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Neuro-fuzzy comprehensive assemblability and assembly sequence evaluation

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Abstract

Analysis of assembly properties of a product is needed during the initial design stage in order to identify potential assembly problems, which affect product performance in the later stages of life cycle. Assemblability analysis and evaluation play a key role in assembly design, assembly operation analysis and assembly planning. This paper develops a novel approach to assemblability and assembly sequence analysis and evaluation using the concept of the fuzzy set theory and neuro-fuzzy integration. Assemblability is described by assembly-operation difficulty, which can be represented by a fuzzy number between 0 and 1. Assemblability evaluation is therefore fuzzy evaluation of assembly difficulty. The evaluation structure covers not only the assembly parts' geometric and physical characteristics, but also takes into account the assembly operation data necessary to assemble the parts. The weight of each assemblability factor is subject to change to match the real assembly environments based on expert advice. The approach has the flexibility to be used in various assembly methods and different environments. It can be used in a knowledge-based design for assembly expert system with learning ability. Through integration with the CAD system, the developed system can effectively incorporate the concurrent engineering knowledge into the preliminary design process so as to provide users with suggestions for improving a design and also helping to obtain better design ideas. The applications in assembly design and planning show that the proposed approach and system are feasible.

Keywords: Assemblability; Design for assembly; Integration; Intelligent CAD; Neuro-Fuzzy Approach

1. INTRODUCTION

It has long been recognized that the decisions made during the design stages have a great impact on the total cost of a product. Design for assembly (DFA) techniques not only help to rationalize a product design from the perspective of its assemblability but also result in substantial savings in the total manufacturing costs, provided that the techniques are implemented at the early conceptual stages of a product design. The benefits of DFA include simplification of a product design, lower assembly and manufacturing costs, reduced overheads, improved quality, and reduced time to market. By extending DFA to include consideration of manufacturing difficulties for each individual part, this methodology can provide the necessary foundation for simultaneous engineering (Boothroyd & Dewhurst, 1989; Boothroyd & Alting, 1992; Zha, 1999).

The essence of DFA is to evaluate and rationalize the parts and assembly processes. It integrates the specific domain knowledge of product design, manufacturing and assembling, and decision-making automation in the assembly process. The analysis of assembly properties of a product is needed during the initial design stage in order to identify potential assembly problems affecting product performance in the later stages of a product's life cycle. To produce a low-cost product, designers need to know whether the designed product can be assembled and what the assemblability of its components is. Assembly evaluation is the means to recognize design quality in terms of assemblability or feasibility. The information feedback from such an analysis and evaluation process in the early design stage is a key to improving design quality for better assemblability.

On the other hand, an effective and efficient evaluation method for assemblability should indicate the cause of design weakness by identifying the tolerances, form features, and geometries of assembly parts, rather than simply provide an evaluation score for the assembly parts or assembly operations. During the assembly design process, a set of

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solution alternatives is evaluated, and a solution is suggested based on the degree of satisfaction resulting from selection of alternative functional requirements. In view of assembly design as "generate and test," the most important step in design decision making is comprehensive evaluation and justification to develop a final solution from a set of alternatives determined by multiple factors or suggested by many evaluators.

This research aims to provide a methodology to quantitatively evaluate assemblability and assembly sequence for design. In the following sections, related work on assemblability or feasibility analysis will be first reviewed, and then a novel fuzzy-set-based approach to assessing the assemblability and assembly sequence of a product will be presented. The approach will be implemented in a neural network through neuro-fuzzy integration.

2. REVIEW OF RELATED WORK

Up to now, related work into assemblability or feasibility analysis using detailed design information is fairly extensive, but research into assemblability analysis during the initial design stage is limited. The related work on assemblability analysis and evaluation methods can be classified into three categories: design heuristics, design rating methods, and assembly geometric analysis. Based on these methods, there have been many systems developed for assemblability analysis and evaluation. In what follows, we give a review on the related work of both assemblability analysis and evaluation methods and systems. But this is not a complete survey (Lim et al., 1995; Zha et al., 1998).

Most of the early work in the analysis of assemblability was rule based. The design attributes of the components, the assembly operations and relationship between components were used to estimate the ease or difficulty of the assembly. This was a breakthrough concept. Plan-based evaluation systems were later developed to address the effects of sequencing of assembling components on assemblability. The pioneering work of Boothroyd and Dewhurst (1989) in developing the design-for-assembly guidelines has resulted in several automated assembly evaluation and advisory systems (Jakiela, 1989; Jakiela & Papalambros, 1989). Swift (1981) also presented a Lucas knowledge-based DFA technique with procedures similar to that of the Boothroyd and Dewhurst approach. Sturges and Kilani (1992) developed a semiautomated assembly evaluation methodology that attempts to overcome some of the limitations of the scheme proposed by Boothroyd and Dewhurst (1989). Although lacking geometric reasoning capabilities, their system serves as an interactive environment to study the effect of various design configurations on assembly difficulty.

Li and Hwang (1992) developed another semiautomated system which closely follows the Boothroyd–Dewhurst methodology. Their assembly difficulty analysis and cost-estimation modules were direct computer implementations of the DFA rules. Their method considers the multiple assembly sequences, calculates the time for all feasible sequences, performs limited feature recognition for assembly, and interactively obtains the nongeometric information that will affect the assembly. The final result is a table similar to a manual assembly worksheet. It is argued that assembly information developed quickly and in a proper format will give the designer enough input to perform further analysis for design modification.

The Hitachi Assemblability System (Miyakawa et al., 1981) has served as a basis for the development of an automated assemblability system. It is based on the principle of one motion per part, with symbols for each type of assembly operation, and penalties for each operation based on its difficulty. The method computes an assembly evaluation score and assembly–cost ratio. An assembly–cost ratio gives an indication of the current assembly cost to the previous cost. The methodology is common for manual, automatic, and robotic systems.

Miles and Swift (1992) also developed an assembly evaluation method in which parts are grouped according to functional importance: "Category A" parts are those required to fulfill the design specification, and "category B" parts are the accessories. The goal is to eliminate as many type-B parts as possible through redesign. Analyses of feeding and fitting were carried out on the parts, with both results combined into a total score. This total is then divided by the number of type-A parts to obtain a final score. A proposed assembly sequence is used to perform fitting analysis. Warnecke and Bassler (1988) studied both functional and assembly characteristics. Parts with low functional value but high assembly difficulty receive low scores, while parts with high functionality and low assembly cost receive high scores. The scoring is used to guide the redesign process. An effective, efficient evaluation method should indicate the cause of design weakness by identifying the tolerance(s), form features(s), and geometry(ies) of assembly parts that cause the problem, rather than simply provide an evaluation score for the assembly parts or assembly operations. Liu and Fisher (1994) used a PDES/STEP-based mechanical system data model as the assembly evaluation information source. This organizes the assembly-related information in a feature-based fashion. The proposed general-purpose assembly evaluation method is built by adopting the basic concepts of multiattribute utility theory. The feature of this method is the linkage of the PDES/STEP product definition to the assembly evaluation method. Jared et al. (1994) presented a DFA system that performs geometric reasoning based on mathematical models for the assembly operations. This reduces the user input requirement. Their system calculates a manufacturability index for individual components and a fitting index between the components.

The need for the integration of assemblability knowledge with current CAD systems has been motivated by the fact that DFA methods have the greatest impact on a product design when they are incorporated into the preliminary design stage. In these integrated CAD-DFA systems, a proposed design is evaluated and recommendations for improvements are presented based on the results of the

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evaluation. AI techniques, such as knowledge-based expert systems, fuzzy logic, and case-based reasoning, and their hybrids may be used for the integration of DFA and CAD. Several methodologies and systems such as IDAERS (integrated design for assembly evaluation and reasoning system; 1992), intelligent CAD-DFA (1993), and DFAES (design for assembly expert system; Zha et al., 1999), have been developed for integrated intelligent design for assembly (IIDFA). IDAERS can provide feedback on the estimated time required for assembling a product. Some of the problems in the integration of CAD systems with DFA methods were also highlighted. Automatic identification of assembly attributes from a CAD description of a component have been investigated (Rosario, 1988; Li & Hwang, 1992). Jakiela and Papalambros (1989) developed an intelligent CAD system by encoding the Boothroyd DFA knowledge with feature-based representation. The system has been able to provide users with suggestions in order to improve a design and also to help obtain better design ideas. They also concluded that concurrent engineering knowledge can be effectively incorporated into the preliminary design process through the use of the suggestive CAD system.

3. FUZZY JUSTIFICATION AND EVALUATION

The multiorder fuzzy justification and evaluation (MFJE) has been applied to a wide variety of decision problems (Bellman & Zadeh, 1970; Kickert, 1978). The major steps of MFJE are: 1) set up performance evaluation index and evaluation factors; 2) determine the fuzzy linguistic variables, weights matrix, and voting matrix; 3) collect the advice of domain experts, and check the consistency of expert opinions; and 4) calculate the evaluation matrix. In the following, we discuss the procedures of multiorder fuzzy evaluation and justification.

3.1. Evaluation factor set

To carry out the evaluation of an object performance, the first step is to set up the performance evaluation index and decision factors. Suppose that there are n factors $(u_i, i = 1,2,\ldots,n)$ to describe the performance of an object. Then, we can define a finite set, $U = \{u_i, i = 1,2,\ldots,n\}$, as an evaluation factors set. If each evaluation factor u_i has m_i $(m \geq 1)$ items, then the evaluation-factor item set of u_i can be expressed as $u_i = (u_{i1},\ldots,u_{imi})$. Thus, the classification of evaluation factors can be described as

$$U = \begin{bmatrix} u_1 \begin{bmatrix} u_{11} \\ \cdots \\ u_{1m_1} \end{bmatrix} & u_2 \begin{bmatrix} u_{21} \\ \cdots \\ u_{2m_2} \end{bmatrix} & \ldots u_n \begin{bmatrix} u_{n1} \\ \cdots \\ u_{nm_{1_n}} \end{bmatrix} \end{bmatrix}^T.$$

3.2. Linguistic variables and weights matrix

Suppose that the value matrix is composed of the evaluated value of each performance index or factor, which is determined by the domain expert according to its degree of importance in the decision. We define Q and q as linguistic variable matrices composed by the evaluated values of each factor and its item, respectively.

3.2.1. Fuzzy linguistic variables and consistence function

The evaluated value is a linguistic variable in the fuzzy set (FS). Therefore, we should first quantify it in terms of fuzzy set theory. In natural language, a single (or multiple) frequency word, also called mood operator, is often combined with a attributive qualifier word to represent the positive degree. By this way, the original word can be changed into a new word. For example, if a basic linguistic variable is W, then the following new words such as "most W," "very W," "quite W," "somehow W," and "more or less W" can be obtained by using the corresponding mood operators, such as "most," "quite," "somehow," "more or less," and so forth. If the consistency function of the original W is μ, then the consistency functions of the above new words can be described as $\mu_1 = \mu^4$, $\mu_2 = \mu^2$, $\mu_3 = \mu^{1.5}$, $\mu_4 = \mu^{0.75}$, $\mu_5 = \mu^{0.5}$, $\mu_6 = \mu^{0.25}$, respectively (Zimmermann, 1987).

For the sake of simplicity, but without loss of generality, we assume that the consistency function μ is constant in the course of evaluation. For the design process, we select the following linguistic variables in the fuzzy set, that is, $FS =$ (very important, important, medium important, almost not important, no relation) as an evaluation value set. Considering that $\mu > 1$, but μ_i is required to be less than 1 $(\mu_i < 1)$, the consistency functions set of its relative value of μ is employed as follows:

$$C = (\mu^{1.5} - 1, \mu - 1, \mu^{0.75} - 1, \mu^{0.5} - 1, \mu^{0.25} - 1, 0). \quad (1)$$

Generally, in engineering,"almost not important" means that the effect on a whole is less than 5%, that is, its weight is less than 0.05 (Bellman & Zadeh, 1970). Hence, we have

$$\frac{\mu_5}{\sum_{i=1}^{6} \mu_i} = \frac{\mu^{0.25} - 1}{\mu^{1.25} + \mu + \mu^{0.75} + \mu^{0.5} + \mu^{0.25} - 5} \leq 0.05, \quad (2)$$

and then we obtain $\mu = 1.2$. Substitute $\mu = 1.2$ to C, we have $C = (0.32,0.20,0.15,0.10,0.046,0)$. After normalizing, $C = (0.38,0.25,0.18,0.12,0.056,0)$.

3.2.2. Criteria for expert opinion consistency

As the value of each factor in U is crucial for the evaluation, we should check again the criteria for the consistency of expert opinions suggested by domain experts or expert-simulator systems (e.g., expert systems) so as to avoid the wrong evaluation caused by too large a difference between expert decisions. The consistency checking criteria is mainly dependent on the statistical results of expert opinions.

Suppose that v_i is a consistency function value of the ith item, μ_{ij} is the evaluated value of ith item given by jth domain expert; then we have

$$v_i = \sigma_i / \overline{\mu_i}, \quad (3)$$

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where

$$\overline{\mu_i} = \sum_{j=1}^{n} \mu_{ij}/n, \qquad D_i = \sum [(\mu_{ij} - \overline{\mu_i})^2/(n-1)], \qquad \sigma_i = \sqrt{D_i}.$$

If $v_i \gg \frac{1}{3}$, then the difference between opinions is considered to be too large, and the expert or expert system should rediscuss or renegotiate internally, and revote; If $v_i \leq \frac{1}{3}$, then the opinions on the ith item factor is considered to be consistent.

Using the consistency function, the evaluated values of each factor and its item in evaluation factors set $U = \{u_i, i = 1,2,\ldots,n\}$, $u_i = (u_{i1},\ldots,u_{im_i})$ can be determined. Then, correspondingly, the linguistic variable matrices Q and q can be obtained. Q and q are also called the second-order and the first-order weight matrices. It is noted that such value matrices for a problem can be obtained from the previous work or from the similar work by allocating the relative values of each factor item through similarity.

3.3. Determination of the linguistic evaluation variable set

The linguistic evaluation variable set E, $E = (v_1, v_2, \ldots, v_l)$, is used for describing the goodness or weakness of object performance under the evaluation. It is determined based on whether the problem is simple or complex. For instance, $E =$ (good, medium, bad) or $E =$ (very good, better, good, worse, bad, very bad). The voting matrix can facilitate evaluating each factor or factor item for object performance in terms of evaluation linguistic variable matrix E. It can be described by a form, of which each expert has one. The second-order and first-order voting matrices, R and r, can be shown as follows, respectively:

$$R = \begin{array}{c} \\ u_1 \\ u_2 \\ \ldots \\ u_n \end{array} \begin{array}{c} \begin{array}{cccc} v_1 & v_2 & \ldots & v_l \end{array} \\ \begin{pmatrix} z_{11} & z_{12} & \ldots & z_{1l} \\ z_{21} & z_{22} & \ldots & z_{2l} \\ \ldots & \ldots & \ldots & \ldots \\ z_{n1} & z_{n2} & \ldots & z_{nl} \end{pmatrix} \end{array},$$

$$r = \begin{array}{c} \\ u_{11} \\ u_{12} \\ \ldots \\ u_{1m_1} \\ u_{21} \\ u_{22} \\ \ldots \\ u_{2m_2} \\ \ldots \\ u_{n1} \\ \ldots \\ u_{nm_n} \end{array} \begin{array}{c} \begin{array}{ccc} v_1 & \ldots & v_l \end{array} \\ \begin{pmatrix} r_{11} & \ldots & r_{1l} \\ r_{21} & \ldots & r_{2l} \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots \\ r_{(m_1+m_2+\ldots m_n)1} & \ldots & r_{(m_1+m_2+\ldots m_n)l} \end{pmatrix} \end{array}.$$

After carrying out the statistics of expert replies, we can obtain the percentage r_{ij} $(i = 1,\ldots,(m_1 + m_2 + \ldots m_n); j = 1,\ldots,l)$ and z_{ij} $(i = 1,\ldots,n; j = 1,\ldots,l)$ of the evaluated values of each factor and its item with respect to the evaluation linguistic variable matrix E.

3.4. Calculation of the evaluation matrix

Let an evaluation vector be Z, weight vector be Q, and evaluation matrix be R; then $Z = Q \circ R$. As there may be many hierarchical-level factors to be considered in a complex design problem, it is reasonable to adopt a multiorder model to comprehensively evaluate the performance of an object. This is dependent on the hierarchical classification of the evaluation factors as described in Section 3.1.

From the evaluation factors set above, we can define two-order evaluation models as such that are composed of $U = (u_i, i = 1,2,\ldots n)$ and $u_i = (u_{ij}, j = 1,2,\ldots, m_i)$. For the first-order model, the value matrix and its voting matrix are $q_i = (q_{ij}, j = 1,2,\ldots, m_i)$ and r_{ij}, respectively. Based on the definition of evaluation matrix, we have

$$z_i = q_i \circ r_i \tag{4}$$

and

$$z_i = \vee_{j=1}^{m_i}(q_{ij} \wedge r_{ij})(i = 1,2,\ldots,n), \tag{5}$$

where $\vee$ and $\wedge$ are union and intersection operators. For example, typical operators in the fuzzy set theory are maximum and minimum, "+" (addition) and "−"(minus). For the second-order model, considering the first-order evaluation results, its voting matrix and value matrix can be represented as $R = (z_i, i = 1,2,\ldots n)$ and $Q = (q_i, i = 1,2,.,n)$, respectively. Thus, the final evaluation results are determined as follows

$$Z = Q \circ R. \tag{6}$$

To illustrate the above procedures of fuzzy justification and evaluation, we give a simple but typical example for a weapon performance justification and evaluation.

The evaluation factors of a weapon performance can be defined as a set, $U =$ {killing ability, shooting accuracy, shooting distance, cost}. The evaluation was carried out by using linguistic variables, which can be described by a five-point system, that is, $E =$ (1 point, 2 points, 3 points, 4 points, 5 points). The statistic results of expert consultation are as follows. For killing ability, no one gave 1 point and 2 points, 30% of the experts gave 3 points, 60% of the experts gave 4 points, and 10% of the experts gave 5 points. Then, the evaluation vector can be described as (0,0,0.3,0.6,0.1). Similarly, we can obtain the evaluation vector of shooting accuracy, shooting distance, and cost as (0,0,0.7,0.2,0.1), (0,0,0,0.1,0.9), and (0,0,0.4,0.5,0.1), respectively. Hence, the evaluation matrix can be written as

$$r = \begin{bmatrix} 0 & 0 & 0.3 & 0.6 & 0.1 \\ 0 & 1 & 0.7 & 0.2 & 0.1 \\ 0 & 1 & 0 & 0.1 & 0.9 \\ 0 & 0 & 0.4 & 0.5 & 0.1 \end{bmatrix}$$

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If we only consider two factors, killing ability and shooting distance, and the weight vector is $q = (0.5, 0, 0.4, 0.1)$, then the comprehensive evaluation vector z for this weapon can be described as $z = q \circ r = (0.5,0,0.4,0.1) \circ r$. If we use the operators, such as $\sum$, $-$, $\times$, for $\circ$, then $z = (0, 0, 0.19, 0.39, 0.42)$, whereas $z = (0, 0, 0.3, 0.5, 0.4)$ for the operators *max-min* for $\circ$. From the calculation, it can be seen that the probability of 4 points and 5 points for this weapon is high ($\geq$80%). That is to say, this weapon is satisfactory with good performance.

4. FUZZY EVALUATION OF ASSEMBLABILITY

Fuzzy-evaluation theory described in the previous section can be used to evaluate the design through value measurement in decision analysis. In this section, we will discuss in detail the fuzzy evaluation of assembly difficulty.

4.1. Assemblability factors

To adopt a fuzzy set theory for assembly evaluation, the assemblability factors must be first identified. Since assemblability of a product is very much dependent on the assembly environment, the following assumptions need to be made before considering the assemblability factors (Liu & Fischer, 1994):

1. Designers use design guidelines to avoid parts' nesting and tangling.
2. Only the assembly time or cost is considered.
3. The method does not consider the feedability and gripping characteristics, because they are sensitive to the assembly method and part configuration (pertinent to the assembly system).
4. The method does not consider the material-handling equipment.
5. All part quality is in the acceptable range for assembly operations.

In addition, the effects of dimensional and geometric tolerance are only considered in the assemblability and assembly operation difficulty analysis and evaluation, but neglected in assembly sequence generation by geometric reasoning (Zha, 1999). For nongeometric factors which may influence the assembly process, only those which impose explicit constraints are investigated.

The assemblability factors are selected to be suited for manual, robot, and automated assembly. Such a selection is based on the strong correlation between the degree of assembly difficulty and the mode of assembly; and because market demand can change the production mode, for example from manual to automated. The major parameters that affect the degree of difficulty of the assembly operations are related to the part's geometry and to the mating operations.

From the above assumptions, the factors that affect the assemblability are classified into two categories: geometry-based parameters and nongeometric parameters. Four types of characteristics of the parts and operations involved are of significance: geometry characteristics (related to parts' geometry), physical characteristics, connection characteristics (related to the type of contact between the components), and operation characteristics. They are described as an evaluation factor tree (Liu & Fischer, 1994). In practice, these parameters are defined in terms of fuzzy linguistic descriptors, which can correspond to a range of actual parameter values (e.g., length), or to a qualitative description of a value of the parameter (e.g., interference).

4.1.1. Geometry-based factors

The geometry-based factors considered in this research for evaluation include shape, symmetry, and ease of assembly form feature. They will be discussed as follows. The shape of the mating objects is particularly important. In general, any assembly operation with irregular or asymmetrical shape requires a high degree of difficulty. There are two main families of shapes: cylinder-type and prism-type. The family of cylinder-type shapes can be described by four linguistic parameters or features: *cylinder*, *spline*, *taper* and *key* (Fig. 1). When defining the shape of the mating components, the user specifies the degree of membership of the shape to one of the above major shape elements. For example, a component with the shape of an eccentric cylinder can be defined as "cylinder" with a qualifier of "medium" (linguistic variable) similarity. The prism-type shape is further defined using two feature parameters: the number of feasible orientations and the directions of the mating operations. The former parameter can exist as two possible values: single orientation and multiple orientations. As be-

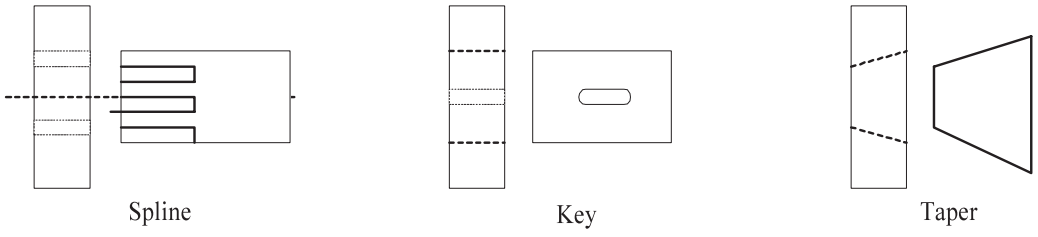


Fig. 1. Cylinder type.

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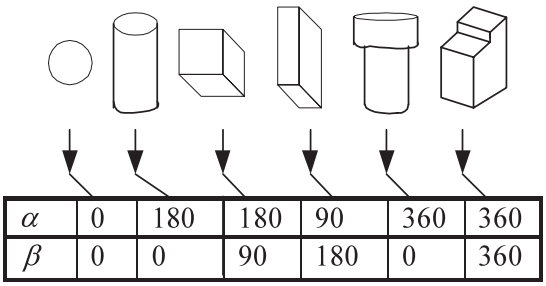


Fig. 2. Symmetry of a part.

fore, the user can specify the degree of acceptance of one of these two linguistic values. The latter parameter is further discussed below.

As Boothroyd and Dewhurst (1989) defined, the symmetric features of the part are classified into two types, α-symmetry and β-symmetry as shown in Figure 2. An α-symmetry is defined as the rotational symmetry of a part about an axis perpendicular to the axis of insertion; a β-symmetry is defined as the rotational symmetry of a part about its axis of insertion.

An assembly aid, such as lead-in chamfers (Fig. 3), can assist the assembly operations. For ease of assembly, at least one of the mated parts should have one such assembly aid.

4.1.2. Physical factors

The physical factors considered in this research for evaluation only include the size and weight of assembly part. The sizes and weights of assembly parts definitely affect the assembly cost. Because of the uncertainty of the assembly method and auxiliary devices, it is difficult to measure the assembly difficulty based on the sizes and weights of parts. We use linguistic variables such as very big (or heavy), medium big (or heavy), medium, medium-small (or light), and very small (or light) to describe the size and weight effects.

4.1.3. Connection factors

In some cases, an assembly operation cannot be clearly specified by the components geometry, and additional parameters have to be defined. To accommodate this need, two parameters, contact-type and fit-type, were defined as connection factors, which can be used to specify a predefined assembly operation (Ben-Arieh, 1994). The first parameter can take one of the following values, such as position contact, snap contact, spring contact, gear contact, clamp fit, belt contact, and so on. Each of such parameters has specific properties associated with it such as the spring tension in a spring contact, and a different degree of difficulty is associated with the different values. The different contact types carry different degrees of difficulty, for example, gluing is considered easier than welding. The other parameter, fit-type, can affect the force needed to perform insertion operations. There are five symbols used to represent the different types of fit (Liu & Fischer, 1994): RC (running or sliding fit); LC (locational clearance fit); LT (locational transition fit); LN (locational interference fit); and FN (force or shrink fit).

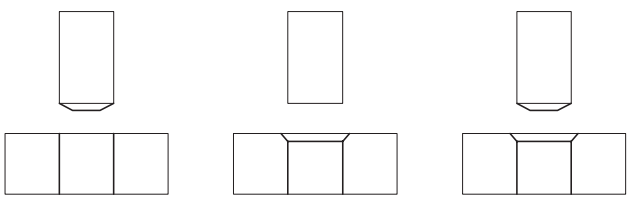


Fig. 3. Assembly form feature.

4.1.4. Operation factors

Generally, the operation factors include number of operations, position (assembly space), orientation, mating direction, translation, rotation, force/torque, alignment of component, and so on. These factors will be discussed as follows.

The more operations needed for an assembly process, the higher the degree of assembly difficulty. As a general rule, permanent connection and assembly methods that do not use auxiliary parts are more economical that disassemblable connections that employ auxiliary assembly parts. This factor also takes into account additional operations to assemble the mated parts in space, if the parts do not provide interlock or self-contained features.

Adequate assembly space must be available in the assembly position of the base part in order to assemble the parts without obstruction.

Assembly direction of parts should preferably be in a vertical straight line, and specifically the assembly process should include press-in or press-on operations. Horizontal operations can be performed without difficulty, if the required assembly forces are low. Nonlinear operations are necessary when obstacles occur in a linear assembly operation.

The mating direction has two different value families based on the shape values of components. For cylinder-type components, the following four values exist: axial, axial eccentric, radial, and radial eccentric. These possible values are described in Figure 4(a). The values that the user assigns, as before, describe the membership value of the selected linguistic value. For example, *high* for *axial eccentric* means a distance between 50 and 60 mm between the holding point and the insertion point. The prism-type shape elements have four possible values for these parameters: axial access, axial and one-side access, axial and two-side access (parallel), and axial and two-side (perpendicular). These possible values are described in Figure 4(b), and again, have a fuzzy qualifier associated.

The cost of operational translation of an assembled part is proportional to the energy and time spent to perform the operational movement.

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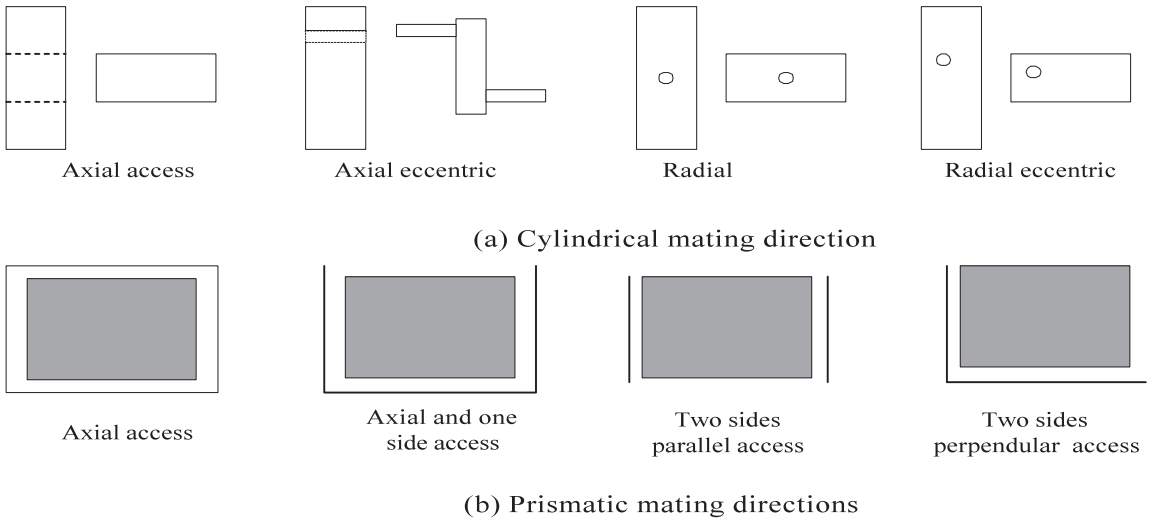


Fig. 4. Mating direction.

Operational rotation is necessary to assemble threaded features. The screwing operation requires rotation of the threaded part and needs a certain torque to fasten the parts together. The degree of assembly difficulty is proportional to the required amount of rotation and torque for the thread-related operations.

The force/torque parameter defines the amount of force required to complete the assembly operation. Its linguistic values range from "very low" to "very high." Each such value corresponds to a range of force values. For example, the value *high* means force requirements of 5–15 kg.

The parameter alignment of component defines the type of alignment necessary to complete the assembly, and has three possible values: fit to any location, fit to a specific location, and fit to a mechanical stop. These values are also represented as fuzzy values using linguistic qualifier or variables. A graphical description of this parameter is shown in Figure 5.

Other parameters related to the components geometry, and sequence of assembly operation are: length of components mating, length of components intersection, ratio of length to width (diameter) of the mating component, ratio of the mating component's weight to the mated one, stability of the resultant assembly, amount of support required for the assembly operation, interference (reachability) to the assembled component, and so forth. The stability parameter reflects the degree to which the assembly is self-contained or stable without additional support. An example of two similar assemblies with low and high value of this parameter is shown in Figure 6. The left side figure has lower level stability than the right side one. The amount of support required reflects the necessary fixturing and use of support tools in order to perform the assembly. Figure 7 shows an example for an assembly with high support required. The last parameter reflects the degree of interference and obstacles that restrict the access of the mating component to the assembly position. Once again, these parameters are defined in terms of fuzzy linguistic descriptors. These fuzzy values can correspond to a range of actual parameter values (e.g., length), or to a qualitative description of the parameters' value (e.g., interference).

4.2. Weight of parameters

The various parameters used above have different degrees of importance, meaning that they have various degrees of influence on the overall difficulty. The acquisition of fuzzy quantities or knowledge is mainly referred to as acquiring the weights of assemblability factors. The fuzzy contribution of each parameter can be acquired based on expert advice, a time study analysis, or even on experimentation

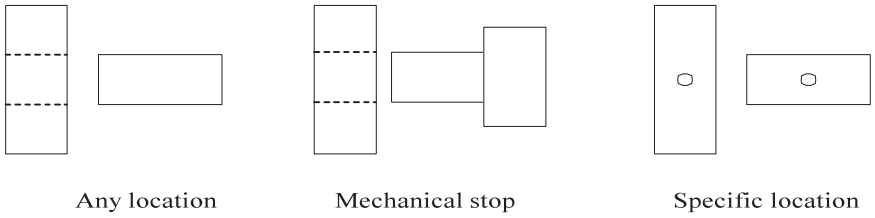


Fig. 5. Alignment of components.

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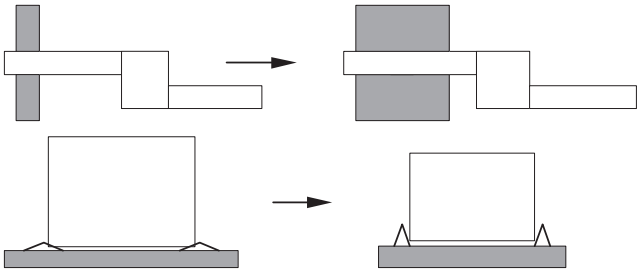


Fig. 6. Assemblies with different levels of stability.

with the various values of each parameter and analysis of the added difficulty.

To describe these parameters, fuzzy values are used. These values of the parameters are represented by linguistic variables with corresponding membership functions. For example, the amount of interference expected in the assembly can be described as "low," "low-medium," "medium," "medium-high," and "high." Each such descriptor implies a certain degree of difficulty that is described as a triangular fuzzy number. For example, a fit of type "pressure fit" with "high" amount of force required implies a basic difficulty of (26,35,55). A "push fit" with "low" force required contributes difficulty of (16,20,26) to the assembly operations. The range of difficulty levels is from 0 to 100 with 100 representing an impossibly difficult operation.

The widely used methods to find the relative importance of each parameter are: pairwise comparison, block distance model, and rank reciprocal rule (Ben-Arieh, 1994). In this research, a new fuzzy justification and evaluation method is proposed as follows. As there are many factors involved, multiorder (2-order) model is required in ranking them for comprehensive fuzzy evaluation and justification for assembly. The first-order factors set can be described as: $(u_{11}, u_{12}, u_{13}, u_{21}, u_{22}, u_{31}, u_{41}, u_{42}, u_{43}, u_{44}, u_{45}) = (\alpha$ symmetry, β symmetry, number of ease of assembly form features, size, weight, fit type, position, orientation, translation, rotation, force/torque). The second-order factors set are described as: (u_1, u_2, u_3, u_4) = (geometric factor, physical factor, connection factor, operation factor). The degree of importance for the first-order factors on assemblability can be described using a linguistic variables set: (very important, important, medium important, almost not important, no relation), while the degree of importance for the second-order factors on assemblability is described as a linguistic variables set: (almost not important, medium important, very important). Then, the expert advice on each factor for assemblability evaluation can be collected using the following tables (Figs. 8). Using the consistency function above, the relative values of linguistic variables can be determined and normalized as shown in the Figure 8. The final weight of each parameter is the average of weights from the advice of every expert. Hence, the weight of each first-order factor can be obtained as (0.0875, 0.0875, 0.175, 0.080, 0.040, 0.18, 0.065, 0.133, 0.042, 0.065, 0.042), and the weight of each second-order factor as (0.35, 0.12, 0.18, 0.35).

4.3. Additive aggregation model for fuzzy assemblability evaluation

Based on the weight of parameters, the allocated score of each parameter can be obtained if the total score is supposed to be 100. This means that the allocated score of the first-order and the second-order factors are (8.75, 8.75, 17.5, 8.0, 4.0, 18.0, 6.5, 13.3, 4.2, 6.5, 4.2) and (35, 12, 18, 35). For a specific design or in a specific assembly environment, each assemblability factor has a reasonable range. Specifying a reasonable range for each factor constrains the evaluation method to provide a better response. For example, a 20-kg part may be considered heavy for manual assembly, but light for robot assembly.

In fuzzy logic, a variable v can belong to more than one set, according to a given membership function $\mu_X(v)$. The possible values of a linguistic variables are not numbers but so called "linguistic terms," such as *S* (small), *M* (medium), and *L* (large). Standard membership function types such as *Z*, λ, π, *and S* types can be mathematically represented as

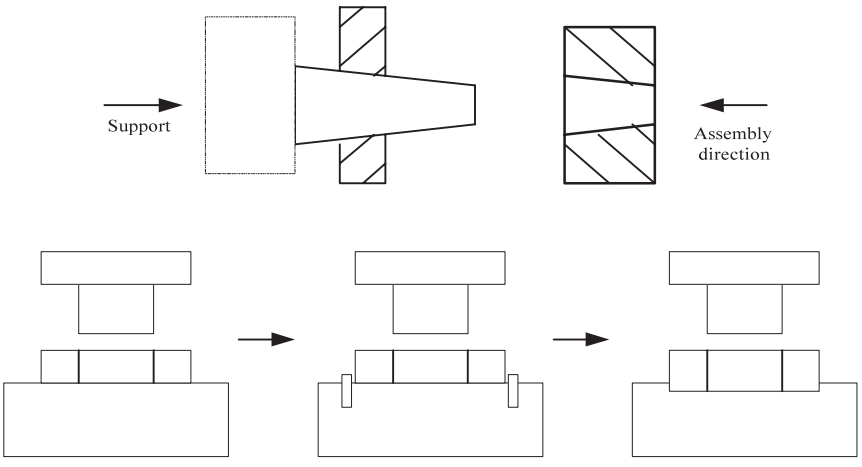


Fig. 7. An assembly operation that requires support.

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Expert Advice \ 1st-order Factors	α Symmetry	β Symmetry	...	Force/Torques
1	Very Important	Very Important	...	Important
2	Very Important	Important	...	Medium Important
...	...	...	...	...
n	Very Important	Important	Important	Medium Important

Expert Advice \ 2nd-order Factors	Geometric Factor	Physical Factor	Connection Factor	Operation Factor
1	Very Important	Very Important	Very Important	Important
2	Very Important	Important	Important	Medium Important
...	...	...	...	...
n	Very Important	Important	Important	Medium Important

Fig. 8. Expert advice on the first and second-order factors for assemblability.

piecewise linear functions. In Figure 9, the variable $v = 2.5$ belongs to S with a membership grade $\mu_S(v) = 0.75$ and to M with $\mu_M(v) = 0.25$. As such, the acceptable range of each assemblability factor can be categorized by the grade. The grade of each assembly factor is subject to change for refining the resolution of an evaluation. The membership function of each assemblability factor is shown in Figure 10. Considering this, Figure 11 lists assembly factors, their acceptable ranges, and grades for a specific environment.

After the allocated difficulty scores are obtained, they can be easily used to evaluate the assemblability in design. This can be accomplished by evaluating the assemblability of a joint (Liu & Fischer, 1994; Zha, 1999). Two types of joint are considered: fastener joint (with agent, e.g., screw, pin, bolt, and nut) and operation joint (without agent).

For an operational joint, the secondary part is mated into the primary part, and the assembly difficulty score as an Assembly Evaluation Index (AEI) is calculated using the following equation:

$$AEI(J) = \frac{1}{100} \sum_{i=1}^{n} ds_i(x_i), \tag{7}$$

where $ds_i(x_i)$ is the relative difficulty score of the joint for the ith assembly factor. $AEI(J)$ is the assembly difficulty score of joint J, which is regarded as an assemblability evaluation index of joint J.

For a fastener joint, the primary part and secondary parts are mated together first, and then the agent(s) is used to join the mated parts. Assuming all the assembly characteristics among the mated parts and the agents are equally important, the assembly score for a fastener joint is calculated as follows:

$$AEI(J) = \frac{1}{100p} \sum_{j=1}^{p} \left(\sum_{i=1}^{n} [ds_i(x_i)]_j \right), \tag{8}$$

where p is the total number of secondary parts and agents involved in the fastener joint.

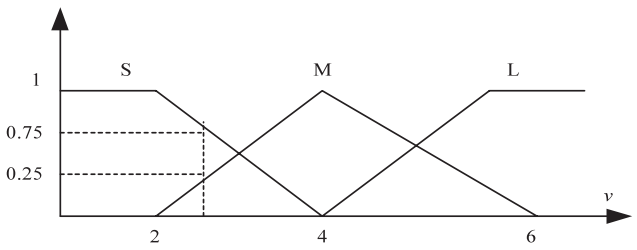


Fig. 9. Membership function of v.

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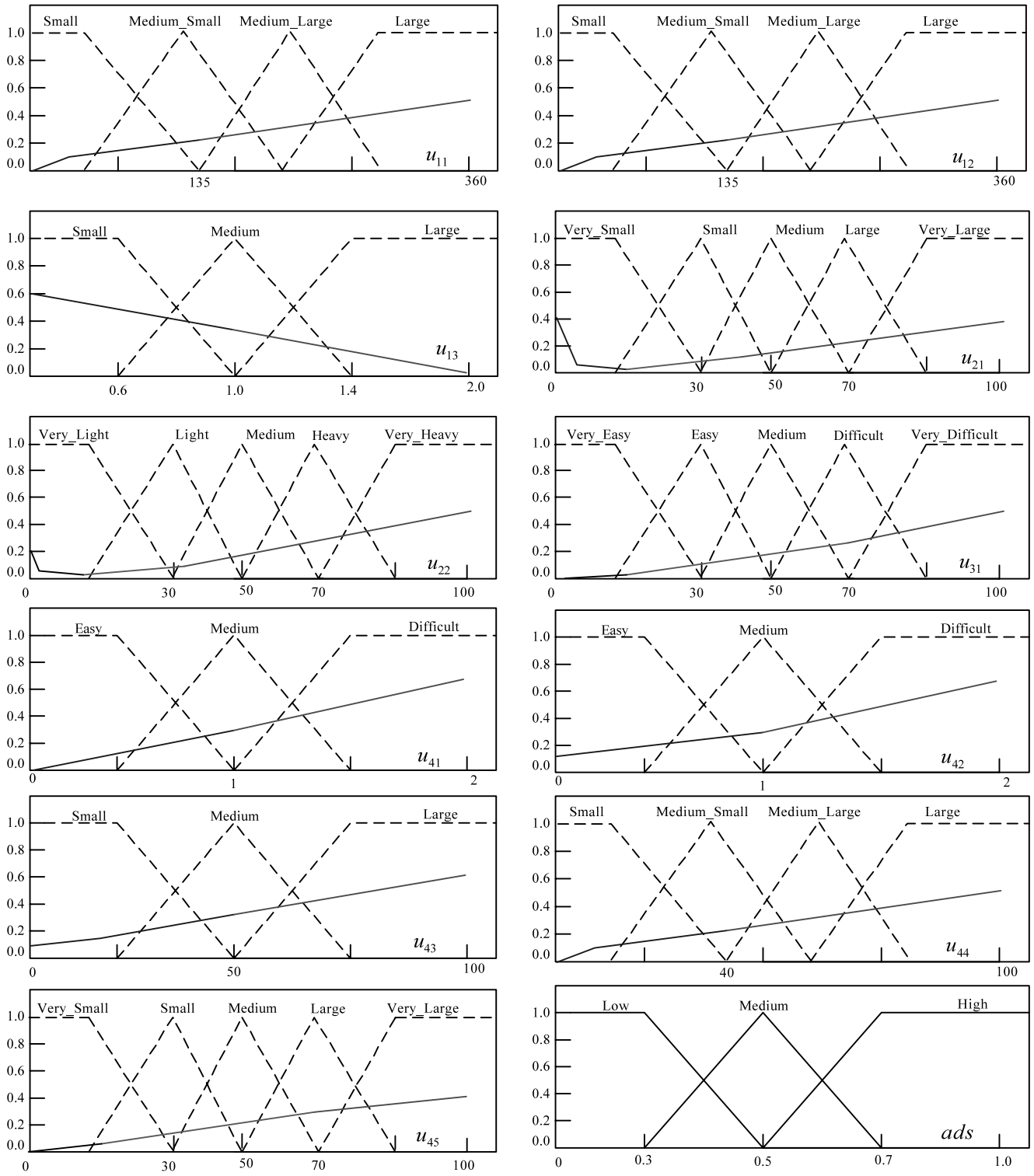


Fig. 10. Membership functions of assemblability factors and assembly difficulty.

4.4. Comprehensive fuzzy assemblability justification and evaluation

To evaluate the assemblability of a design, each assembly factor makes a different contribution. This can be represented by the membership function defined in the universe of discourse of linguistic variable set $E = (v_1, v_2, v_3)$ = (Low, Medium, High). Then the voting matrix or evaluation matrix can be derived as a form shown in Figure 12.

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Assemblability Factors		Acceptable Ranges	Weight (w_i)	Total Scores	Assemblability Factor Fuzzy Levels	Trained Membership Function Values (μ_i)	Allocated Difficulty Scores (ads_i)
Geometry (u_1)	α -symmetry (u_{11})	0-360	0.0875	8.75	α<45 (Small)	(0.067)	(0.586)
					45≤α<135 (Medium Small)	(0.133)	(1.164)
					135≤α<270 (Medium Large)	(0.267)	(2.336)
					α≥270 (Very large)	(0.533)	(4.664)
	β- symmetry (u_{12})	0-360	0.0875	8.75	β<4 (Small)	(0.067)	(0.586)
					45≤β<135 (Medium Small)	(0.133)	(1.164)
					135≤β<270 (Medium Large)	(0.267)	(2.336)
					β≥270 (Very Large)	(0.533)	(4.664)
	Number of ease of assembly form features (u_{13})	0-2	0.1750	17.50	0 (Small)	(0.600)	(10.500)
					1 (Medium)	(0.300)	(5.250)
					2 (Large)	(0.100)	(1.750)
Physical (u_2)	Size (u_{21})	0-100	0.0800	8.00	0-1(Very Small)	(0.400)	(3.200)
					1-5 (Small)	(0.080)	(0.640)
					5-15(Medium)	(0.040)	(0.320)
					15-40(Large)	(0.120)	(0.960)
					40-100(Very Large)	(0.360)	(2.880)
	Weight (u_{22})	0-100	0.0400	4.00	0-0.2 (Very Light)	(0.200)	(0.80)
					0.2-2 (Light)	(0.100)	(0.400)
					2-10(Medium)	(0.050)	(0.200)
					10-35(Heavy)	(0.150)	(1.800)
					35-100(Very Heavy)	(0.500)	(2.000)
Connection (u_3)	Fit type (u_{31})	(0,1,2,3,4)	0.1800	18.00	RC (Very Easy)	(0.063)	(1.125)
					LC (Easy)	(0.063)	(1.125)
					LT (Medium)	(0.125)	(2.250)
					LN (Difficult)	(0.250)	(4.500)
					FN (Very Difficult)	(0.500)	(9.000)
Operation (u_4)	Position (u_{41})	(0,1,2)	0.0665	6.65	Clear (Easy)	(0.000)	(0.000)
					Unclear (Medium)	(0.330)	(2.190)
					Difficulty (Difficult)	(0.670)	(4.460)
	Orientation (u_{42})	(0,1,2)	0.1330	13.30	Vertical (Easy)	(0.125)	(1.663)
					Others (Medium)	(0.250)	(3.325)
					Horizontal (Difficult)	(0.625)	(8.312)
	Translation (u_{43})	0-100	0.0420	4.20	0-10 (Small)	(0.143)	(0.600)
					10-50 (Medium)	(0.286)	(1.200)
					50-100 (Large)	(0.571)	(3.400)
	Rotation (u_{44})	0-100	0.0665	6.65	0 (Very Small)	(0.000)	(0.000)
					0.1-10 (Small)	(0.143)	(0.600)
					10-50 (Medium)	(0.286)	(1.200)
					50-100 (Large)	(0.571)	(3.400)
	Force/torque (u_{45})	0-100	0.0420	4.20	0 (Very Small)	(0.000)	(0.000)
					0.1-2 (Small)	(0.1000)	(0.420)
					2-10 (Medium)	(0.2000)	(0.840)
					10-50 (Large)	(0.3000)	(1.260)
					50-100 (Very Large)	(0.4000)	(1.680)

Fig. 11. Acceptable range of assemblability factors (Liu & Fischer, 1994).

U	M	v_1 (Low)		v_2 (Medium)		v_3 (High)	
	Schemes	I	II	I	II	I	II
u_1	u_{11}	√					
	u_{12}			√			
	u_{13}					√	
u_2	u_{21}	√					
	u_{22}	√					
u_3	u_{31}			√			
u_4	u_{41}			√			
	u_{42}			√			
	u_{43}			√			
	u_{44}			√			
	u_{45}			√			

Fig. 12. Assembly evaluation voting form.

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For the first-order model, the following voting matrices are used as

$$r_1 = \begin{bmatrix} r_{11}^1 & r_{12}^1 & r_{13}^1 \\ r_{21}^1 & r_{22}^1 & r_{23}^1 \\ r_{31}^1 & r_{32}^1 & r_{33}^1 \end{bmatrix}$$

$$r_2 = \begin{bmatrix} r_{11}^2 & r_{12}^2 & r_{13}^2 \\ r_{21}^2 & r_{22}^2 & r_{23}^2 \end{bmatrix}$$

$$r_3 = [\, r_{11}^3 \quad r_{12}^3 \quad r_{13}^3 \,]$$

$$r_4 = \begin{bmatrix} r_{11}^4 & r_{12}^4 & r_{13}^4 \\ r_{21}^4 & r_{22}^4 & r_{23}^4 \\ r_{31}^4 & r_{32}^4 & r_{33}^4 \\ r_{41}^4 & r_{42}^4 & r_{43}^4 \\ r_{51}^4 & r_{52}^4 & r_{53}^4 \end{bmatrix}$$

The first-order value matrix is $q_1 = (q_{11}, q_{12}, q_{13}) = (0.0875, 0.0875, 0.175)$, $q_2 = (q_{21}, q_{22}) = (0.080, 0.040)$, $q_3 = (q_{31}) = (0.18)$, $q_4 = (q_{41}, q_{42}, q_{43}, q_{44}, q_{45}) = (0.065, 0.133, 0.042, 0.065, 0.042)$. Thus,

$$z_1 = q_1 \circ r_1, \qquad z_2 = q_2 \circ r_2, \qquad z_3 = q_3 \circ r_3, \qquad z_4 = q_4 \circ r_4.$$

Similarly, for the second-order model, the corresponding linguistic variables set for assemblability can also be described as (Low, Medium, High). The evaluation matrix $R = (z_1, z_2, z_3, z_4)$ can be described as

$$R = \begin{bmatrix} z_{11} & z_{12} & z_{13} \\ z_{21} & z_{22} & z_{23} \\ z_{31} & z_{32} & z_{33} \\ z_{41} & z_{42} & z_{43} \end{bmatrix}$$

and, the value matrix $Q = (Q_1, Q_2, Q_3, Q_4) = (0.35, 0.12, 0.18, 0.35)$, and

$$Z = Q \circ R = (Z_1, Z_2, Z_3). \tag{9}$$

Therefore, the final evaluation results can be obtained from Eq. (9) as Z_1, Z_2, Z_3. It means that the membership function of assembly difficulty with respect to the linguistic variable set (Low, Medium, High) is Z_1, Z_2, and Z_3. Using the *max-min* principle, the evaluation result is $\max(Z_1, Z_2, Z_3)$.

4.5. Integration of CAD and assemblability evaluation

The primary goal of integration between CAD and assemblability evaluation is to extract characteristics information of a part from the CAD database for design for assembly. With this information and other nongeometric information, the time and cost for assembling the part can be determined by assemblability analysis. Generally, the integration is carried out by the use of three steps: assembly model from assembly modeling system; feature recognition; and assemblability analysis (Zha 1999). Two algorithms, DIMENSION and SYMMETRY, were developed to calculate the overall dimensions and rotational symmetries (α-angle, β-angle) of the part data (Rosario 1988). Information from a CAD system is first translated into a wire-frame representation and a solid CSG representation scheme before it is processed by the algorithms. The system (Fig. 13) implementation in this research consists of two main modules: the preprocessor and the assembly analysis module. The preprocessor reads part data from a CAD system and the assembly description from the user. The part data is translated into a suitable format for the assembly analysis module. The analysis module contains two algorithms and analyzes all assembly components as translated by the preprocessor. These algorithms are based on topology relationships and a palindrome search. Different CAD system representation schemes can be translated into the wire-frame scheme. The overall part dimensions are defined as the dimensions of the smallest prism with sides parallel to the part orthogonal axes. The part rotational symmetries are measured with respect to the part insertion axis and an axis perpendicular to the insertion axis. The rotational symmetries and overall dimensions are used in the design for assembly analysis procedure for assembly cost analysis.

5. NEURO-FUZZY LEARNING FOR ASSEMBLABILITY EVALUATION

Due to the complexity and uncertainty of the assembly problems, the above additive aggregation model and comprehensive fuzzy evaluation methods require further improvement. One of the aspects of improvement is learning ability. In this section, we propose a neuro-fuzzy approach to analyze and evaluate the assembly.

In the proposed neuro-fuzzy approach, a fuzzy evaluator is reflected in three basic elements: fuzzification, fuzzy inference, and defuzzification. The fuzzification in the input interfaces translates analog inputs into fuzzy values. The fuzzy inference takes place in rule blocks which contain the linguistic control rules. The output of these rule blocks is linguistic variables. The defuzzification in the output interfaces translates them back into analog variables. It can be easily implemented and adjusted by using neural networks. The fuzzy rule block is the kernel of the whole fuzzy neural network model. It forms the basic scheme of knowledge representation exploited in the fuzzy controller. These rules appear as:

IF: (input1 = S and input2 = M)
THEN: output = S
IF (input1 = M and input2 = L)
THEN: output = M

The computation of the *IF* part uses minimum operator for *AND* aggregation and maximum operator for *OR* aggregation. To implement using neural network, a degree of support (DOS) in the range 0–1 is introduced, $\mu_{THEN} = \mu_{IF} \cdot DOS$, because neural training methods usu-

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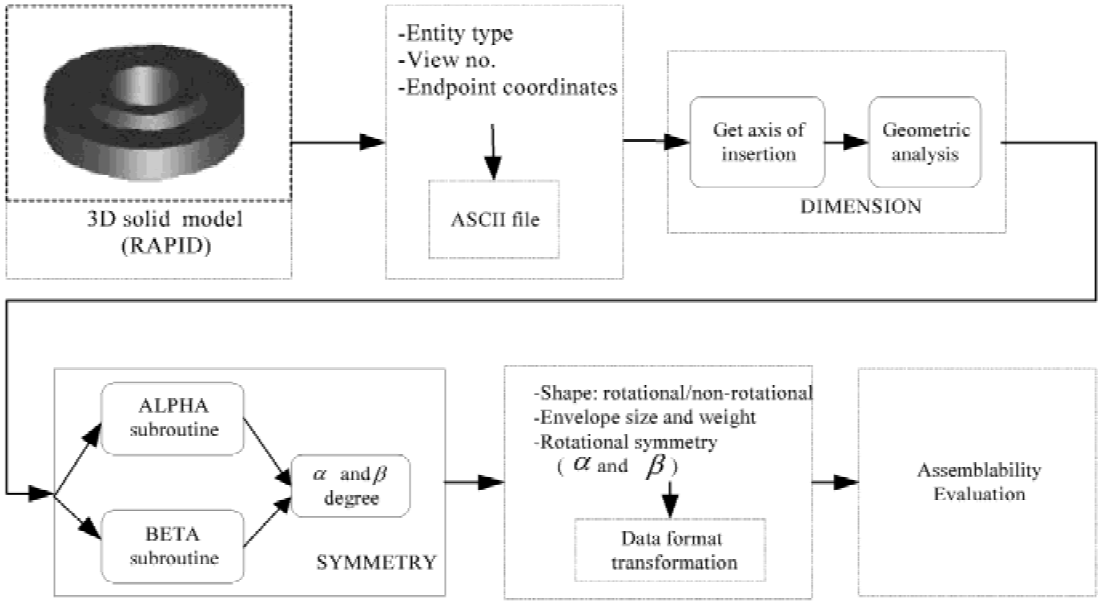


Fig. 13. Integration of CAD and assemblability evaluation.

ally use error gradients to heuristically find the best search direction and a gradient cannot be calculated when discrete rules are used. The output of the fuzzy evaluator is a fuzzy set of evaluation. As an assembly under evaluation requires a nonfuzzy value, a defuzzification stage is needed. Hence, we use a method suitable for the problem of pattern recognition and classification: mean of maximum (MOM), which calculates the crisp output value only with the maximum value of each term. If the maximum is not crisp unique (like a π-shaped membership function), the mean of the maximum interval is computed. The neural network uses the error back propagation algorithm to learn from the data sets, and find a suitable fuzzy evaluator. In this research, competitive learning is used to increase the training capacity. Each time only update the connection weight of the "winner neuron."

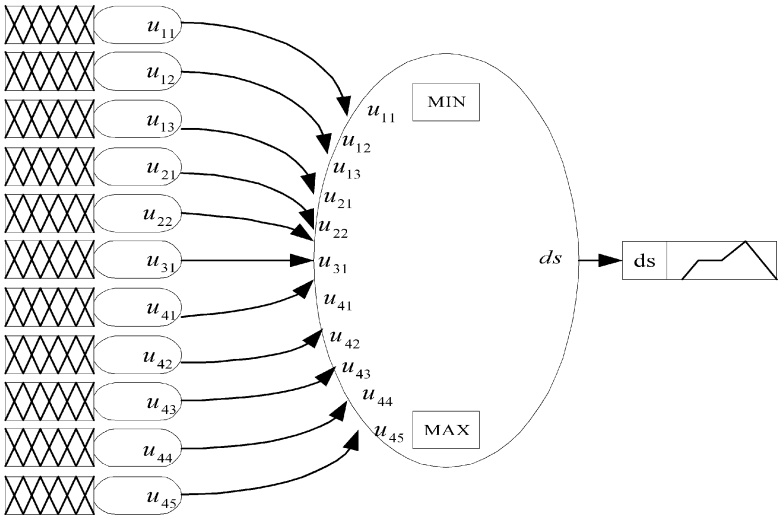
Based on the discussion above and other assembly knowledge, we can obtain many fuzzy rules to describe the effect of each parameter on assemblability. For example, Figures 11 and 12 can be represented as many fuzzy rules, for which the inputs are one or more combined assembly factors and their linguistic values, and the output is an assembly difficulty score, as shown in Figure 14. These fuzzy rules may constitute many rule blocks. All these fuzzy rules can be represented by a four-layered fuzzy neural network as shown in Figure 15. The input layers are assemblability factor variables, and the output layer is an assembly difficulty score or assembly evaluation index. The network can automatically tune the membership functions of assemblability factors so as to adjust the assembly difficulty score. Using the neuro-fuzzy approach, the relationships between product definition data, assembly factor, and assemblability can be formulated, and the sensitivity analysis can be performed to predict how a design parameter change will affect the assemblability.

The optic lens product assembled by eight parts which are, respectively, O_1-doublet 1, O_2-spacer, O_3-doublet 2, O_4-lockring, O_5-subassembly 1 (composed of sp_1, sp_2, sp_3, and sp_4) is taken as an example to illustrate the feasibility and efficiency of the proposed approach and system. Figure 16 is a solid model of this product. Figure 17 evaluates a joint operation for the design of optic lens. After all joints are evaluated, the total assembly difficulty score can be obtained by summing all evaluated scores of these joints. As a different assembly sequence, the required assembly operation is different. The total assembly difficulty score is therefore different. This will be discussed in the next section. For the sequence: *lockring* $\rightarrow$ *doublet*2 $\rightarrow$ *spacer* $\rightarrow$ *doublet*1 $\rightarrow$ *subassembly*1, the total assembly difficulty score and assemblability evaluation index (AEI) after training and learning are 14.81 and 0.1481 (0.15), respectively. Using the comprehensive fuzzy assemblability justification and evaluation, the evaluation result is (0.41, 0.63, 0.85), which means that assemblability is HIGH (85%).

6. ASSEMBLY SEQUENCE EVALUATION

The choice of the assembly sequence in which parts or subassemblies are put together can drastically affect the efficiency of the assembly process. For example, one feasible and reasonable sequence may require less fixturing, less changing of tools, and include simpler and more reliable operations than others. Assembly sequence generation plays an important role in designing and planning the product assembly process and assembly system. To select the optimal assembly sequence that most nearly meets the needs for a particular purpose within the available resources, it is essential to develop some procedures to reduce the sequence count. The generation of assembly sequence and its econotechnical justification and evaluation was discussed

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IF							THEN		
u_{11}	u_{12}	u_{13}	u_{21}	u_{22}	u_{31}	u_{41}	u_{42}	DoS	ds
L	L	L	VL	VL	VL	H	H	0.70	H
S	S	S	VS	VS	VS	LO	LO	0.50	LO
...	...	...	...	...	...	...	...	...	...
L-large, VL-very_large, H-high, S-small, VS-very small, LO-low									

Fig. 14. Fuzzy rules block.

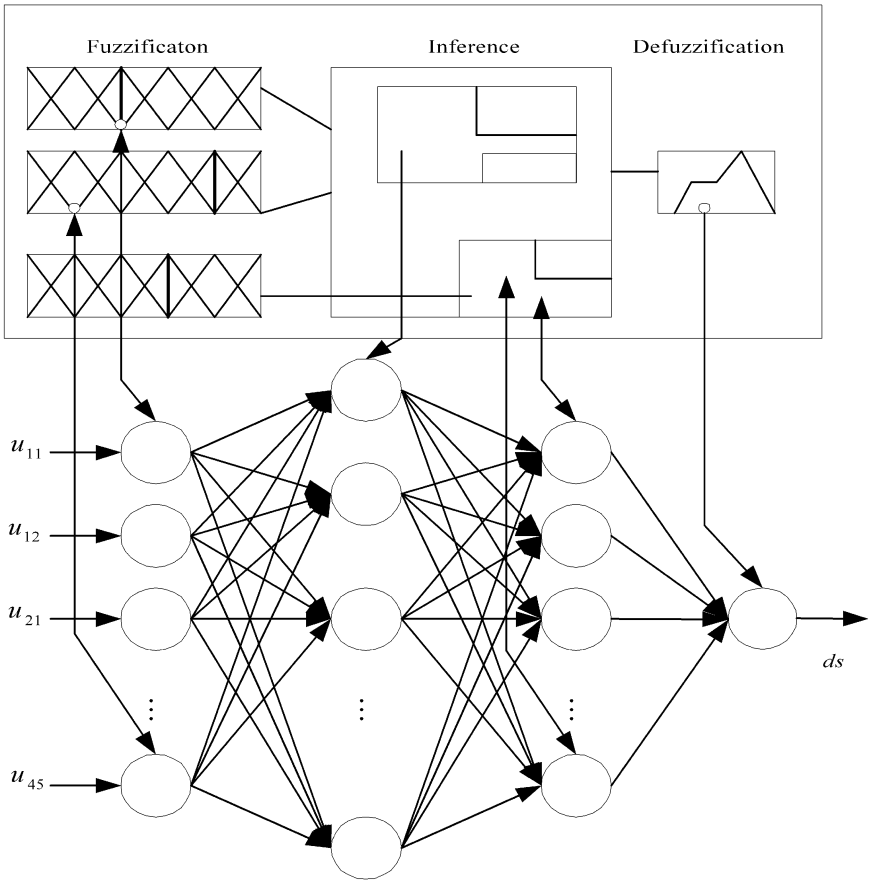


Fig. 15. Neuro-fuzzy assemblability evaluation learning.

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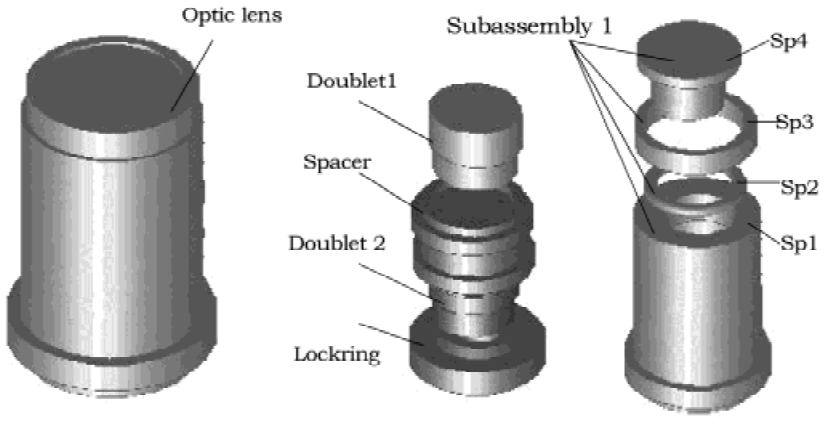


Fig. 16. Optic lens product.

in detail (Zha & Lim, 1998; Zha, 1999). Using the proposed integrated knowledge-based approach, all the feasible assembly sequences can be generated, and the optimal assembly sequence can be obtained by Petri net modeling and simulation. In the following, fuzzy evaluation of assembly sequence will be discussed.

In Sections 4 and 5, we discussed the fuzzy assemblability evaluation based on the degree of difficulty of assembly operations. As a matter of fact, once the mating operation is evaluated, the entire sequence of operations can be evaluated. The evaluation of the entire sequence needs to support comparison and selection of a preferred one; therefore, the aggregate measure of difficulty for the entire sequence is represented as a crisp number.

Suppose that the following notation is used: S_i = sequence i, $i = 1,\ldots,n$; n_i = number of operations in sequence S_i; S_{ij} = operation j in sequence i, $j = 1,\ldots,n_i$; ds_{ij} = assembly difficulty score (fuzzy number) that represents the degree of difficulty of operation j in sequence i. For the entire sequence, the assembly difficulty score for the sequence i is calculated using the following equation:

$$SEI(S_i) = \frac{1}{100n_i}\left\{\sum_{i=1}^{n_{i_1}} ds_i(x_i) + \frac{1}{p}\sum_{k=1}^{p}\left(\sum_{j=1}^{n_i-n_{i_1}} [ds_j(x_j)]_k\right)\right\}, \tag{10}$$

where $SEI(S_i)$ is the sequence evaluation index which is represented by the assembly difficulty score; $n_i = n_{i_1} + n_{i_2}$, n_{i_1} is the number of operational joints in sequence i, and n_{i_2} is the number of fastener joints in sequence i; $ds_i(x_i)$ is a relative difficulty score of the joint for the ith assembly factor; p is the total number of secondary parts and agents involved in the fastener joint. Based on Eq. (10), the preferred sequence is the one with the lowest SEI.

Using the approach proposed in Zha & Lim (1998) and Zha (1999), all the feasible sequences for the optic lens assembly can be generated by Petri net modeling and simulation. The Petri net graph for representation of the generated assembly sequences of the optic lens is shown as Figure 18, in which there are 12 feasible assembly sequences for linear assembly. The subnet models of the assembly sequence Petri net can also be shown in different colors in this figure. One of subnet models is $O_1 \rightarrow O_2 \rightarrow O_3 \rightarrow O_4 \rightarrow O_5$. It is in fact one of the assembly sequences. To obtain the total assembly time or cost, motion time analysis and design for assembly analysis should be carried out for evaluation (Zha & Lim, 1998). To be in line with fuzzy evaluation of assemblability, the fuzzy evaluation of difficulty score was carried out for assembly sequences. Effects of four different assembly sequences ($O_1 \rightarrow O_2 \rightarrow O_3 \rightarrow O_4 \rightarrow O_5$, $O_3 \rightarrow O_2 \rightarrow O_1 \rightarrow O_4 \rightarrow O_5$, $O_4 \rightarrow O_3 \rightarrow O_2 \rightarrow O_1 \rightarrow O_5$, $O_5 \rightarrow O_3 \rightarrow O_2 \rightarrow O_1 \rightarrow O_4$) on the minimum

	Assembly Factor	u_{11}	u_{12}	u_{13}	u_{21}	u_{22}	u_{31}	u_{41}	u_{42}	u_{43}	u_{44}	u_{45}
Mating Operation	Data	360	0	2	5cm	2lb	LN	clear	vertical	4cm	0	0
	Score	4.66	0.59	1.75	0.64	0.40	4.5	0.0	1.67	0.60	0.0	0.0
	Total assembly difficulty score=14.81, assembly evaluation index=0.15											

Fig. 17. Evaluation data of the design of optic lens.

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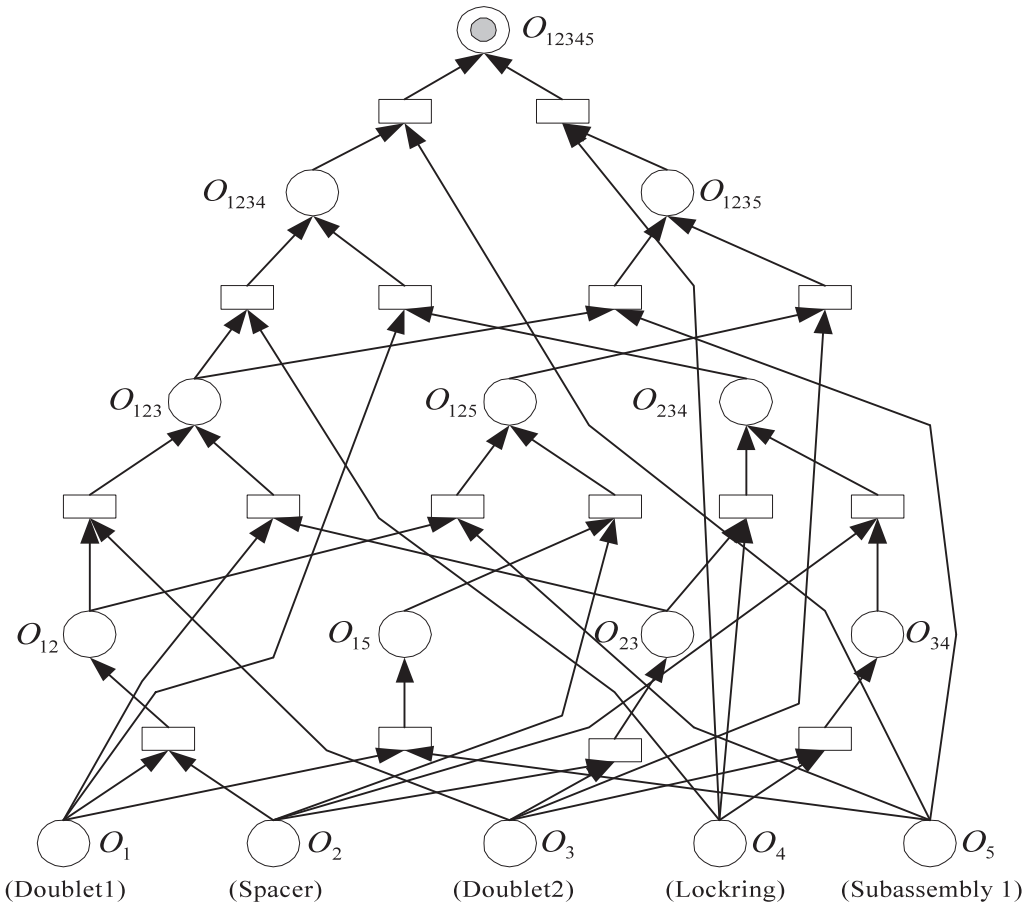


Fig. 18. Assembly sequence Petri net.

assembly difficulty score are shown in Figure 19. Hence, among four assembly sequences, the optimal one is $O_3 \rightarrow O_2 \rightarrow O_1 \rightarrow O_4 \rightarrow O_5$.

7. DISCUSSIONS AND CONCLUSIONS

The nature of assembly evaluation is not a decision-making analysis, which involves risk or probability estimation; rather it is a value evaluation of design. Hence, the proposed assembly evaluation method uses the riskless outcome stimuli. It is important to note that the methodology developed does not use certainty factors or uncertain reasoning. The fuzziness is a property of the degree of difficulty assigned to the operation, but it is not a property of the decision process.

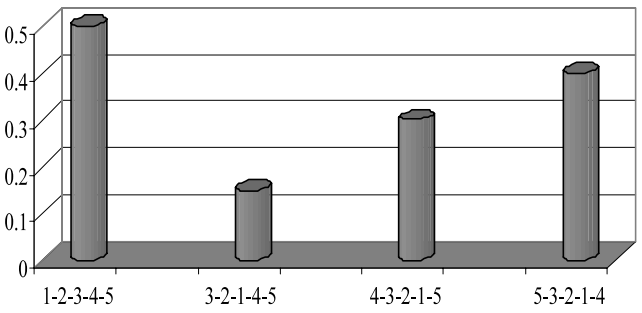


Fig. 19. Assembly difficulty score under different assembly sequences.

The assembly operations were evaluated based on various criteria, such as the time and the equipment required; however, this article focuses on analysis of the difficulty of operation. Assemblability is described by assembly operation difficulty, which can be represented by a fuzzy number between 0 and 1. The operation difficulty is an important factor that can be translated into time, probability of quality failure, and other significant factors. In addition, this parameter can serve as a useful tool for design evaluation.

This article presented a novel fuzzy-set-based approach to assessing the assemblability and assembly sequence of a product. The approach was implemented in a neural network, hence the name "neuro-fuzzy." It can be used as an alternative to the Boothroyd/ Dewhurst approach of a straight numeric (linear) metric. The approach is designed for general purpose assembly evaluation. It can find wide applica-

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tion in developing a knowledge-based expert system of design for assembly with learning ability. The evaluation structure covers not only the assembly parts' geometric and physical characteristics, but also takes into account the assembly operation data necessary to assemble the parts. The weight of each assemblability factor is subject to change to match the real assembly environments based on expert advice. This approach has the flexibility to be used in various assembly methods and different environments. The features of this novel approach can be summarized as follows.

1. The assemblability evaluation is referred to as a multiorder fuzzy justification and evaluation of assembly difficulty. Using this approach, the evaluation task is broken down into attributes or evaluation factors. For each factor, a single-attribute fuzzy membership function is constructed. Then the tradeoffs among evaluation factors are qualified as importance weights. Weights of the evaluation factors are decided based on the importance rank of the same attribute level. Different assembly experts are allowed to change the weights of factors without impairing the whole evaluation structure, so long as the changes remain at one level below the working domain of the expert. Finally, a fuzzy evaluation matrix is applied to aggregate and rate all single-attribute evaluations.
2. The membership function of an assemblability factor is assessed under a certain acceptable range and users or experts can assign the membership function and the difficulty grade for each characteristic category. This leaves flexibility to the users. The same factor may have a different assembly score in different environments.
3. The acceptable range assessment of each factor is helpful for estimating the "best design" and "worst design" in a specific product design and assembly environment. The assembly and assembly sequence evaluation index (AEI and SEI) can be used as the target values to improve the design and the assembly process or operation.
4. The proposed multiorder fuzzy assembly evaluation model gives the user the freedom to select appropriate techniques to estimate the single-attribute membership function and weights of the evaluation factors. It can reduce the deviations of justification and evaluation. New assemblability factors such as feedability, nesting and tangling characteristics, and gripability to cover a wider range of evaluation capability is relatively easy to expand and reapply in the multiorder evaluation model.

The developed integrated intelligent system can provide users with suggestions to improve a design and also to help obtain better design ideas. The concurrent engineering knowledge can be effectively incorporated into the preliminary design process through the use of the developed system. However, the developed system itself is not a complete system, and requires further development and refinement. The applications in assembly design and planning show that the integrated intelligent approach and system are feasible. The results from this research can also be used in other similar applications such as manufacturability evaluation.

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