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An integrated computational intelligence approach to product concept generation and evaluation

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Abstract

Product concept generation and evaluation are two major activities for obtaining an optimal concept in conceptual design. In this paper, an integrated computational intelligence approach is proposed for dealing with these two aspects. A group of satisfactory concepts are generated first by using genetic algorithm and incorporating the information from knowledge base. Then concept evaluation and decision making are implemented using fuzzy neural network to obtain an optimal concept. Our procedure of using computational intelligence in conceptual design is described. The key issues in implementing the proposed approach are discussed, and finally the applicability of the proposed method is illustrated with an engineering example.

Keywords: Conceptual design; Computational intelligence; Optimal concept; Genetic algorithm; Fuzzy neural network

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1. Introduction

The goal of conceptual design in product design is to obtain an optimal design concept as a starting point for further engineering development. In the current literature, the approaches of morphology matrix, bond graph, and design catalogues combined with expert system [1,2] are used for concept generation, in which concepts are usually combined and enumerated through function analysis. However, owing to the combinatorial nature, it is difficult to evaluate the large number of concepts one by one to obtain the best concept. With the expert system, great difficulties exist in knowledge acquisition, knowledge representation and reasoning. In fact, besides logical reasoning, intuition, experience, association, and even inspiration are synthetically used in the process of designer's thinking in conceptual design. However, they cannot be fully captured by knowledge-based reasoning. Compared with the detailed design stage, more emphases are laid on creativity in the conceptual design stage. Since conceptual design is in the preliminary stage of design, design requirements are usually approximate, imprecise and even uncertain. As a result, the best design concept cannot be easily obtained using existing methods in artificial intelligence [3,4]. The intellectualization of the conceptual design process becomes critical.

Computational intelligence, which consists of neural network, fuzzy logic and evolutionary computing, and so on, is a novel technology to bring intelligence into computation. Compared with the traditional artificial intelligence, a significant characteristic of computational intelligence is that the precise model need not to be established when dealing with imprecise, uncertain, and incomplete information. Therefore it is especially useful for solving those problems in which valid and formalized models cannot be established with ease. It is also effective to deal with the combinational problem in designing complicated systems. Conceptual design is a highly intellectual and creative process. Neural network, fuzzy logic and genetic algorithm can simulate the human activities naturally.

Attempts have been made in recent years to introduce computational intelligence into conceptual design. Wang and Zou [5] proposed a method of three-level fuzzy synthetical evaluation to deal with the fuzzy and multi-layer characteristics of concept evaluation metrics. They used fuzzy logic to evaluate the mechanical design concepts. Venugopal and Naredran [6] utilized a discrete Hopfield neural network to preserve the component concepts in manufacturing system and an appropriate design concept is retrieved during conceptual design using the associative memory. Xue and Dong [7] developed a fuzzy-based design function coding system to identify appropriate design concepts from stored design candidates classified based on design functions. Chang and Tsai [8] proposed a prototype of a feature-based design retrieval system using a modified ART1 neural network with destructive solid geometry for identifying similar design candidates for design improvement. Their proposed system has been demonstrated as an efficient and robust design retrieving tool. Ng and Leng [9] investigated the feasibility of automating the conceptual design of a micro-air vehicle on a personal computer system. Their proposed design methodology uses genetic algorithm as the search engine. Sun and Kalenchuk [10] proposed a method for design candidate evaluation and identification using neural network-based fuzzy reasoning, in which the relationship between design specifications and customer requirements is modeled using a multi-layer feed-forward neural network, and the satisfactory conceptual design candidate is retrieved by fuzzy reasoning based on requirements. Shu and Hao [11] proposed a CAD system model based on genetic algorithm to improve design efficiency and accuracy for mechanical products.

Park et al. [12] explored the method to develop an approximate life cycle assessment for products in the early conceptual design phase by classifying products into groups according to their environmental and product characteristics. A novel method based on neural networks and statistical analysis was proposed for the assessment of environmental impacts. Gu et al. [13,14] used genetic algorithm, simulated annealing and fuzzy logic for building models that expand conceptual design to studying the full process of life cycle engineering.

While these above methods contribute greatly to the progress of the intellectualization of conceptual design, they are still less than ideal and each possesses limitations. Above all, most of them aim at a certain aspect of conceptual design, e.g. some use computational intelligence in the concept generation phase, some use computational intelligence in the concept evaluation phase, and some lay emphasis on the modeling aspect in conceptual design. In our view, conceptual design is a complicated design process which cannot rely on only one method or one tool. A promising approach is to integrate computational intelligence techniques, such as neural network, fuzzy logic and evolutionary computing, with artificial intelligence throughout the whole conceptual design process.

In this work, computational intelligence is used as a key technology to address the two critical aspects in conceptual design, i.e., concept generation and concept evaluation. Supported by the knowledge base that contains the information of alternative design concepts for achieving various design functions, a group of satisfactory concepts, i.e., most-likely-to-succeed concepts, are generated by using genetic algorithm and a preliminary evaluation mechanism. Based on the analysis of the most-likely-to-succeed concepts, concept evaluation and decision making are implemented using fuzzy neural network. An engineering example is given in this paper to show the applicability of the proposed method. It demonstrates that the proposed method can facilitate not only generating a set of satisfactory concepts, but also acquiring the best candidate. In other words, it treats the intellectualization of conceptual design as a whole, which greatly facilitates the automation of a conceptual design process.

2. Computational intelligence-based process model for conceptual design

In the current theories of conceptual design, Pahl and Beitz's design process theory has a profound impact [15]. On the basis of this theory, computational intelligence-based process model for conceptual design is proposed in Fig. 1 and explained as follows.

Based on design requirements, conceptual design is a process to develop the best candidate that can be used as a starting point for further engineering development. Design requirements are provided as the preliminary information for conceptual design, which are usually defined by interpreting customer needs. First, mapping from the requirement domain to the function domain is achieved by the mode of human–machine interaction, i.e., acquiring the general-function, implementing the function decomposition, and constructing the function tree. Second, mapping from the function domain to the physical domain is accomplished by searching the knowledge base for each sub-function in the function tree. Alternative design concepts for each sub-function are combined to generate system design concepts using the morphological synthetical approach based on morphology matrix. Since there exists many possibilities of combining sub-function concepts, the problem of concept combination, generation, evaluation, and decision making becomes

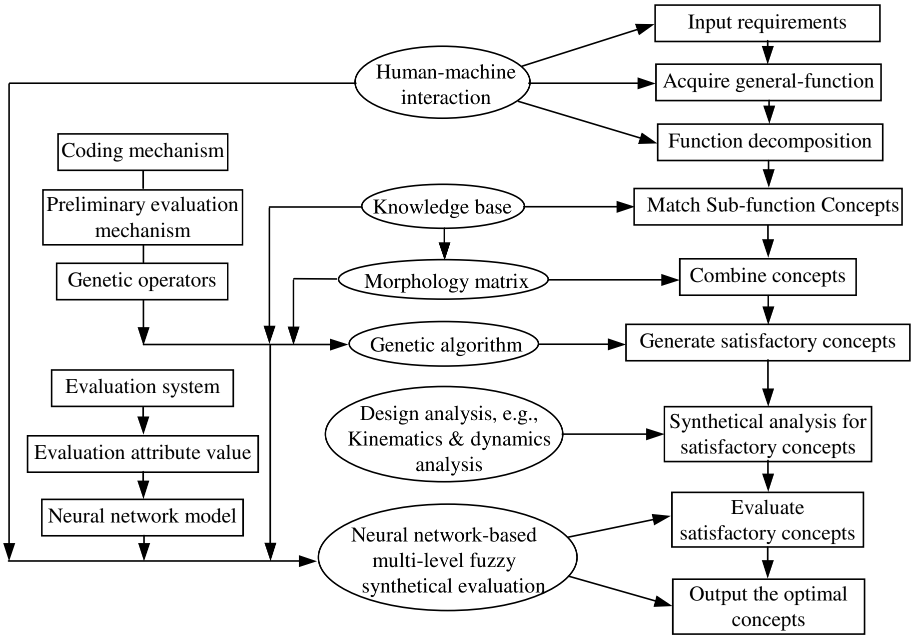

Fig. 1. Process model for conceptual design based on computational intelligence.

challenging. In this work, based on the knowledge base that contains the information of alternative concepts for various mechanical functions, different system concepts are first generated using the individual coding and population initialization in genetic algorithm. Then a group of satisfactory concepts with better fitness are produced through the evolution process which is directed by genetic operators, i.e., reproduction, crossover, mutation, and fitness calculation. In the next phase, satisfactory concepts are further analyzed. The fuzzy neural network is used to synthesize the design requirements and design preference, also utilizing the knowledge base and reasoning engine of expert system. Finally the optimal concept satisfying all design requirements is obtained as a result of conceptual design.

3. Acquisition of satisfactory concepts based on genetic algorithm

3.1. Solution process

Searching for the optimal conceptual design can be considered as global optimization over a population consisting of different design concepts, i.e., a process of searching the best candidate among a large set of combinatorial solutions. The key for improving the efficiency of conceptual design is to apply a search algorithm that can find the optimal solution by minimizing the search space and controlling the search process adaptively according to certain rules. Genetic algorithm provides a feasible tool for solving the problem of combinatorial optimization in searching for an optimal concept [16].

Genetic algorithm is essentially a stochastic search algorithm for global optimization that simulates the characteristics of the process of evolution in nature. Based on the fitness measure, a new generation of population is produced by reproduction, crossover, and mutation. Then the fitness measure for the new population is evaluated again and the average fitness value is expected to exceed that of the old generation. This process is repeated and finally a group of better solutions can be received as a result of this step-by-step evolution process. The method is effective in finding better product concepts to satisfy all requirements. The problem of artificial combination and combination explosion resulted from morphology matrix can be avoided, and the expert knowledge can be effectively utilized in calculating the fitness value to improve system performance. The major steps of genetic algorithm are depicted in Fig. 2.

3.2. Key issues

3.2.1. Individual coding and population initialization

The flowchart of genetic algorithm starts with individual coding. Binary string structure coding based on morphology matrix is introduced in this work [17]. In the process of generating concept solutions by genetic algorithm, function decomposition for a general-function is first performed by designers to acquire the function tree. For every sub-function in the function tree, multiple concept alternatives to perform this sub-function are identified through the knowledge base to establish the morphology matrix. These sub-function concept alternatives are first encoded using the binary string based on morphology matrix, e.g., if there are four concepts to achieve a sub-function, these four alternative solutions can be represented with two digits binary strings, namely, 00,

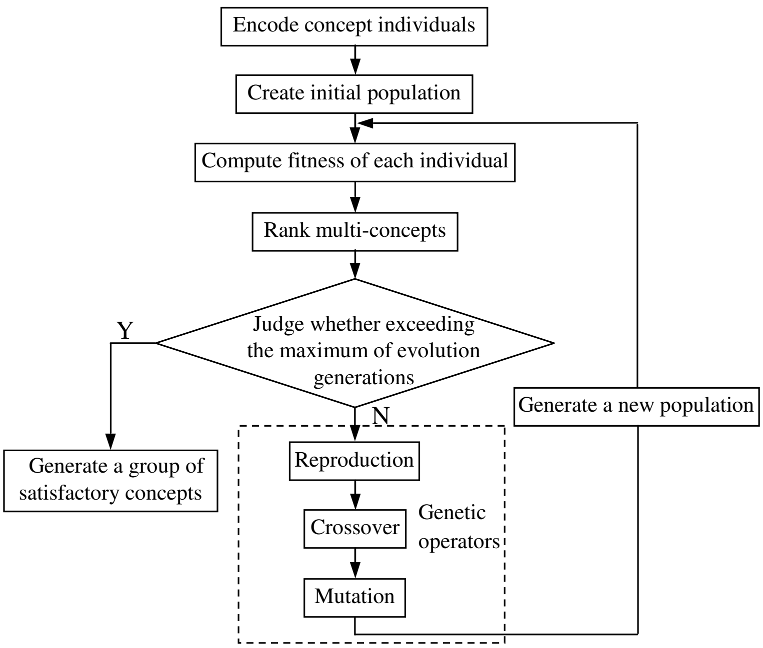

Fig. 2. Flow chart of GA.

01, 10, and 11. After encoding every alternative concept to each sub-function, one concept is selected for each sub-function, then code strings representing concepts for multiple sub-functions are connected from the beginning to the end, and a chromosome is formed to represent a system concept solution. For example, if a certain general-function is made up of five sub-functions and there are four solutions to each sub-solution, a random system concept can be represented with 0000010110. All the feasible solutions to conceptual design constitute a solution space.

Genetic algorithm is a global optimization method based on the evolution of populations. Genetic operators act on the initial population first, which is filled with a certain number of system concept individuals that are generally created at random. The performance of a system concept individual in the initial population is comparatively poor, but with the step-by-step evolution directed by genetic operators, its performance will get better and better than its ancestors from the first generation until the satisfactory solutions are generated.

Genetic algorithm uses a separate search space and a solution space. The search space is the space of coded solutions and the solution space is the space of actual solutions. However, the relationship between these two spaces does not satisfy the one-to-one relationship, i.e., there may be no feasible solution in the solution space to match the new system concept individual which is produced by crossover and mutation. For instance, there are three alternative concepts to a certain sub-function, expressed with two digits binary string, namely, 00, 01, and 10. Yet a solution to this sub-function which is denoted as 11 may appear after crossover and mutation. Any concept solution represented with a binary string structure, so long as it contains the code 11 in this place, is an infeasible solution. In this work the penalty function method is used to handle this constraint condition for solution. This method is illustrated as below. For the infeasible solution, when calculating its fitness value, a penalty function should be exerted on it to reduce its fitness value. As a result the probability to hand down by hereditary will cut down. This method can be expressed as

$$F'(x) = \begin{cases} F(x) & \text{if } x \text{ is a feasible solution} \\ F(x) - P(x) & \text{otherwise} \end{cases} \tag{1}$$

where $F(x)$ is the original fitness for a concept individual, $F'(x)$ is the new fitness when considering the penalty function, and $P(x)$ is the penalty function. This research allows $P(x) = F(x)$, i.e., the fitness value of an infeasible solution reduces directly to zero to ensure this concept individual cannot be passed down to the next generation.

3.2.2. Establishment of preliminary evaluation mechanism and fitness function

In genetic algorithm each system concept solution in population needs to be evaluated using the fitness function to judge whether the heredity termination criteria are satisfied. Fitness function is constructed according to the evaluation mechanism including the evaluation rule, evaluation indicators, and the weight distribution, etc. Since the objective of using genetic algorithm is to generate a set of satisfactory concepts, i.e., the most-likely-to-succeed concepts, it is unnecessary to build an accurate evaluation indicator system. Here a preliminary evaluation mechanism is used, which is a single-layer evaluation indicator system including several major indicators. It should be noted that at this stage, these preliminary evaluation indicators correspond to the design requirements. Different evaluation systems should be adopted for different design tasks for the reason that their function structures are different from each other. Evaluation indicator tree and the corresponding weight of each sub-function can be obtained using the previous function decomposition. In this work, the fitness value is calculated using a method of quantitative evaluation to the concept individual. Before calculating, the first step is to judge whether every sub-function design concept satisfies the compatibility condition. This can be carried out according to the related knowledge base. If not, the fitness value of this concept equals to zero. Since the concept to realize the general-function is constructed with compatible sub-function solutions, the fitness of a concept individual is equal to the weighted summation of the fitness for each gene, i.e., sub-function, calculated by Eq. (2).

$$F_i = \sum_{j=1}^{m} G_{ij} \cdot W_j \tag{2}$$

where F_i is the fitness value of the ith individual where $1 \leqslant i \leqslant l$ and l is the number of concepts, G_{ij} is the fitness value of the jth gene of the ith individual where $1 \leqslant j \leqslant m$ and m is the number of genes, W_j is the weight of the jth gene which represents the importance of different sub-functions and $\sum_{j=1}^{m} W_j = 1$.

The above shows that the fitness calculation of a concept individual is based on the fitness calculation of each sub-function which can reflect the satisfaction degree of the alternative concepts to the sub-function. The fitness value of a sub-function is calculated by Eq. (3).

$$G_{ij} = \sum_{k=1}^{n} f_{ij}(V_{ijk}) \cdot W_{ijk} \tag{3}$$

where G_{ij} is the fitness value of the jth sub-function, V_{ijk} is the kth evaluation indicator where $1 \leqslant k \leqslant n$ and n represents the number of evaluation indicators in the preliminary evaluation mechanism, W_{ijk} is the weighting value of the corresponding indicator where $\sum_{k=1}^{n} W_{ijk} = 1$, and $f_{ij}(V_{ijk})$ is the satisfaction degree of a sub-function concept realizing the jth sub-function to the kth evaluation indicator, which is determined based on the knowledge base. Comparatively speaking, this kind of knowledge is easily acquired, expressed, and accumulated to construct a database. For instance, in the equation of fitness = 0.6, 0.6 is a fuzzy value which represents the satisfaction degree of the Geneva mechanism to indicator "noise" in completing the intermittent rotation.

3.2.3. Criteria for heredity termination

A set of most-likely-to-succeed concepts will be obtained as the result of the concept generation phase. In the process of using genetic algorithm, some feasible solutions may be destroyed because of genetic operators. Thus the criterion of maximal generation is used for heredity termination to acquire the satisfactory concepts. The required acceptance condition for solutions is that the fitness exceeds a specified satisfactory fitness, i.e., $F_{\max}$. All concepts that satisfy the criterion are collected to form a set of satisfactory concepts. Obtaining the optimal concept from this set is discussed next.

4. Evaluation and decision making for choosing the optimal concept based on fuzzy neural network

After acquiring a group of satisfactory concepts using genetic algorithm, it is necessary to analyze them through engineering analysis, e.g., based on kinematics and dynamics theory for mechanical systems. This process is helpful for screening out those concepts that are infeasible based on the physical principles. As the goal of conceptual design is to obtain an optimal concept for further product development, there is a need for further narrowing the remaining set down to a set of superior concepts based on the fitness ranking. The optimal concept can be obtained among a set of superior concepts using a multi-level and multi-objective synthetical evaluation model. Commonly used methods, such as fuzzy synthetical evaluation [18,19], system engineering evaluation, and value engineering evaluation, suffer from the following two major problems to varying degrees:

(1) Subjective errors exist to a large extent. Most of the evaluation criteria are subjective inputs from designers according to their experience. Inferior results may be obtained due to lacking of experience. Moreover, weighting factors for each evaluation indicator need to be provided, which have a direct influence on the evaluation result. However, because multi-level synthetical evaluation covers a large number of evaluation indicators in a tree structure, it is very difficult to fulfill the task of weight distribution.
(2) Existing methods have not fully utilized the insight and related expertise gained from the previous successful evaluation cases.

This work presents a fuzzy neural network-based method for concept evaluation, in which neural network is combined with fuzzy synthetical evaluation. A multi-level and multi-objective concept evaluation model is constructed utilizing the feature of neural network in capturing nonlinear performance. Through the learning of evaluation samples, the neural network expresses the relationship between the evaluation indicators and the end evaluation result, as well as the weights assigned to the evaluation indicators. To some extent, the proposed method collects knowledge from the experienced experts and then implements an evaluation as a substitution for experts [20].

4.1. Evaluation process

The process of concept evaluation for conceptual design covers six elements which can be expressed with a sextuplet, i.e., $[S, C, L, X_C, E, Y]$. where, S represents the set of satisfactory solutions, C represents the evaluation indicator system, L represents the evaluation knowledge base, X_c represents the evaluation attribute value assessed through the evaluation indicator system C, E represents the neural network-based evaluation model, and Y is the end evaluation result. The corresponding process for evaluation is shown in Fig. 3.

4.2. Key issues

4.2.1. Establishment of the evaluation indicator system

A valid evaluation result for design concept rests with a reasonable evaluation indicator system which is developed according to the concrete design requirements. For different design tasks, the

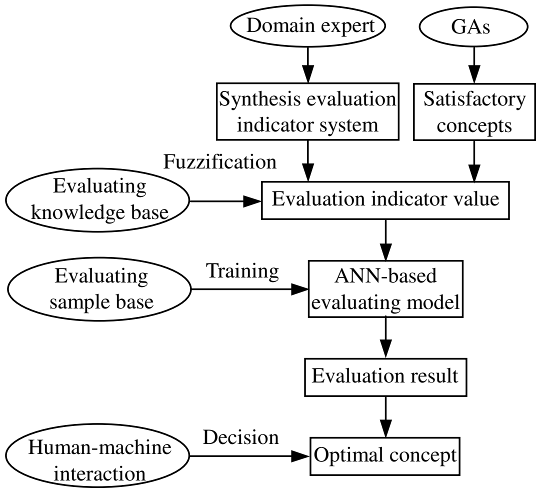

Fig. 3. Neural network-based evaluation process.

evaluation indicator systems are different from each other. For example, when the fuzzy synthetical evaluation method is used for the evaluation of kinematic concepts in mechanical products, three groups of indicators are often considered, i.e., the technical indicator, the economic indicator, and the social indicator. These three indicators can be viewed as three first-level sub-indicators which can be further cascading to 16 second-level sub-indicators. All these evaluation indicators constitute a three-level evaluation indicator tree, as shown in Fig. 4.

4.2.2. Fuzzy quantification for the attribute value of an evaluation indicator

The input value of the neural network needs to be numerical data, however, the above evaluation indicators are fuzzy in substance and it is difficult to perform a precise quantification. Here, a fuzzy logic method is used to build the membership function for each evaluation indicator that belongs to the bottom level of an evaluation indicator tree and to obtain the corresponding membership degree [21]. For example, for the indicator of "*dimensional compactness*" under the technology indicator, the number of components and kinematic pairs or the relative length of the transmission chain in a mechanism can be used as an independent variable (noted as x) of the membership function. The maximum and the minimum of membership degree for all the mechanisms is 1 and 0, respectively. Correspondingly. the numbers of components and kinematic pairs are a and b, and a membership function of "half-trapezoid distribution" is expressed in Eq. (4).

$$\mu_A(x) = \begin{cases} 1 & x \leqslant a \\ \dfrac{x-a}{b-a} & a < x < b \\ 0 & x \geqslant b \end{cases} \tag{4}$$

The degree value for all the mechanisms can be calculated by the above equation. For those evaluation indicators that cannot be easily measured by constructing the linear membership function, the fuzzy statistical method or the dualistic contrast compositor method can be adopted [22]. The

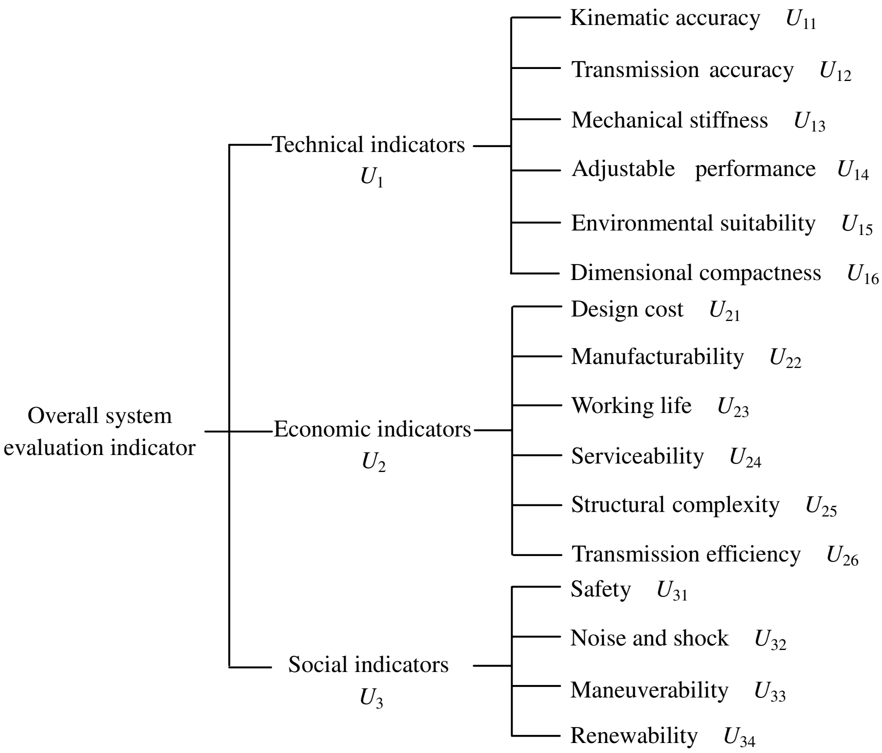

Fig. 4. Evaluation indicator tree of kinematic concepts.

Table 1
Evaluation value of typical mechanisms

Mechanism type	Linkages mechanism	Cam mechanism	Gear mechanism	Geared linkage mechanism
Semantic expression	Not compact	Compact	Very compact	Somewhat compact
Attribute value	0	0.8	1	0.65

evaluation attribute values for the indicator of dimensional compactness for four typical mechanisms are given in Table 1.

4.2.3. Multi-level evaluation model based on neural network

A neural network-based evaluation method needs to be supported by enough training samples that are collected from successful engineering cases. In the process of developing an evaluation model, if lacking training samples, a method of fuzzy synthetical evaluation for all kinds of related kinematic concepts can be implemented by experienced experts to obtain the values of the evaluation indicators. For different design tasks, the output evaluation values of the same input sample may be different. The evaluation values of the economic indicator for three mechanisms used in a certain textile machinery, as depicted in Table 2, can serve as three training samples following the fuzzy synthetical evaluation. A large number of samples are required to train the neural

Table 2
Some training examples for neural network

Samples	1	2	3
	Linkage mechanism	Geared linkage mechanism	Cam mechanism with roller followers
Input value			
Low design cost	0.35	0.26	0.45
Convenient for manufacture	0.9	0.18	0.15
Long life	1	0.82	0.80
Simple structure	0.7	0.22	0.95
Convenient for maintenance	0.92	0.8	0.45
High transmission efficiency	0.66	0.7	0.66
Output value			
Good economic indicator	0.862	0.69	0.75

network until the network satisfies the convergence condition. Then the trained network will be used as an evaluation model for evaluations and decision makings of new concepts. In this way, the nonlinear continuous space consisting of points of evaluation samples is expressed by the trained weights and the threshold matrix of the neural network.

The BP neural network [10,20,23] is used to construct the evaluation model in this work. Taking an example of the evaluation system shown in Fig. 4, three first-level evaluation model, i.e., technical indicator, economic indicator, and social indicator, are established at first, in which three first-level sub-indicators serve as the output respectively and the values of the corresponding second-level sub-indicators serve as the input. The number of neurons for I/O nodes depend on the structure of the evaluation indicator system. For instance, in the evaluation sub-model of the economic indicator, there are six nodes in the input layer because there are six evaluation attribute values of second-level sub-indicators serving as input values; there is one node in the output layer for economic indicator as an output value; $l = 2m + 1 = 12$ nodes is used in the hidden layer according to the Kolmogorov theorem where m is the number of input nodes [24]. The evaluation model of the economic indicator is constructed as shown in the sub-evaluation model 2 in Fig. 5, where, $X_{21}, X_{22}, \ldots, X_{26}$ are the input attribute values of six sub-indicators and Y_2 is the output

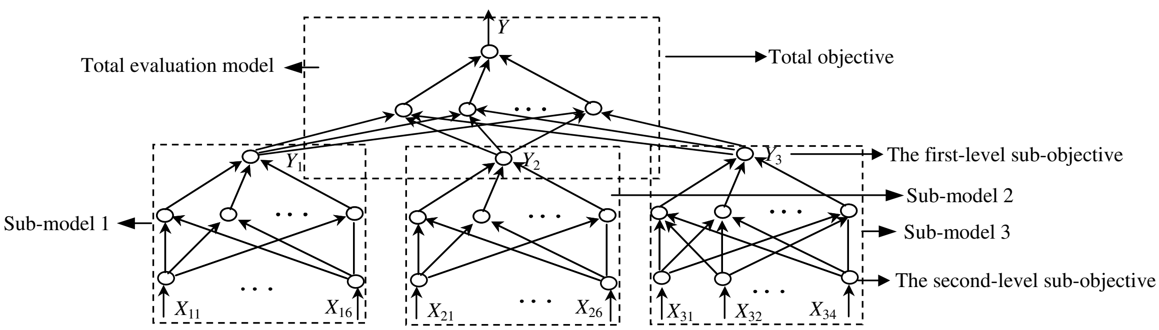

Fig. 5. Multi-level evaluating model for kinematical concept.

value corresponding to the evaluation result of the economic indicator. After generating three one-layer evaluation sub-models, the system evaluation model can be constructed. Since the evaluation system of mechanism concepts in Fig. 4 is a three-level evaluation system, a two-layer evaluation model as shown in Fig. 5 is required. The lower layer possesses three first-level sub-indicator evaluation network whose inputs are the fuzzy attribute values of the second-level sub-indicators and whose outputs are the inputs of the top-layer network. The top-layer is the top system evaluation network whose output is the end evaluation result of a concept. Each evaluation sub-indicator network and the top system objective network can be established according to the corresponding evaluation system. When enough training samples are provided, the final evaluation model based on neural network is generated. For other multi-level evaluation systems, the evaluation models can be constructed in a similar way.

After constructing the multi-level evaluation model based on neural network, the next step is to evaluate the satisfactory concepts synthetically. The evaluation process starts with the bottom-level leaf-nodes. First, the tree-shaped structure of design requirements need to be understood by designers. Every leaf-node in the tree is evaluated separately and the corresponding fuzzy attribute value is given. Next, each evaluation sub-model is used to calculate the evaluation value of the upper branch node. From bottom to top, the input values of the top system evaluation model are acquired. Finally, the top system evaluation model is used to obtain the evaluation value of the root node as the final evaluation result of a mechanism kinematical concept. After all the concepts are evaluated, the best concept can be obtained by ranking the evaluation results.

5. A case study

A concept design problem for weft insertion mechanism in a certain rapier loom is given as an example to illustrate the solution process using the proposed computational intelligence approach. Weft insertion mechanism is the core component of rapier loom which is widely used in textile machinery. Now in most of rapier looms, combined mechanism is utilized to implement the function of weft insertion, which is further combined with linkage mechanism, gear–rack mechanism, epicyclic gear train, and cam mechanism, etc. Such concept possesses many disadvantages, e.g. complicated structure, long transmission chain, large placing room, which will undoubtedly result in great kinematic error, low transmission precision, and low mechanical efficiency. Accordingly, the major design requirement is to simplify the structure as much as possible, to shorten the transmission chain, to improve the working performance and the kinematic precision, and to advance the transmission efficiency subject to the required kinematic rules of rapier. Besides, the design should be convenient for manufacture.

5.1. Function decomposition and establishment of morphology matrix

Function analysis is carried out at first according to the design task, including acquiring the general-function and decomposing it into sub-functions. In rapier loom, weft insertion is achieved by the mode that the main shaft implements a positive and negative rotation through the transmission mechanism to drive the flexible rapier, therefore to realize the reciprocating movement. The stroke of rapier can be obtained by adjusting the stroke of the transmission mechanism.

Decomposing the general-function of weft insertion into sub-functions is depicted in Fig. 6. Mapping from the requirements domain to the function domain is achieved by the mode of human–machine interaction. Next step is to search the alternative concept solutions to each sub-function based on the function tree and to develop the morphology matrix. The corresponding knowledge base that contains the mapping between concepts and functions needs to be built first. The knowledge base should include the types of alternative design concepts for all sorts of familiar sub-functions and the related knowledge for design concept, for example, performance characteristics, technical parameters, working conditions, applicable ranges, and compatibility conditions, etc. This knowledge base should be elaborated as much as possible and easy to be extended and maintained. At the same time it should be convenient for retrieval based on the type of a function. In this design problem, the knowledge base is built based on the design handbook, technical reports, and experts' experience from textile machinery. The proposed solution process retrieves the alternative design concepts for every sub-function from the developed knowledge base. The morphology matrix for sub-functions and their solutions is established, as shown in Table 3.

5.2. Acquisition of satisfactory concepts using genetic algorithm

From the morphology matrix in Table 3, it is noted that there are five sub-functions, i.e., $m = 5$, each possessing four principle solutions. Thus the number of combined concepts is 1024. To reduce the amount of detailed engineering analysis work for such a large set of concepts, genetic algorithm is used to narrow the set to a reduced set of satisfactory concepts. The first step is to

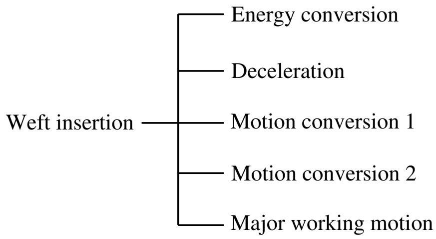

Fig. 6. Function tree for weft insertion.

Table 3
Morphology matrix for principle solutions of weft insertion

Sub-function	Principle solutions			
	1	2	3	4
A Energy conversion	General asynchronous motor	DC motor	Adjustable speed motor	Gear head motor
B Deceleration	Synchronous belt transmission	Flat-belt transmission	V-belt transmission	Chain drive
C Motion conversion 1	Crank–slider mechanism	Gear mechanism	Epicyclic gear train	Cam mechanism
D Motion conversion 2	Crank–slider mechanism	Spatial-linkage mechanism	Gear–rack mechanism	Variable-pitch screw mechanism
E Major working motion	Gear–rack mechanism	Gear mechanism	Crank–slider mechanism	Cam mechanism

encode the concepts with binary strings. A certain number of encoded concept individuals are assembled to form a concept population. The individual number of a population is 8, i.e., $l = 8$. To improve the performance of the initial population, a certain number of individuals are generated first, then the better ones are selected among them to join the initial population. This process is repeated by computer until the individual number arrives at the requested number. In this way, a long binary string is generated which represents an initial population. Next step is to calculate the fitness value of each individual in population through performance evaluation. A preliminary evaluation system is built first. For simplification, two evaluation indicators ($n = 2$) are considered, i.e., satisfying the function of weft insertion and with structure simplicity. The weighting factors for five sub-functions are 0.14, 0.16, 0.25, 0.25, and 0.20 in order. The weighting factors for two indicators are 0.6 and 0.4. Fitness for each concept individual and the average fitness can be calculated based on the related evaluation knowledge of alternative concepts. The next step is to judge whether the search arrives at the maximum of evolution generation, which is specified as 100. Otherwise genetic operators, i.e., reproduction, crossover, and mutation, are used to produce a new generation, where the probability of crossover is 0.90 and the probability of mutation is 0.05. The evolution process is repeated until the evolution generation arrives at the maximum and the average fitness of population remains consistent. All the solutions whose fitness values exceed $F_{\max}$ ($F_{\max} = 0.85$) in the evolution process are noted as the satisfactory concepts. Three concepts are acquired by decoding, i.e.,

Concept 1: A1 + B1 + C1 + D4 + E2, named as variable-pitch screw driving of weft insertion mechanism,
Concept 2: A1 + B1 + C2 + D1 + E1, named as parallel linkage driving of weft insertion mechanism,
Concept 3: A1 + B1 + C3 + D2 + E3, named as epicyclic gear train-linkage combination mechanism driving of weft insertion mechanism.

Compared with other concepts, these three concepts not only realize the movement of weft insertion more effectively, but also possess simpler structures.

5.3. Acquisition of the best concept using fuzzy neural network-based synthetical evaluation

After acquiring three satisfactory concepts, the multi-level synthetical evaluation is implemented using fuzzy neural network and the best concept is obtained based on the evaluation results. The first step is to build an evaluation indicator tree for the weft insertion mechanism, as shown in Fig. 4. Important indicators include kinematic accuracy, transmission accuracy, structural complexity, reliability, noise and shock, transmission efficiency, and manufacturability. Next, a BP network-based evaluation model is constructed as shown in Fig. 5. Because the rapier loom has been widely used in textile machinery, the related evaluation samples are abundant. Evaluation samples for successful weft insertion mechanisms are selected and provided for the BP network until the training error satisfies the specified level. Ten samples are utilized to train this network with the ‘traingdx’ function provided by Matlab 6.5. When the convergence precision is set at 0.005, the network converges after 320 trainings. The trained network is then used to evaluate the satisfactory concepts obtained earlier. Fuzzy attribute values of 16 second-level sub-indi-

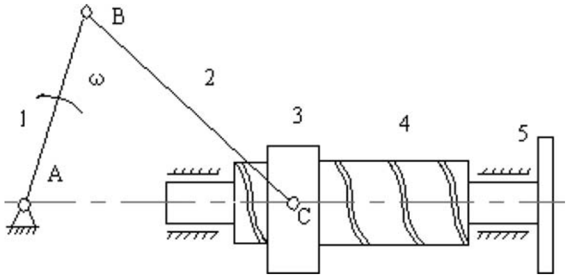

Fig. 7. Variable-pitch screw mechanism.

cators for three concepts are required and taken as the input values of the lowest-layer sub-model. The final evaluation result is obtained using the trained network. The evaluation values for the three concepts are 0.922, 0.9, and 0.87 in order. It is apparent that concept 1 is the best concept among the three. Its combination of mechanisms is

$$A1 + B1 + C1 + D4 + E2,$$

as shown in Fig. 7. Its core component is a variable-pitch screw driving mechanism. The movement of weft insertion is derived through the movement of the main shaft. Its transmission process goes through the sequence of "main shaft-synchronous belt transmission-rotation of crank". Crank 1 drives the slider (nut 3) through linkage 2 to implement the reciprocating movement. The slider further drives the meshed screw 4 to perform the positive and negative rotation. Gear 5 is connected with screw 4, both rotate together, driving the rapier to accomplish the movement of feed and withdrawal. Because the pitch of screw is variable, it is convenient to realize the desirable movement to satisfy the requirement of weft insertion.

6. Conclusions

In this work, an integrated computational intelligence approach is proposed for concept generation and concept evaluation in conceptual design. Function analysis is carried out first according to the given design task to establish the morphology matrix. Then, supported by the knowledge base of alternative design concepts for sub-functions, a group of satisfactory concepts are generated using genetic algorithm. Finally the synthetical evaluation is implemented using fuzzy neural network to obtain the best concept as a result of conceptual design. In the process of searching a set of satisfactory concepts, genetic algorithm is used to avoid the problem of combination explosion when combining the alternatives for sub-functions. Neural network is used to establish the reasoning engine for the evaluation based on existing knowledge. The neural network is also effective in distributing the weighting factors to multiple evaluation indicators at different levels. Fuzzy logic is used to provide fuzzy quantifications of the attribute values of evaluation indicators, which can be used as both I/O values in neural network. This work shows that the techniques of computational intelligence can greatly benefit conceptual design, a critical stage of product design. The proposed method is still in the stage of basic research which requires the support of an integrated design platform. In designing large and complex engineering systems, the method of computational intelligence needs to be combined with other intelligent design approaches such as the use of expert system.

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