IEEE International Conference on Intelligent Robots and Systems*, St Louis, USA, 11-15 October 2009, pp.29-34. New York: IEEE.

159. Vogel C, Poggendorf M, Walter C, et al. Towards safe physical human-robot collaboration: A projection-based safety system. In: *Proceeding of the 2011 IEEE International Conference on Intelligent Robots and Systems*, San Francisco, USA, 25-30 September 2011, pp.3355-3360. New York: IEEE.

Appendix I

Notation

c	Removal cost
$\mathbf{C_i}$	Disassembly interference matrix along direction i, i = X+, X-, Y+, Y-, Z+ or Z-
DPN	Disassembly Petri net
$\boldsymbol{E_c}$	Directed dotted edge
$\boldsymbol{E_{fc}}$	Directed solid edge
G	Disassembly network graph
$\mathbf{I}$	Place-transition matrix
m	Number of the transitions
$\mathbf{M}$	Disassembly state of product
n	Number of the places
$\mathbf{O}$	Transition-place matrix
$\mathbf{P}$	Places in the Petri net
R	The original product
$\boldsymbol{Ra}$	A set of arcs
$\boldsymbol{S}$	A subassembly
$\mathbf{T}$	Transitions in the Petri net
$\boldsymbol{V}$	Minimum part of EoL products
w	Weight functions related to the transition

Figure captions

Figure 1. The three steps in DSP.

Figure 2. Disassembly modelling process.

Figure 3. A disassembly tree.

Figure 4. Disassembly network graph.

Figure 5. State-representation based disassembly graph: (a) disassembly stages; (b) disassembly levels.

Figure 6. Directed flow disassembly network.

Figure 7. Disassembly Petri net.

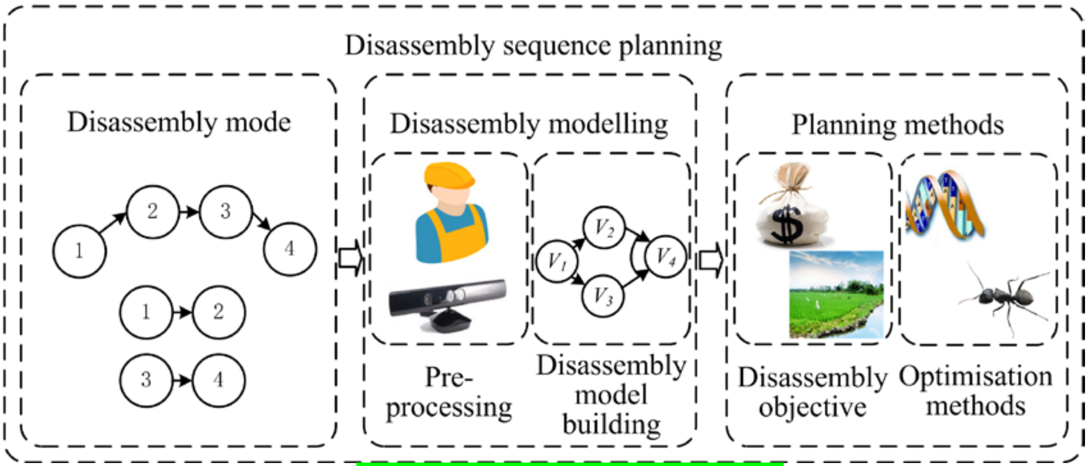


Figure 1. The three steps in DSP.

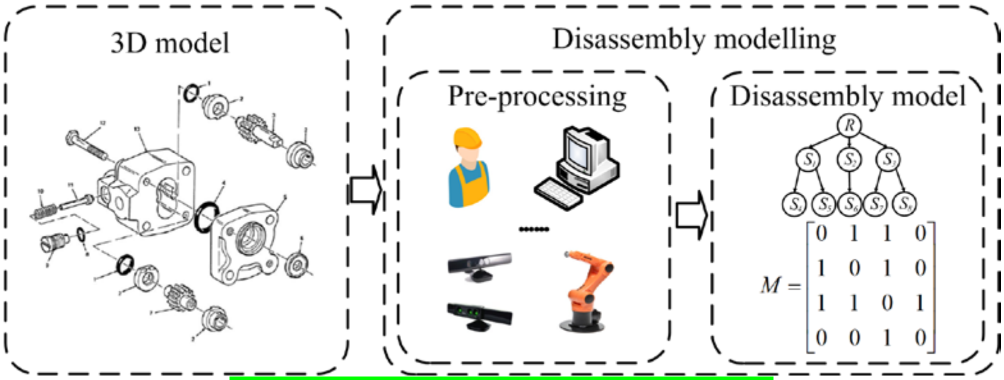


Figure 2. Disassembly modelling process.

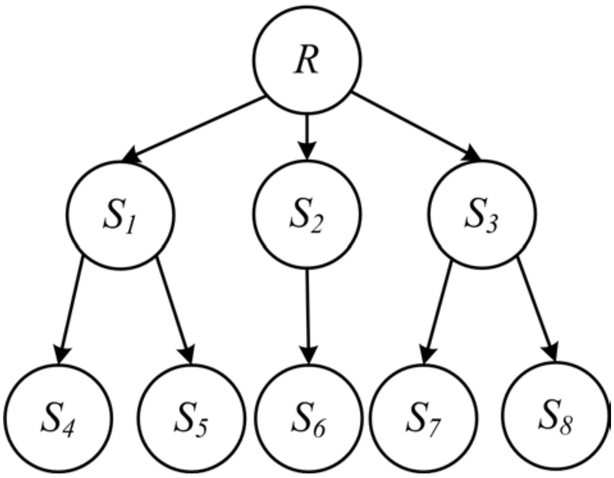


Figure 3. A disassembly tree.

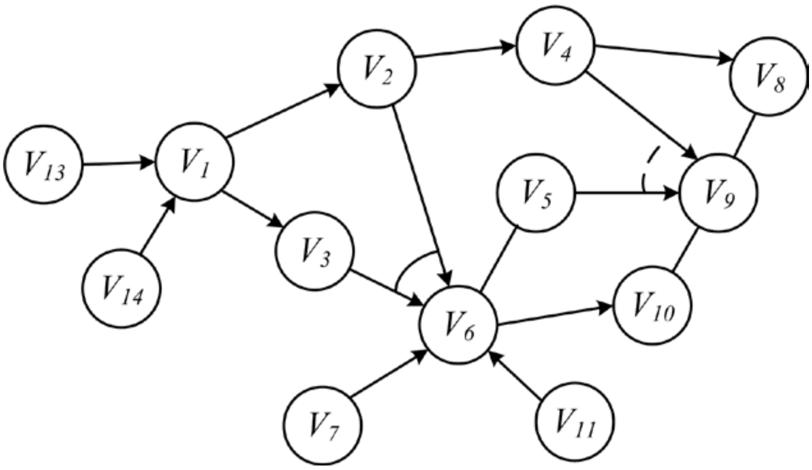
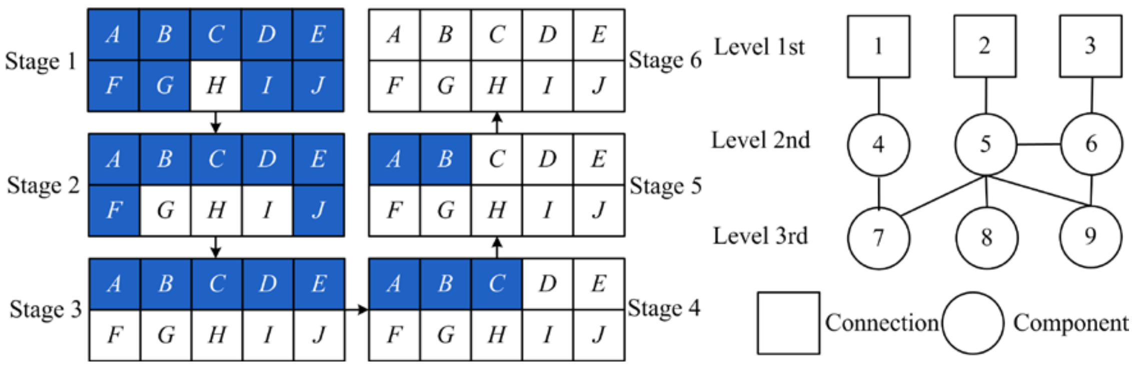


Figure 4. Disassembly network graph.



(a) (b)

Figure 5. State-representation based disassembly graph: (a) disassembly stages; (b) disassembly levels.

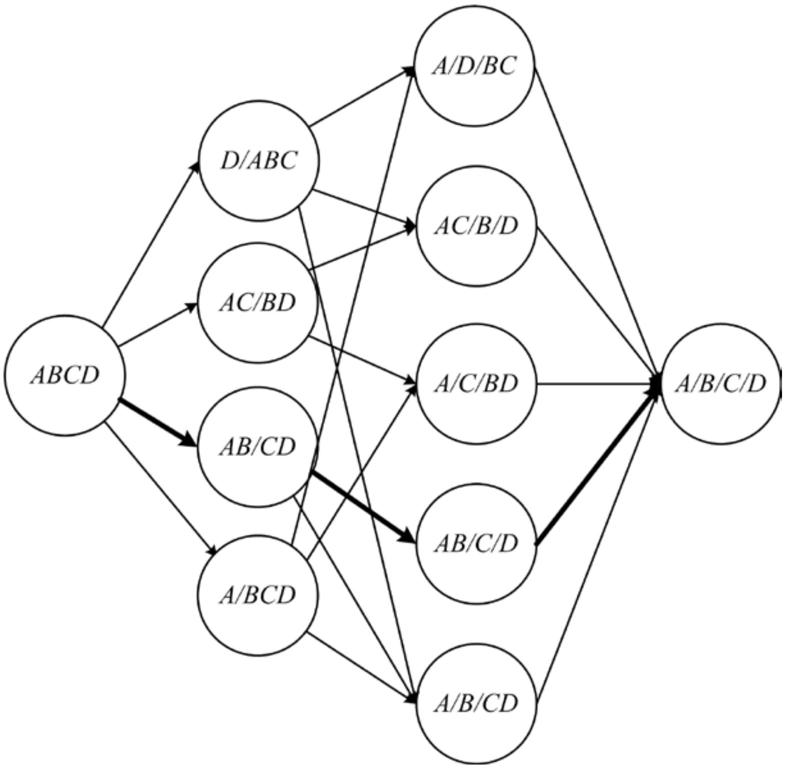


Figure 6. Directed flow disassembly network.

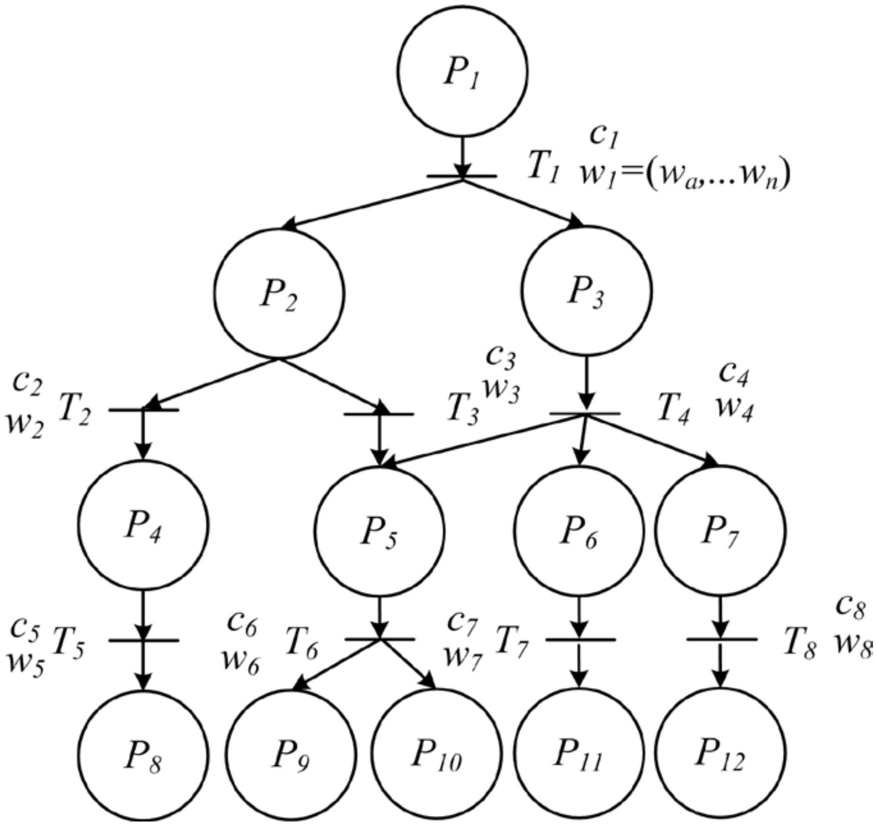


Figure 7. Disassembly Petri net.