

A DECISION SUPPORT SYSTEM FOR INTEGRATED ASSEMBLY AND DISASSEMBLY PLANNING USING A GA APPROACH

Yuan-Jye Tseng, Hsiao-Ting Kao and Feng-Yi Huang
Department of Industrial Engineering and Management, Yuan Ze University
135 Yuan-Tung Road, Chung-Li, Taoyuan 320, Taiwan

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Abstract: In a decision support system for a complete product life cycle management, both assembly planning and disassembly planning need to be considered for producing an assembled product. To produce an assembled product, an assembly planning scheme is required to generate a proper assembly sequence with which the components can be grouped and fixed to construct a final product. At the end of the product life cycle, a disassembly planning scheme is performed to generate a disassembly sequence to disassemble and recycle the product. In this research, a new decision support system for a complete product life cycle management by integrating assembly and disassembly planning is presented. First, the spatial relationships of the components and the precedence of the assembly and disassembly operations are analyzed. Second, a genetic algorithm approach is applied to evaluate the integrated assembly and disassembly costs to find the good assembly sequences and disassembly sequences. A cost function by integrating the assembly costs and disassembly costs is formulated and used as an objective function. An example product is demonstrated and discussed. The test result shows that the decision support system is feasible and effective for integrating assembly and disassembly planning with a complete product life cycle management.

1 INTRODUCTION

In a complete product life cycle management system of an assembled product, both an assembly sequence and a disassembly sequence are required. An assembly sequence is required to produce a new product by applying a series of assembly operations on a group of components at the start of the life cycle. A disassembly sequence is needed to decompose the product into disposable or recyclable parts or components by applying a series of disassembly operations at the end of the life cycle. The main purpose of assembly planning (assembly sequence planning) is to arrange a proper assembly sequence with which the components can be grouped and fixed together to build a final product. The assembly sequence can be defined as an ordered sequence of assembly operations required to produce a product. On the other hand, the purpose of disassembly planning (disassembly sequence planning) is to arrange a disassembly sequence with an ordered disassembly operations for disassemble a product. Therefore, in a decision support system for

a complete product life cycle management, both the assembly planning and disassembly planning need to be considered and integrated.

In the traditional way, the assembly planning models and the disassembly planning models are performed as two independent tasks. As a result, the two planning models are executed separated without interaction. Therefore, a good assembly sequence may sometimes contradict the considerations in the disassembly planning model. In addition, a good disassembly sequence may not support the requirements in the corresponding assembly planning model. Given a set of components, a good assembly sequence can be planned by considering the contact and spatial relationships between the components. A series of assembly operations need to be determined by analyzing the contact and spatial relationships between components. Once the assembly operations are determined, the assembly operations need to be ordered in sequence by evaluating the required cost objective in the assembly planning model. In the traditional planning scheme, the cost objective considers only

the assembly costs occurred in the assembly planning scheme.

Traditionally, the assembly sequence is determined by evaluating the assembly cost objective. In this case, although a low assembly cost can be achieved, it may cost more to disassemble the product at the end of the product life cycle. The key issue is that an assembly operation with a low cost may not correspond to a disassembly operation with the same low cost. In some cases, if a relatively low cost is used for fixing the two specific components, it may require a higher cost to perform the corresponding disassembly operation for separating the two components. As a result, an assembly sequence with a low cost may result in a disassembly sequence with a high cost for the same product at the end of the product life cycle.

Therefore, a complete decision support system must include both assembly planning and disassembly planning. To deal with the special characteristics of a complete product life cycle, organizing and sequencing of assembly and disassembly operations must be considered concurrently in order to generate an integrated sequence.

In the related research for assembly planning, it can be summarized that assembly planning can be performed in three stages: (1) assembly modelling and representation, (2) assembly sequence generation, and (3) assembly evaluation and optimization. A recent review can be found in Abdullah et al. (2003). The previous research in assembly planning can be classified into three categories. The first category uses rules or knowledge bases to perform generation of different assembly sequences such as developed in DeFazio and Whitney (1987), Heemskerck and Van Luttervelt (1989), Ye and Urzi (1996), and Swaminathan and Barber (1996). The second category presents automatic generation of feasible assembly sequences using graph representation forms including the research presented in de Mello and Sanderson (1991), Santochi and Dini (1992), Lin and Chang (1993), and Choi et al (1998). The third category focuses on assembly analysis and evaluation for searching the better or the optimal assembly sequence. The research in this class includes de Mello and Sanderson (1991), Ben-Arieh, and Kramer (1994), Laperriere and ElMaraghy (1996), Gottipolu and Ghosh (1997), Tseng and Liou (2000), and Chen et al. (2004).

With a given set of components, sequencing a given set of components may become a combinatorial problem with an explosive number of potential sequences. From a mathematical point of view, this is an NP-hard problem with the number of

assembly and disassembly sequences proportional to the factorial of number of components. From the solution aspect, genetic algorithms (GAs) have been proven to be effective and efficient in solving NP-hard problems such as TSP (traveling salesman problem). In the research by De Lit et al. (2001), Chen et al. (2002), Marian et al. (2003), Li et al. (2003), and Smith (2004), GA method has been applied to find solutions in assembly planning models.

In this research, a decision support system for a complete life cycle management by integrating assembly and disassembly planning is presented. First, two graph-based models called assembly precedence diagram and disassembly precedence diagram are presented to represent the spatial relationships of the components and the associated precedence relationships of assembly and disassembly operations. Next, two precedence matrices called assembly precedence matrix and disassembly precedence matrix are built for checking the feasible sequences. Finally, several operation cost functions are developed to evaluate the costs of the integrated assembly and disassembly sequences. A method using the genetic algorithm (GA) approach is developed for finding the solutions with an objective of minimizing the costs.

In this paper, section 2 presents the graph-based representation models for integrating assembly and disassembly planning. Section 3 discusses the cost functions for evaluating the sequences. Section 4 presents a GA method for finding the solutions. Section 5 discusses the test results with an example. Finally, section 6 concludes this study.

2 REPRESENTATION MODELS

The input of the decision support system includes the definitions of the components, the spatial relationships of the components, the available assembly and disassembly operations, and the associated assembly and disassembly costs. Two graph-based models are presented to represent the integrated assembly and disassembly sequences. The graph-based models can be summarized as follows.

- (1) Assembly precedence diagram (APD),
- (2) Disassembly precedence diagram (DPD).

An assembly precedence diagram (APD) is a directed graph showing the precedence of the components and the associated assembly operations (Lin and Chang, 1993). In this research, the concept of APD is applied to represent the spatial connectivity relationship and precedence between

two components. To assemble a group of components with collision-free assembly operations, a proper precedence is specified in the APD. In this research, the concept is expanded for use in disassembly planning by defining the disassembly precedence diagram (DPD). An example product A is shown in Figure 1. The APD and DPD of the product A are shown in Figure 2 and Figure 3.

In order to analyze and evaluate the feasible sequences, the two graph-based models of APD and DPD are transformed into two matrix forms. The concept of matrix form has been introduced by Santochi and Dini (1992) for representing the precedence relationship between a pair of components. In this research, the two new matrices forms, assembly precedence matrix (APM) and disassembly precedence matrix (DPM), are developed for integrated assembly planning and disassembly planning. The two matrix models for the example product A is shown as follows.

$$APM = \begin{matrix} & p_{j-1} & p_{j-2} & \cdots & p_{j-n} \\ p_{i=1} & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & \\ \vdots & \vdots & \vdots & p_{ij} & \vdots \\ p_{i=n} & p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \end{matrix}$$

$$DPM = \begin{matrix} & p_{j-1} & p_{j-2} & \cdots & p_{j-n} \\ p_{i=1} & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & \\ \vdots & \vdots & \vdots & p_{ij} & \vdots \\ p_{i=n} & p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \end{matrix}$$

where p_i and p_j are components, a value of $p_{ij} = 0$ represents that there is no precedence between two components p_i and p_j , a value of $p_{ij} = 1$ represents that there is precedence between two components p_i and p_j .

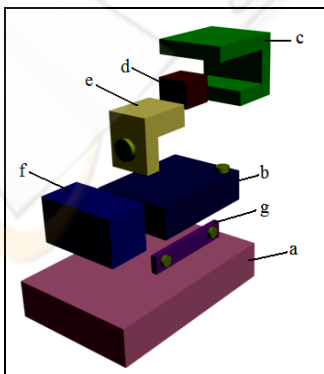


Figure 1: Graphical illustration of the example product A.

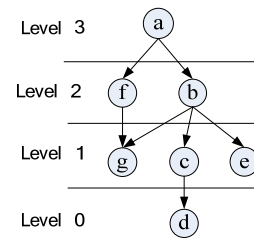


Figure 2: The assembly precedence diagram APD of the example product A.

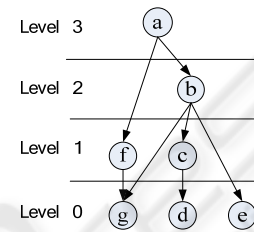


Figure 3: The disassembly precedence diagram DPD of the example product A.

3 COST FUNCTIONS

In the presented decision support system, the related assembly and disassembly costs are identified and modelled. The operation cost functions (OCFs) define the operation costs required in an integrated assembly and disassembly sequence. The operation cost functions include two types of costs, assembly costs and disassembly costs. A cost function by integrating the assembly costs and disassembly costs is formulated and used as an objective function. The assembly costs include assembly operation cost, assembly instability cost, assembly accessibility cost, assembly tool setup cost, and assembly weight effect cost. The disassembly costs include disassembly operation cost, disassembly instability cost, disassembly accessibility cost, disassembly tool setup cost, and disassembly weight effect cost.

The cost items are described as follows.

- (1) Assembly operation cost (*ACC*): To complete the assembly operations, proper operation cost is required. The assembly operation cost is the basic operational cost for performing an assembly operation.
- (2) Disassembly operation cost (*DCC*): To complete the disassembly operations, proper operation cost is required. The disassembly operation cost is the basic operational cost for performing a disassembly operation.
- (3) Assembly instability cost (*SC*): The instability cost is used to describe the cost for maintaining

- the stability of the components and the assembled product in the assembly operations.
- (4) Disassembly instability cost (*USC*): instability cost is used to describe the cost for maintaining the stability of the product and the disassembled components in the disassembly operations.
 - (5) Assembly and disassembly accessibility cost (*ADC* and *DDC*): The accessibility cost is used to describe the degree of difficulty in accessing the parts to complete the assembly operations (*ADC*) or disassembly operations (*DDC*).
 - (6) Assembly and disassembly tool setup cost (*ATC* and *DTC*): To perform the assembly operations, proper tools and tool setups are required (*ATC*). To perform the disassembly operations, proper tools and tool setups are required (*DTC*).
 - (7) Assembly and disassembly weight effect cost (*WAI* and *WDI*): To complete the assembly operations and the disassembly operations, the components and subassemblies need to be moved to different orientations or different positions. Therefore, proper weight effect cost for moving and handling needs to be defined for assembly operations (*WAI*) and disassembly operations (*WDI*).

The value of each of the cost functions is measured on a consistent scale with proper weighting factors. Given a feasible sequence and the associated assembly and disassembly information, the required cost values can be calculated and evaluated with a consistent unit in dollars. In practice, the data of each cost function can be evaluated and recorded according to the information and the formulations set by the manufacturing plant. The numerical data of each cost item can be recorded in a knowledge base and can be checked using a table format in the process for evaluating a feasible sequence. The summation of the cost items is performed using a consistent cost scale. The total cost function (*TC*) is the sum of all the operation cost functions and can be described using the following equation:

$$TC = (ACC+SC+ADC+ATC+WAI) + (DCC+USC+DDC+DTC+WDI) \quad (1)$$

4 SOLUTION USING GENETIC ALGORITHM

4.1 Overall Flow

In the decision support system, the GA approach is applied to evaluate costs of the integrated sequences

and find the good solutions. The input includes the definitions of the product and components and the APD, DPD, APM, and DPM information. The overall flow of the GA method is illustrated in Figure 4. First, a new encoding scheme is developed for representing the integrated assembly and disassembly sequence. The ordered list of components is encoded as a chromosome. The fitness function is defined using the total cost (*TC*) of the operation cost functions (*OCF*). To run the GA method, an initial population is given first. The operators of genetic algorithms are performed to find the solutions. The output sequence is represented using the ordered components and operations. The final output of the decision support system represents the integrated assembly and disassembly sequence for producing the product.

The GA starts with an initial population and the population evolves at each generation. An evaluation is performed to find the chromosome with a high fitness value to replace the chromosome with a low fitness value.

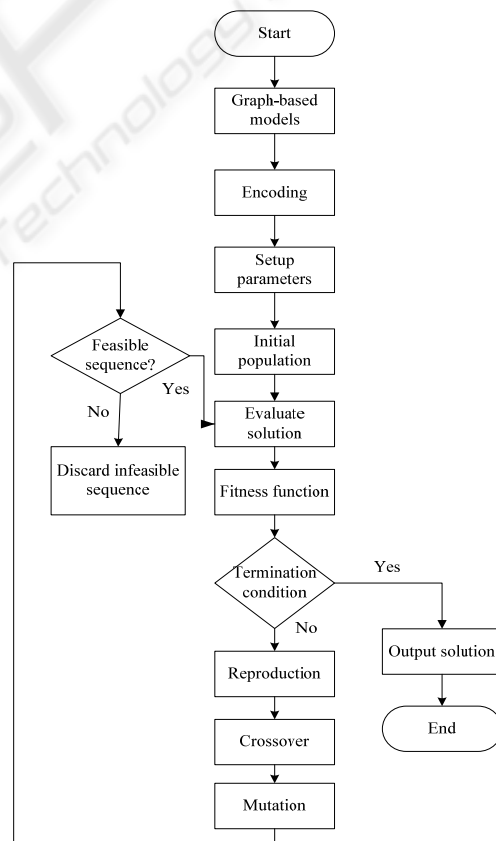


Figure 4: The overall flowchart of the GA method.

4.2 Encoding

In the GA method, a sequence represented by an ordered list of components and operations and is used in the chromosome encoding format. In the genetic algorithm approach, the populations are represented by the codes of chromosomes. The format of the encoded chromosome is shown in Table 1.

Table 1: The encoding format of a chromosome representation of an integrated assembly and disassembly sequence.

Component Name	1	2	...	N
Operation Number (OP)	OP(1)	OP(2)	...	OP(n)
Operation Type: Assembly (A) Disassembly (D)	A	A	...	

Component name denotes the name of a component. The operation number is an indexed number of the operation performed on the component. The operation type includes assembly operation (A) and disassembly operation (D). The encoded chromosome represents a list of sequenced components. The validity of a chromosome for representing a feasible sequence can be checked from the APD and APM for assembly sequences, and DPD and DPM for disassembly sequences.

4.3 Setup Parameters and Fitness Functions

The parameters used in the genetic algorithms are defined as follows.

- (1) P_{Size} : the population size defining the number of chromosomes in the populations, with a setup value of 10,
- (2) C_{Method} : the crossover method, partially mapped crossover, cycle crossover, and order crossover can be applied,
- (3) C_{Rate} : the crossover rate, with an initial value of 0.7,
- (4) M_{Rate} : the mutation rate, with an initial value of 0.3,
- (5) G_{Number} : the generation number representing the condition that the computation stops, with a setup value of 100.

The fitness function is used to evaluate the chromosomes and to make choices leading to a good solution. The decision making of a good solution is made according to the fitness function. The fitness function of the integrated assembly and machining

sequences can be derived from the OCF. The fitness function $fit(i)$ can be defined as follows. The objective is to find a good sequence by minimizing the OCF. In the GA method, a chromosome with a lowest fitness value is chosen to the next generation.

$$fit(i) = OCF(i), \quad (2)$$

$fit(i)$: the fitness function value of chromosome i ,
 $OCF(i)$: the operation cost of chromosome i .

4.4 Solution with GA Method

The step-by-step GA method for finding solutions is described as follows.

Step 1. Initialization.

- (1) Define the chromosome representation format.
- (2) Encode the chromosome.
- (3) Determine the population size, the probability for crossover, the probability for mutation.

Step 2. Initial population.

- (1) Initialize the chromosome index number $i = 1$.
- (2) Generate a feasible sequence from the APD.
- (3) Encode the ordered entities to model a chromosome i .
- (4) $i = i + 1$, until $i > P_{Size}$.

Step 3. Evaluation of fitness function value.

The objective of fitness function can be represented as shown in formulation (2). The fitness function value is calculated for each feasible sequence.

Step 4. Reproduction.

In reproduction operator, the fitness value of a chromosome is used for making decision for copying to the next generation. The fitness value of each chromosome and the total fitness of the population are calculated. The reproduction probability for each chromosome and the cumulative reproduction probability for each chromosome are calculated. The best chromosome with the lowest fitness value is chosen to the next generation.

Step 5. Crossover.

Crossover combines the elements from two parent solutions to create new solutions. The crossover operator is performed by splitting, exchanging, and recombining the elements from two parent chromosomes to create new solutions in the next generation. Based on different splitting, exchanging, and

recombining methods, different types of crossover methods can be used.

Step 6. Mutation.

Mutation operator is used to increase the population variety by randomly selecting and replacing elements between two chromosomes. In the exchanging method, two elements in the two selected chromosomes are chosen randomly and exchanged. In the inserting method, an element is chosen randomly and shifted a random number of ordered positions to the right or to the left. In this step, the reciprocal exchange mutation is used. The mutation number can be calculated as $(M_{Number}) = (M_{Rate}) \times (P_{Size})$.

Step 7. Evaluation of the solution.

By checking the APM and the DPM, if a solution is not feasible, then it will be discarded. If a sequence is not feasible, the ordered operations of components will be changed to a feasible sequence without violating the precedence. The feasible solutions and the fitness values are collected and recorded.

Step 8. Termination condition.

Repeat step 3 to step 7 and $C_{Time} = C_{Time} + 1$,
If $(C_{Time} > G_{Number})$, the computation stops.

Step 9. Output solution with the best fitness value.

The evolution stops when the generation number G_{Number} is reached. Finally, the method outputs the solution with the best fitness value.

5 IMPLEMENTATION AND TEST RESULTS

In the presented decision support system, the models were implemented and tested by developing software on a personal computer. The input data includes the product definition, the component definition, the assembly operations and disassembly operations information, and the cost information.

With the given product and component definition, the geometric data is processed to generate spatial and contact information between the components. With the spatial and contact information between components, the corresponding APD and DPD and can be build. The matrix forms APM and DPM can be calculated from the APD and DPD.

Using the constructed graph-based models and matrix forms, the feasibility of the integrated assembly and disassembly sequences can be examined. Next, the GA method is applied to find the solutions. The example product A is illustrated and discussed in this section. The example product A is shown in Figure 1. There are 7 components, a, b, c, d, e, f, and g. The APD and DPD is shown in Figure 2 and Figure 3. The APM and DPM for the example product A is shown in the following forms.

$$APM = \begin{matrix} & a & b & c & d & e & f & g \\ \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{matrix},$$

$$DPM = \begin{matrix} & a & b & c & d & e & f & g \\ \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{matrix} & \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}.$$

Finally, the GA algorithm is applied for finding solutions. The test result of the GA method is shown in Figure 5. Figure 5 shows that the computation converges after 15 generations with the near optimized low cost of \$369.701. The solution of the integrated assembly and disassembly sequence is shown in Figure 6. Figure 6 describes that the 7 components can be assembled and disassembled with the described integrated assembly and disassembly sequences with a near optimized low cost. The For example, in the integrated sequence 1, $a \rightarrow b \rightarrow f \rightarrow c \rightarrow d \rightarrow g \rightarrow e$ represents the assembly sequence, and $g \rightarrow e \rightarrow d \rightarrow c \rightarrow f \rightarrow b \rightarrow a$ represents the disassembly sequence.

It is observed that the combinatorial number of sequences increases as the component number grows. A larger number of components of the product may lead to a longer computational time. It can be concluded in general, if the component number grows, the advantage of the GA method may be highlighted with a comparatively shorter computational time. Although the presented methods can be useful for generating and evaluating feasible sequences with good solutions, much remains to be done to manage complicated products with a large number of components.

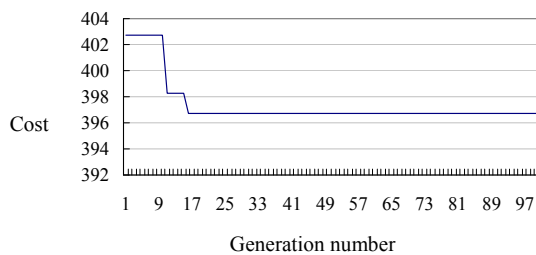


Figure 5: The test result of the GA method.

Integrated sequences	
Assembly sequence	Disassembly sequence
a→b→f→c→d→g→e	g→e→d→c→f→b→a
a→b→e→f→c→d→g	g→e→d→c→b→f→a
a→b→e→f→c→d→g	g→d→c→e→f→b→a
a→b→e→f→c→d→g	g→d→c→f→e→b→a
a→b→e→c→f→d→g	g→e→d→c→f→b→a
a→b→e→f→c→d→g	g→d→e→c→f→b→a
Cost = 194.64	Cost = 202.061
Integrated cost = 369.701	

Figure 6: The test results of the integrated assembly and disassembly sequences with the GA method.

6 CONCLUSIONS

In a complete decision support system for product life cycle management of assembled products, both the assembly and disassembly sequences need to be planned. In a complete product life cycle of a product, an assembly sequence is required to produce a new product at the start and a disassembly sequence is needed at the end to decompose and recycle the product. In this research, the assembly planning model and the disassembly planning model are integrated to generate integrated assembly and disassembly sequences. First, an assembly precedence diagram (APD) and a disassembly precedence diagram (DPD) are built by analyzing the spatial relationships of the components and the operations. The precedence relationships are represented as assembly precedence matrix (APM) and disassembly precedence matrix (DPM) for checking feasibility of the generated sequences. Second, a solution method using a GA approach is applied to search for the good assembly sequence and disassembly sequence. A cost function by integrating the assembly costs and disassembly costs is formulated. Example products are modeled and tested. The final output of the decision support system presents solutions of assembly sequences and disassembly sequences. The test results show

that the GA method converges within a small number of generations with a near optimized low cost. It can be generally concluded that the developed model in the decision support system is feasible and effective for integrating assembly planning and disassembly planning. The decision support system is capable of finding complete assembly and disassembly sequences with a near optimized low cost. Further research should be concerned with different genetic operators. Moreover, more detailed assembly and disassembly decision support factors and other related cost functions can be further explored.

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