Noise Detection Model based on Collaborative Design

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***Abstract* - In order to solve the problem of Noise detection in collaborative design, the hierarchical constraints and constraint satisfaction were analyzed. Constraints were divided into two sets: one set with known constraints and another set with unknown constraints. The constraints of two sets were detected respectively. The set with known constraints was detected by interval propagation algorithm. Meanwhile, BP neural network was proposed to detect the set with unknown constraints. Immune algorithm (IA) was utilized to optimize the weights and thresholds of BP neural network, and the steps of optimize process was designed. Simulated results indicated that BP neural network optimized by IA has better performance in convergent speed and global searching ability compared with genetic algorithm (GA). Constraints were described by XML (eXtensible Markup Language), so that computers can automatically recognize and establish the constraint network. The implementation of Noise detection system based on constraint satisfaction was designed. Taking collaborative design of wind planetary gear train for example, a Noise detection system in collaborative design was developed.**

Keywords - Collaborative Design; Noise Detection; Constraint Satisfaction; Immune Algorithm; BP Neural Network.

I. INTRODUCTION

As an important branch of CSCW, collaborative design is considered as a group-working style based on effective communication and cooperation for complex product. Designers form different disciplines participate in the collaborative design process. The variables of designers are interrelated, interdependent and mutual restraint. Noises inevitably occur because of different background knowledge, different views of issue and different standards of evaluation. In consequence of reducing the efficiency of design, Noise detection is regarded as one of the important functions in collaborative design. So far, no effective way is proposed to detect Noises in collaborative design.

To detect Noises effectively in collaborative design, extensive research has been conducted. Pierre [1] considered that the design process can be modeled in the form of a constraint satisfaction problem (CSP). Meng [2] described the CSP in a formal expression and explored the problem of Noise detection. Hu [3] investigated a method of Noise detection based on vertical constraint network model. Slimani [4] proposed to eliminate Noises by sharing and exchange knowledge in collaborative design process. Zhu [5] put forward a Noise detection algorithm based on the design history in collaborative CAD design. Zhao [6] and Xie [7] used constraint verification and interval propagation algorithms to detect the Noises. Wang [8] proposed a consistency model of operation sequence and Noise detection algorithm based on geometry level. Xiong [9] raised an approach of distributed Noise detection for supporting concurrent design.

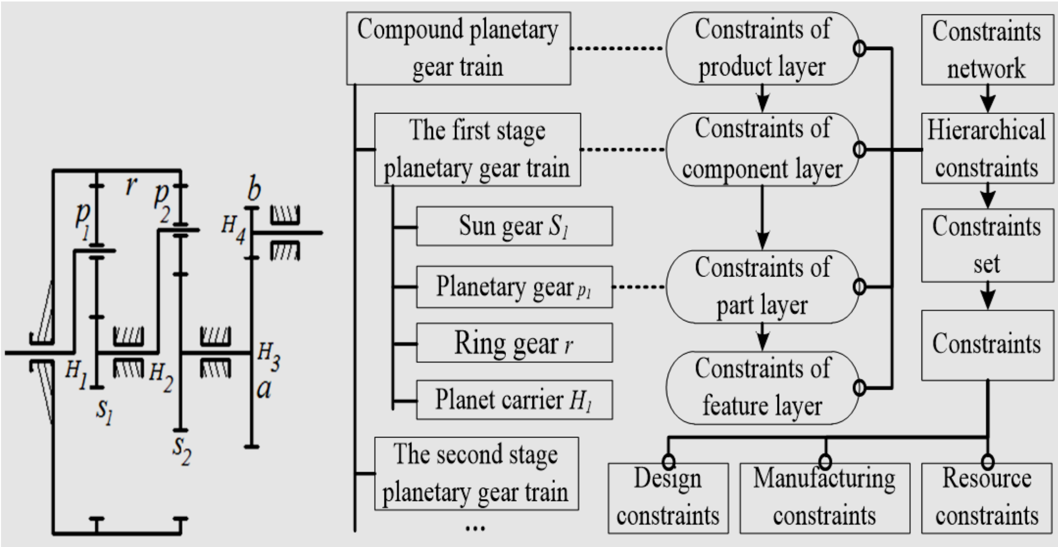
However, the existence of massive implicit Noises causes that the exact ranges of some constraints are difficult to be determined. Noises can't be detected comprehensively and accurately. Based on the hierarchical constraints and constraint satisfaction, this paper raises a detection method of Noise, which provides a theoretical basis for the Noise digestion.

II. CONSTRAINT ANALYSIS OF COLLABORATIVE DESIGN

There are many types of constraints in collaborative design, such as design constraints, process constraints, manufacturing constraints, etc. They are associated with the product attributes, formed as a network, and constituted the boundary of the possible design solutions. Each design problem can be converted to a solution process based on the constraints network. Noises will occur when the constraints cannot be satisfied.

A. Analysis of Hierarchical Constraints

During the collaborative design process, design goals are mapped onto the product object tree with hierarchical structure. From the top to bottom of the tree, there are product, component, part and feature. Fig. 1 shows the transmission diagram of a compound planetary gear train and the relationships between the object tree and hierarchical constraints.



(a) (b)

Fig. 1 Transmission diagram of compound planetary gear train and its constraints.

Constraints reflect the restrictive relationships between the product and design purposes. Taking collaborative design of wind planetary gear train for example, the constraint network can be divided into layers of product, component, part and feature. The layer of product describes the product performance, weight and structures, such as train power and transmission ratio, etc. The layer of component describes the design requirements of component and the constraints among the different parts, such as design of sub gear train and design of cabinet, etc. The layer of part describes the design requirements of the parts, such as design of gears and shafts, etc. The layer of feature describes the design parameters of the parts, such as geometry dimensions and strength requirements of the parts, etc.

The interaction between different levels of constraints can be reduced since the controllable network of hierarchical constraints has been set up. It is convenient to manage the relationships of constraints when the design attributes change. As shown in Fig. 1, if the teeth number of the sun gear changes, designers have only to modify the corresponding layer of part. The constraints of different layers are related. When Noises of a high-level constraint have occurred, the lower levels that caused the Noise can quickly be found. Noises can be detected through verification of constraints form layer to layer, starting from the layer of feature.

B. Analysis of Constraint Satisfaction

The solutions of the constraint network can be expressed by CSP, according to the following equation:

$$K(X)=\{(X_1=x_1, X_2=x_2, \cdots, X_n=x_n)\,|\,\forall c_i, \quad (1)$$

$$\prod V(c_i)R(c)\subseteq R(c_i)\} \quad (2)$$

Where:

$$\prod V(c_i)R(c)\subseteq R(c_i)$$

is the projection of variables set $V(c_i)$ in constraints set $R(c_i)$. If Eq. (1) has a solution, it indicates that there is no Noise. While there is no solution, Noises occurred.

The collaborative design is a continuous process of discovering and digesting Noises. So it's impossible to confirm all the possibility constraints of design variables before the design has been completed. With the deepening of the design, identified constraints may change constantly, and new constraints will appear. However, some constraints can't be expressed specifically, such as resource allocation, data sharing and data cooperating between different design departments. Therefore, the set of constraints C can be divided into one set C_1 with known constraints and another set C_2 with unknown constraints. Unknown constraints may convert into known constraints in the design process, and the set of constraints can be written as:

$$\begin{cases} C=C_1\cup C_2 \\ C_1=f_1(X,D) \\ C_2=f_2(X,D) \end{cases} \quad (3)$$

The solution of Noises in collaborative design process can be transformed to the solution of Eq. (3), so as to make sure whether the Noises have happened or not.

III. DESIGN OF NOISE DETECTION MODEL

The set of constraints C_1 can be verified directly by the interval propagation algorithm [11]. The implicit Noises make it difficult to confirm some constraints of the set of C_2, which can't be solved by interval propagation algorithm. The relationship between constraints and Noises is highly nonlinear, and the influence of constraints impacting on Noise is different. BP neural network can approach the complex nonlinear system in arbitrary precision. It gets a good application in the multivariate nonlinear problems, such as fault diagnosis and life prediction [12-13]. But BP neural network has the disadvantages of slow convergence rate, local extreme point and weak generative ability. Based on the biological immune mechanism, immune algorithm (IA) is an improved genetic algorithm, which is combined the immune theory with genetic algorithm [14]. On the basis of retaining the global random searching ability, it involves the mechanisms which exist in biological immune system such as antigen recognition, antibody diversity, immune memory, antibody encouragement and restraint, antibody diversity keeping, etc. It avoids premature and guarantees that result converges to the global minimum.

This paper uses interval propagation algorithm to detect the set of constraints C_1, while the set of constraints C_2 is simulated by BP neural network. IA is utilized to optimize the BP neural network's weights and thresholds (IABP). IABP not only improves the mapping ability of generalization, but also ensures algorithm convergence rapidly in globally optimal solution and strong learning ability. Finally, it can accurately detect whether there is Noise or not. Fig. 2 shows the detection process of collaborative design.

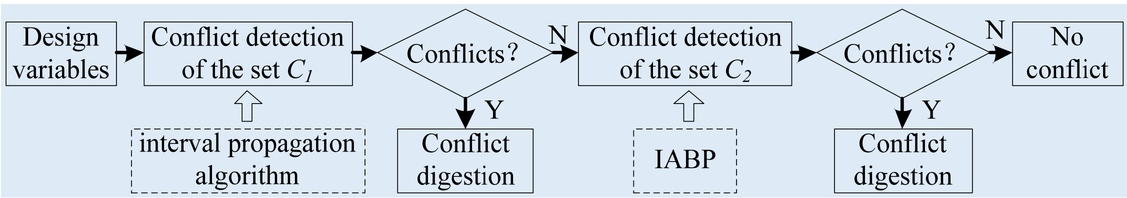


Fig. 2 Process of Noise detection.

A. Noise Detection based on Interval Propagation Algorithm

A1. Description of Algorithm

According to the interval propagation algorithm, the answer of design variable x_i by solving the set of constraints C can be written as:

$$d_i^{'} = f^{-1}\left[R\left(c_i\right), x_i\right] \tag{4}$$

So the new solution interval of x_i can be written as:

$$d_i^{''} = d_i^{'} \bigcap d_i \tag{5}$$

If the Eq. (5) is not empty, d_i will be replaced by $d_i^{''}$. The feasible solution interval of all design variable x_i can be written as:

$$D^{'} = \left[d_1^{''}, d_2^{''}, \cdots, d_n^{''}\right] \tag{6}$$

If $d_i^{''}$ is empty, the constraint network is a unsolved problem, and there must be Noise in collaborative design process. Fig. 3 shows the detection process based on interval propagation algorithm.

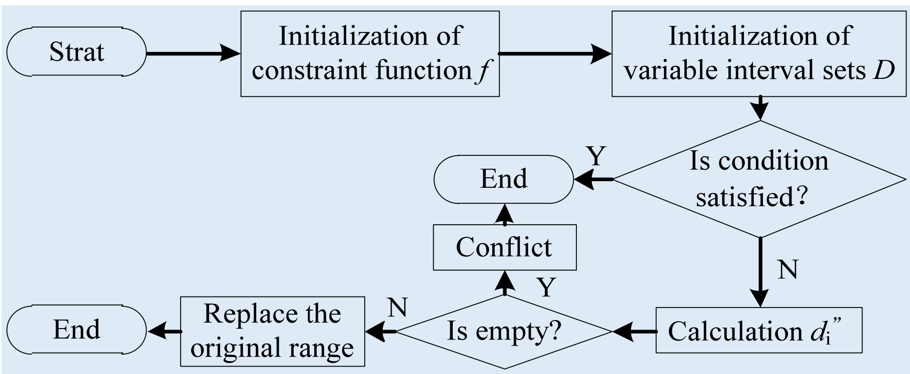


Fig. 3 Detection process based on interval propagation algorithm.

A2. Validation of Interval Propagation Algorithm

As is shown in Fig.1, the first stage planetary gear train in wind turbines gearbox consists of one sun gear, one ring gear, one planet carrier and three planetary gears. Interval propagation algorithm will be used to detect whether Noise occurs, when the adjacent planetary gear trains are installed. Fig. 4 shows the constraint network of the adjacent planetary gear trains without Noise. Z_1 is the teeth number of the sun gear, Z_2 is the teeth number of the planetary gear, Z_3 is the teeth number of the ring gear, and i is transmission ratio. Detection process is given by:

a) Initialization of Constraint Function:

$$f=\left\{Z_1 \geqslant \frac{2\sqrt{3}-3}{3}Z_2+\frac{4\sqrt{3}}{3}, Z_2 \leqslant \frac{\sqrt{3}Z_1-4}{2-\sqrt{3}}, Z_3=Z_1+2\cdot Z_2, \cdots\right.$$

b) Initialization of Variable Interval Sets:

$$D=\left\{d_{Z_1}, d_{Z_2}, d_{Z_3}, d_i\right\}$$

$$=\left\{d_{Z_1}=[17,25], d_{Z_2}=[20,40], \cdots, d_i=[6,8]\right\}$$

c) Calculation Process:

$$Z_1 \geqslant \frac{2\sqrt{3}-3}{3}Z_2+\frac{4\sqrt{3}}{3} \Rightarrow d'_{Z_1}=[8.5,+\infty] \Rightarrow d''_{Z_1}=[17,25]$$

$$Z_2 \leqslant \frac{\sqrt{3}Z_1-4}{2-\sqrt{3}} \Rightarrow d'_{Z_2}=[0,94.96] \Rightarrow d''_{Z_2}=[20,40]\cdots$$

$$i=1+\frac{Z_3}{Z_1} \Rightarrow d'_i=[3,5.7] \Rightarrow d''_i=\varnothing$$

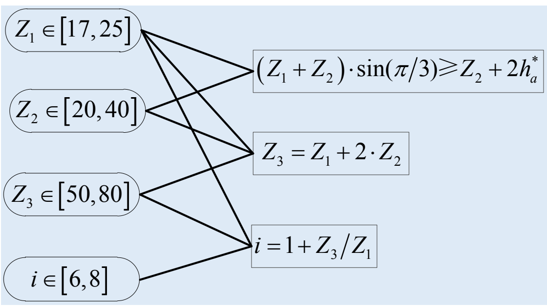


Fig. 4 Constraint network of adjacent planetary gear trains without Noise.

The results indicate that the transmission ratio is unable to meet the constraint requirements. By analyzing the reasons of the Noises in design process, it reveals that the teeth number of ring gear can't match the transmission ratio. To eliminate Noises, the designers should change the relationship between the teeth number of ring gear and the transmission ratio.

A3. Noise Detection Algorithm based on IABP

Model of BP neural network

Hsu [15] found that a three-layer BP neural network can solve random function's fitting and approximation problem. As a result, a three-layer BP neural network is adopted in this paper. As shown in Fig. 5, BP neural network has three layers: input layer, hidden layer and output layer.

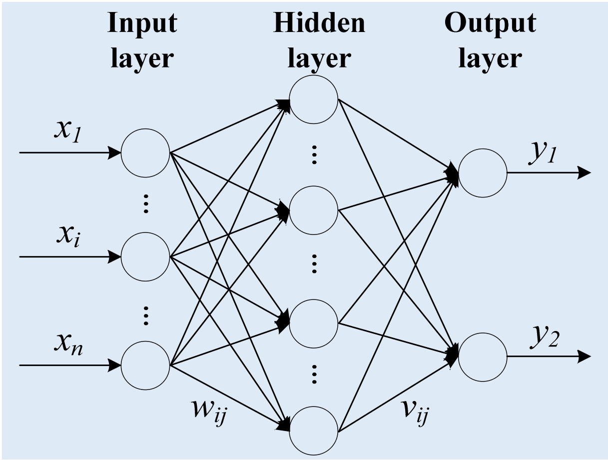


Fig. 5 BP neural network structure.

Input variables are composed by the design variables X (X={x_1, x_2, ⋯, x_n}). The results of Noise detection can be divided into two kinds: one with Noises and another without Noises. The expression of (0, 1) represents the result without Noises, while (1, 0) means Noises occurred. So the number of hidden layer neurons nodes can be given by [16]:

$$n_2=\sqrt{n_1+n_3}+\alpha \tag{7}$$

Where n_1 is the number of input layer neurons nodes; n_3 is the number of output layer neurons nodes; α is a constant, produced random among [0, 1].

The dimensions of variables and goals are different in the design process. If parameters are used to detect Noise directly, the error precision of BP neural network will reduce. Before feeding the data into BP neural network, the data must be normalized in [0.1, 0.9], according to the following equation:

$$x'_i=0.1+\frac{x_i-x_{\min}}{x_{\max}-x_{\min}}*(0.9-0.1) \tag{8}$$

Where x_i is the input variables for all i; x_{min} is the minimum of the data, while x_{max} is the maximum; x_i' is the

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input variables after normalization.

A4. Learning algorithm of BP neural network

The mean square error of the actual and the target output is taken as the training error function of the BP neural network, defined as:

$$E=\frac{1}{2mq}\sum_{j=1}^{q}\sum_{i=1}^{m}\left(y_{ij}-z_{ij}\right)^{2} \tag{9}$$

Where m is the total number of samples; q is the number of output layer neurons nodes; y_{ij} is the actual output, while z_{ij} is the target output.

To improve the convergence speed and generalization, additional momentum method and adaptive training algorithm are used to train the BP neural network [17]. Weight matrix can be amended as follows:

$$w^{t+1}=w^{t}-\eta\left.\frac{\partial E}{\partial w}\right|_{w=w^{t}}+a\eta\left.\frac{\partial E}{\partial w}\right|_{w=w^{t+1}} \tag{10}$$

Where a is dynamic factor, produced random among [0, 1]; η is learning rate; t is iterative steps; w^t is the weight matrix, while w^{t+1} is the weight matrix of next generation.

A5. Process of BP neural network optimized by immune algorithm

For the sake of better initial weights and thresholds, IA is used to optimize the weights and thresholds of BP neural network. Fig. 6 shows a flow chart of BP neural network optimized by IA.

a) Antibody Encoding

By using the binary encoding, individual is made up of connection weights between input layer and hidden layer, thresholds of hidden layer, connecting weights between hidden layer and output layer and thresholds of output layer. Table 1 shows the individual code of BP neural network. The number of antibodies consists of n new antibodies and m memory cells. Therefore, the total number of initial antibodies is p, the sum of n and m.

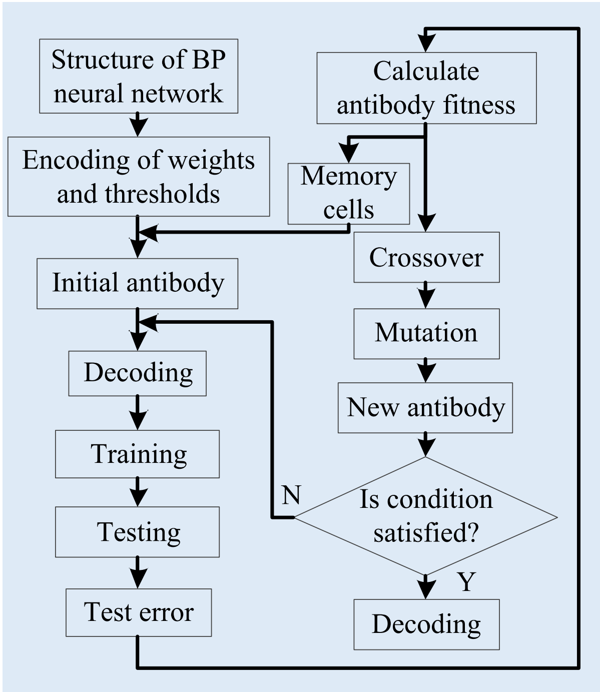

Fig. 6 Flowchart of BP network optimized by IA.

TABLE 1 ANTIBODY ENCODING

Connecting weights between input layer and hidden layer	Thresholds of hidden layer	Connecting weights between hidden layer and output layer	Thresholds of output layer
$n_1 \times n_2$	n_2	$n_2 \times n_3$	n_3

b) Fitness function

For the purpose of less error, fitness function can be defined as:

$$f\left(x_i\right)=\frac{1}{E\left(x_i\right)+\xi} \tag{11}$$

Where $E(x_i)$ is mean square error of antigen; ξ is penalty factor.

c) Concentration of Antibody

To ensure the diversity of antibodies, a method based on the Euclidean distance is used to calculate the concentration of antibody. Concentration of the antibody calculated by:

$$V\left(x_i\right)=\frac{1}{e^{D_{x_i}}} \tag{12}$$

Where D_{x_i} is the sum of all the Euclidean distances of antibodies. The higher the concentration of antibody is, the more similar between antibodies.

d) Expected Reproduction Probability

The expected reproduction probability is determined by the fitness $f(x_i)$ and concentration $V(x_i)$, which can be written by:

$$p(x_i) = \lambda \frac{f(x_i)}{\sum f(x_i)} + (1-\lambda) \frac{V(x_i)}{\sum V(x_i)} \tag{13}$$

Where λ is the reproduction probability. From the above formula, we can conclude that when the concentration of antibody is high, the antibody with high fitness is hard to be selected; when the concentration of antibody is low, the antibody with high fitness is easy to be selected. By this way, good individual is withheld, the choice of similar antibody is reduced, and the variation of individual is ensured.

e) Genetic Manipulation

The basic purpose of an immune system is to recognize foreign cells and molecules. If the difference between an antibody and an antigen is smaller, the affinity between an antibody and an antigen is higher, so recognition is also more likely.

1) Selection: stochastic uniform selecting method is used [18].
2) Crossover: one-point crossing method is used.
3) Mutation: uniform mutation is used for experimentation.

IV. CONCLUSION

From the respective of constraint satisfaction in collaborative design, this paper divided constraints into a known set of constraints C_1 and an unknown set of constraints set C_2, and detected constraints respectively. The set with known constraints was detected by interval propagation algorithm. At the same time, the BP neural network was proposed to detect the set with unknown constraints. IA was utilized to optimize the weights and thresholds of BP neural network. Simulation indicates that the IABP has better performance in convergent speed and global searching ability than GA. Compared with GABP and BP neural network, detection accuracy of IABP has been consumedly improved with the lowest error. On this basis, constraints were described by XML, so that computers can automatically recognize and establish the constraint network. Taking collaborative design of wind planetary gear train as an example, a Noise detection system in collaborative design has been developed. The Noise detection model is proved to be feasible and effective, and provides a solution of Noise detection for collaborative design.

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