Problem Solving Strategy for Product Variant Design Combined with Improved Neural Network Method

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Abstract. Aiming at the fast solution of product variant design problem, a solving strategy combined with improved neural network method was proposed. Past similar cases were extracted as training samples through case-based reasoning (CBR) technology, empirical parameters were predicted based on neural network; computational parameters were solved by the existing calculation templates. The design results visualization was realized through parametric design. To reduce the influence of artificial sample construction on neural network training effect, the sample construction strategy of the multiple input/ single output (MI/SO) structure was proposed to improve the parameter prediction quality. Finally, the feasibility and effectiveness of the proposed method was demonstrated by taking the design of a single-cylinder recuperator for example.

1. Introduction

By reusing past design resources, variant design can obtain products that satisfy users’ needs in a short time on the premise of guaranteeing cost and quality, and effectively alleviate the contradictions in complexity, diversity and timeliness of current product design [1]. It is found that about 70% of the products in enterprises are variant designed on the basis of existing products according to the market demand. At present, the research on variant design mainly focuses on variant design method, variant design plan, design change propagation and so on. Xiao Xinhua et al. [2] proposed variant design technology based on modular product instances; Wu Weiwei et al. [3] studied the variant design method of mechanical product dimension based on parameterization; Du et al. [4] used game theory to optimize variant design schemes based on modules and parameters; Chen et al. [5] proposed a design change analysis method based on structural attributes and object-oriented in view of the cyclic problems of design change. In the process of variant design, some design parameters are selected combined with past design experience, because there are often no clear design criteria. Li Haiqing et al. [6] integrated fuzzy set theory and secondary-CBR technology, proposed a hybrid case-based reasoning mechanism to support feature-based product variant design and rewriting knowledge self-learning; Xu Rongzhen [7] studied the intelligent variant design method based on case-based reasoning and knowledge push; Yangliu [8] introduced neural network based parameter prediction technique based on case-based reasoning, in order to improve the design quality and efficiency for self-propelled artillery. Literature [8] gived a parameter prediction result with relatively small error, but failed to consider the influence of artificial sample selection on parameter prediction, and cannot judge whether the current prediction effect is optimal. Therefore, this paper proposes an improved neural network parameter prediction method to improve the quality of parameter prediction, which
adopts the sample construction strategy of MI/SO and carries out multiple training of neural network model to obtain the best network model. On this basis, an efficient and complete solution strategy for product variant design is determined, case-based reasoning is used to extract similar past cases as training samples, empirical parameters are predicted by improved neural network method, computational parameters are solved by existing calculation models, and the output of design results is realized by parametric design method.

2. Product variant design problem solving strategy combined with neural network

According to the solve requirements of product variant design, variant design parameters can generally be divided into two categories: one is the computational parameters with clear design criteria or rules, which can be directly calculated or taken into account; the other is the empirical parameters without clear design criteria, which need to be solved consideration with design experience. In this paper, the solution strategy of product variant design problem based on neural network is defined as shown in figure 1. The solution of calculating parameters is template, combined with the template-based rapid design technology proposed in literature [9], the parameter calculation template is compiled according to the existing calculating formulas or the rules of value selection, the calculating process is simplified by calling the template to reduce the artificial calculation errors. Empirical parameters are solved by calling the neural network prediction module, similar design cases in the past are extracted as training samples of neural network. Empirical parameter prediction based on neural network is carried out to reduce the dependence of designers on relevant domain knowledge and improve the rationality of parameter selection. Finally, the result of parameter solution is transferred to the parametric design module, which drives the model regeneration and forms the three-dimensional model of the design scheme.

![Diagram](image)

**Figure 1.** Product variant design problem solving strategy combined with neural network.

3. Improved neural network parameter prediction technology for product variant design

Artificial neural network is a mathematical model or computational model that imitates the structure and function of biological neural network and is used to estimate or approximate functions. As an
effective method of data processing, neural network has been widely studied. The representative network models include BP, RBF, Elman network and wavelet neural network. Among them, BP network algorithm uses gradient algorithm based on error back propagation[10], makes full use of the structural advantages of multi-layer feed forward network, and the algorithm is relatively mature. Therefore, this paper chooses BP neural network to realize the empirical parameter prediction of product variant design.

3.1. BP neural network model and principle
BP neural network is a kind of multi-layer feed forward network with one-way propagation. Its main features are signal forward propagation and error back propagation. By transferring errors layer by layer, the weights and thresholds of the network are constantly adjusted to make the final output of the network as close as possible to the expected output, and the purpose of training is achieved. The design of BP network mainly includes input layer, hidden layer, output layer and transfer function between layers [11]. The number of neurons in each layer is related to the structure of training samples, the number of neurons in input layer is determined by input decision; the number of neurons in output layer is determined by output decision; and the number of neurons in hidden layer is determined by input and output layer structure. Sigmoid function or purelin function are usually used in the transmission function of BP network. Generally, sigmoid function is used as input layer transfer function, tansig or purelin function is used as output layer transfer function[12].

3.2. Training sample construction strategy of MI/SO structure
Before training, input and output items and corresponding values should be extracted from similar cases to form training sample A. The structure of training sample A is usually in the form of multiple input/multiple output (MI/MO).

The set $P = \{ p_1, p_2, ..., p_n \} (n \geq 2, n \in N)$ is defined as the input item of training sample A, $p_i (1 \leq i \leq n, i \in N)$ representing an input item of training sample A; the set $Q = \{ q_1, q_2, ..., q_m \} (m \in N)$ is the output item of training sample A, $q_j (1 \leq j \leq m, j \in N)$ representing an output item of training sample A.

The elements $p_i, q_j$ in the set are conceptual objects, which are attributes of the input and output items, representing the set of values of the input and output items in all similar design cases. The sample $A$ is $\{ p_1, p_2, ..., p_n \}/\{ q_1, q_2, ..., q_m \} (P/Q)$, which is the MI/MO structure of n input and m output.

The parameter prediction effect of BP network is influenced by the structure of training samples, if the input and output of the neural network are not correlated, the training effect will be greatly affected because it is difficult to form an effective functional relationship between them. In order to test the correlation between input and output in the initial sample, this paper proposes a training sample construction strategy based on MI/SO structure, studies the corresponding relationship between input and each output, reconstructs multiple training samples in multiple input/single output forms, and trains the neural network in turn for comparison. The specific strategies are as follows:

A non-empty subset $P_s = \{ p_{i_1}, p_{i_2}, ..., p_{i_s} \}$ is formed by selecting s elements in the set P as input of the sample $A_i$, a subset $Q_i = \{ q_1 \}$ is formed by selecting an element $q_1$ in the set Q as the single output of the sample $A_i$. The sample $A_i$ is $\{ p_{i_1}, p_{i_2}, ..., p_{i_s} \}/\{ q_1 \} (P_s/Q_1)$, which is the MI/MO structure of s inputs corresponding to a single output. In order to ensure that the correlation test is carried out without omission, the s values from 2 to n, the i values from 1 to m, and s and i are all integers. After determining the sample scheme, the set of values represented by attribute elements is substituted into $A_i$, and the BP network training samples with MI/SO structure are generated after normalization.

3.3. Empirical parameter prediction method based on improved BP neural network
The empirical parameter prediction process of product variant design based on improved BP neural network is shown in figure 2. Cording to various MI/SO sample schemes, the corresponding BP
network models are created and trained. According to various MI/SO sample schemes, the corresponding BP network models are created and trained. The number of layers and transfer functions of each layer are selected, and the structure of input and output layers is determined according to the sample structure. The number of hidden layer neurons is modified by step-by-step increment method, and the training model is compared to determine the number of hidden layer neurons that make the network have sufficient generalization ability and output accuracy. The BP network models of each MI/SO structure are trained and saved sequentially, and the parameter prediction results and error percentages of each model are compared according to the pre-set error upper limit, so as to eliminate the none&weakly related sample schemes. The most similar design case is used to verify the prediction effect of the model, the training effects of the remaining BP models are compared to obtain the best neural network model, so as to improve the quality of empirical parameter solution for variant design.

4. An example of solving variant design problem of recuperator based on improved BP neural network method
The design of recuperator in artillery recoil mechanism is a typical variant design problem. The initial pressure, compression ratio and initial volume mainly depend on the experience of the designer. Initial pressure, compression ratio and initial gas volume mainly depend on the experience of the designer. In

![Diagram of empirical parameter prediction method based on improved BP neural network](attachment:image.png)

**Figure 2.** Empirical parameter prediction method based on improved BP neural network.
order to verify the feasibility and validity of parameter prediction technology based on improved BP neural network in solving variant design problems of products, this paper takes the design of the recuperator as an example to solve the variant design problems combined with the improved BP neural network method. Specific design requirements are as Table 1.

Table 1. Design task of recuperator.

| Caliber /mm | Maximum recoil distance /mm | Maximum chamber pressure /MPa | Mass of recoiling part /kg | Efficiency of muzzle brake/% | Breech length /mm |
|------------|----------------------------|-----------------------------|---------------------------|----------------------------|-----------------|
| 130        | 950                        | 315                         | 2600                      | 44.9                       | 535             |

4.1. Empirical parameter prediction of recuperator based on improved BP neural network

In order to meet the variant design requirements of the recuperator, a series of past design cases which are close to the design task are obtained on the basis of case retrieval by using the neural network prediction module and selecting the lower limit of similarity. According to the requirements of current design task and the design characteristics of the recuperator, some inputs and outputs of the neural network are selected as shown in TABLE 2. According to the current design task, the most similar case obtained by case-based reasoning is shown in TABLE 3.

Table 2. Partial sample data.

| Maximum recoil distance /mm | Maximum chamber pressure /MPa | Mass of recoiling part/kg | Efficiency of muzzle brake/% | Breech length /mm | Initial pressure /MPa | Compression ratio | Initial gas volume /dm³ |
|----------------------------|-------------------------------|---------------------------|-----------------------------|-------------------|-----------------------|-------------------|-----------------------|
| 820                        | 238                           | 392                       | 40                          | 360               | 3.0                   | 1.62              | 3.66                  |
| 675                        | 255                           | 785                       | 58                          | 420               | 4.8                   | 3.62              | 2.07                  |
| 1180                       | 300                           | 1550                      | 45                          | 500               | 5.2                   | 2.30              | 8.23                  |
| 1400                       | 275                           | 2400                      | 0                           | 535               | 4.5                   | 2.38              | 8.30                  |
| 950                        | 315                           | 2505                      | 59.1                        | 535               | 6.1                   | 2.80              | 8.40                  |
| 1350                       | 315                           | 3029                      | 30                          | 530               | 5.6                   | 2.7               | 16.93                 |
| ...                        | ...                           | ...                       | ...                         | ...               | ...                   | ...               | ...                   |

Table 3. Most similar design case.

| Maximum recoil distance /mm | Maximum chamber pressure /MPa | Mass of recoiling part/kg | Efficiency of muzzle brake/% | Breech length /mm | Initial pressure /MPa | Compression ratio | Initial gas volume /dm³ |
|----------------------------|-------------------------------|---------------------------|-----------------------------|-------------------|-----------------------|-------------------|-----------------------|
| 950                        | 315                           | 2505                      | 59.1                        | 535               | 6.10                  | 2.80              | 8.40                  |

Through the parameter prediction method based on improved BP neural network mentioned above, the correlation between input and output is checked. There are five input elements in the initial training sample. Considering that the input reorganization starts from two elements, the number of reconstructed sample schemes is too large, so the input reorganization of the recuperator starts from three elements. The initial pressure of the recuperator is choosed as the output item, and then sixteen MI/SO sample schemes are constructed. The network model was trained after normalizing the sample data. When the network error performance meets the requirements, the model training is completed and the trained BP network models are saved. Using the most similar case to verify the model, the initial pressure prediction results of each BP network repeater are obtained as shown in TABLE 4.
Preset the upper limit of error to 6%, there are three qualified sample schemes with order numbers 2, 7 and 10. By comparing the training errors of BP model of the three schemes, it is concluded that the BP network model trained by Sample Scheme 2 has the best effect. That is to say, the best sample scheme is {“maximum recoil length”, “maximum bore pressure”, “recoil part mass”, “efficiency of muzzle brake”}/“initial pressure”}. Therefore, the BP network is chosen as the best model to predict the initial pressure.

Taking “compression ratio” and “initial gas volume” as output terms respectively, the prediction process is the same as initial pressure prediction process. Finally, the best sample schemes are {“maximum recoil length”, “maximum bore pressure”, “recoil part mass”, “efficiency of muzzle brake”}/“compression ratio” and {“maximum recoil length”, “maximum bore pressure”, “recoil part mass”, “efficiency of muzzle brake”}/“initial gas volume”.

After obtaining the optimal network model, the design task of the recuperator is inputted, and the predicted results of the experiential parameters are shown in Table 5. Literature [8] also takes the design of recuperator as an example, and takes {“initial pressure”, “compression ratio”, “initial gas volume”} as the whole sample output to predict the parameters of the recuperator. The prediction error is 1.1% for initial pressure, 8.8% for compression ratio and 14.2% for initial gas volume. The predicted results of the parameters of the recuperator in this paper are compared with those in literature [8]. It can be found that the parameter prediction method based on improved BP neural network proposed in this paper further improves the quality of parameter prediction of the recuperator, and satisfies the requirements of variant design of the recuperator better.

### Table 4. Comparison of predicted results.

| Order number | Maximum recoil length | Maximum Chamber Pressure | Mass of Recoiling Part | Efficiency of Muzzle Brake | Breech Length | Model training results |
|--------------|-----------------------|--------------------------|------------------------|---------------------------|---------------|------------------------|
|              |                       |                          |                        |                           | 6.10          | 5.34                   | 12.46%               |
|              |                       |                          |                        |                           | 6.10          | 6.28                   | 2.95%                |
|              |                       |                          |                        |                           | 6.10          | 6.58                   | 7.87%                |
|              |                       |                          |                        |                           | 6.10          | 7.12                   | 16.72%               |
|              |                       |                          |                        |                           | 6.10          | 5.36                   | 12.13%               |
|              |                       |                          |                        |                           | 6.10          | 5.17                   | 15.25%               |
|              |                       |                          |                        |                           | 6.10          | 5.8                    | 4.92%                |
|              |                       |                          |                        |                           | 6.10          | 6.47                   | 6.07%                |
|              |                       |                          |                        |                           | 6.10          | 7.00                   | 14.75%               |
|              |                       |                          |                        |                           | 6.10          | 6.36                   | 4.26%                |
|              |                       |                          |                        |                           | 6.10          | 4.72                   | 22.62%               |
|              |                       |                          |                        |                           | 6.10          | 7.43                   | 21.80%               |
|              |                       |                          |                        |                           | 6.10          | 5.55                   | 9.02%                |
|              |                       |                          |                        |                           | 6.10          | 7.25                   | 18.85%               |
|              |                       |                          |                        |                           | 6.10          | 7.14                   | 17.05%               |
|              |                       |                          |                        |                           | 6.10          | 4.63                   | 24.10%               |

Table 5. The prediction results of the recuperator empirical parameters.

| Empirical parameters | Initial pressure/MPa | Compression ratio | Initial gas volume/dm³ |
|----------------------|----------------------|-------------------|-------------------------|
| Original design      | 6.10                 | 2.80              | 8.40                    |
| Parameters prediction| 6.28                 | 2.70              | 8.89                    |
| Error%               | 2.95%                | 3.57%             | 5.83%                   |

4.2. Example of solving variant design problems

According to the predicted results of parameters, the empirical parameters of the recuperator are selected. The initial pressure of the recuperator is 6.28 MPa, the compression ratio is 2.70, and the initial gas volume is 8.89dm³. According to the existing formula for calculating the parameters of the
recuperator, the program for calculating the parameters of the recuperator is compiled and invoked, and the calculating parameters of the repeater are solved. The results are shown in TABLE 6. The results of parameter solution are input into the parametric design program, which drives the model regeneration of the recuperator, and finally realizes the visualization of the design, as shown in figure 3.

**Table 6.** The values of the recuperator calculation parameters.

| Diameter of recuperator rod/mm | Inner diameter of recuperator barrel/mm | Outer diameter of recuperator barrel/mm | Length of recuperator barrel/mm | Width of piston/mm | Thickness of end cap/mm | Total length of piston and rod/mm |
|-------------------------------|----------------------------------------|-----------------------------------------|-------------------------------|-------------------|------------------------|----------------------------------|
| 38                            | 85                                     | 115                                     | 2100                          | 80                | 18                     | 2200                             |

![Recuperator Parametric Design](image)

**Figure 3.** New variant design scheme of recuperator.

5. Conclusion

Aiming at solving empirical parameters in variant design, the technology of neural network parameter prediction is introduced on the basis of case-based reasoning and parametric design. A solution method of product variant design problem based on neural network is proposed, the solution strategy of product variant design problem combined with neural network and the empirical parameter prediction process of product variant design based on BP neural network are determined. In order to reduce the influence of irrelevant input and output caused by artificial sample construction, a training sample construction strategy based on MI/SO structure is proposed to improve the parameter prediction method of neural network in order to improve the quality of parameter prediction. Finally, taking the variant design of a single cylinder recuperator as an example, a new visual variant design scheme of the recuperator is generated. The feasibility of the proposed method is verified.
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