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Sowing Machine Design Evaluation Model Based on RBF Network

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Abstract

This study first analyzes the features and defects of each product design evaluation method. Then radial basis function (RBF) network is used for the modeling for sowing machines. Considering the characteristics of sowing machines and the general method of design evaluation of electromechanical equipments, 7 primary evaluation indicators for sowing machines are identified, including overall design, form, human-machine interface and color. These primary evaluation indicators were subdivided into 18 secondary indicators. Survey on these indicators was performed by professionals and the scores are assigned to 18 indicators collected from 26 samples. Thus the comprehensive evaluation score of the indicators is calculated using image scale method. The scores of the evaluation indicators are taken as input and the comprehensive evaluation score as the output, then the RBF network for design evaluation is built. After training and verification using 26 samples, it is found that the RBF-based design evaluation model achieves better prediction performance than the BP-based model.

Keywords*: Comprehensive evaluation, design, RBF network, sowing machine*

1. Introduction

Agricultural machinery plays an important role in agricultural economy and daily farming activities, and the rapid development of agricultural machinery usually indicates accelerating industrialization of agriculture [1]. In modern agricultural production, the research and development of agricultural machinery has a direct bearing on the growth of agricultural economy. However, more attention is given to the functionality of the agricultural machinery than to the appearance and agreeableness. Conventional agricultural machines usually give the impression of being coarsely made, heavily built and lacking aesthetic value [2]. To address this problem, efforts should be made in promoting the design and in optimizing the design evaluation method. Comprehensive design evaluation is a must for optimizing product appearance and design and for reducing the new product development cycle based on an accurate understanding of market demand and consumers' needs. Agricultural machinery is divided into several types, including sowing machine, plant protection machine, tillage machine, comprehensive machine and harvesting machine. Design evaluation is rarely studied for agricultural machinery, much less for sowing machines. Here sowing machine is concerned and a design evaluation model is built based on RBF network based on a brief review of the existing methods for design evaluation of industrial products and the unique features of sowing machine.

Methods of design evaluation for industrial products are divided into simple evaluation and multi-factor comprehensive evaluation. The former includes simple scoring, evaluation based on queue model, point evaluation and integral by ranks. The latter includes fuzzy comprehensive evaluation and analytic hierarchy process (AHP). Multi-factor comprehensive evaluation is more commonly used in design evaluation. Z. X. Sun

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proposed the use of multi-factor comprehensive evaluation on the basis of single-factor fuzzy evaluation for product design evaluation [3]. The fuzzy set for multi-factor evaluation was built for machine tool and the proposed model was verified. H. M. Jin *et al*. built a mathematical model for fuzzy comprehensive evaluation of MP3 player, with an analysis of the evaluation indicators and the calculation of membership degree of each indicator. This method was proved effective for optimizing product design [4].

Z. J. Chen *et al*. applied AHP to the evaluation and decision-making over furniture design proposals. According to the hierarchy of evaluation indicators of design proposals, weights were assigned to indicators of each layer and the evaluation model was built [5]. X. Zhong *et al*. attempted to reduce the adverse impact of subjective factors and incomplete design information on design plans during the stage of conceptual design [6]. By using AHP for the conceptual development of electronic products, the problems of arbitrariness and subjectivity in conceptual design were overcome. The practicability of this evaluation model was further demonstrated through an example of mobile design.

Intelligent algorithms are now widely applied in the era of computer technology for dealing with non-linear problems. But given the inevitable subjectivity in consumers' evaluation of product design and the involvement of causal relationship, contradiction and inaccuracy of the data will exist. Neural network algorithm has been used to tackle with this problem [7, 8]. K. G. Zhao conducted an evaluation of passenger car design using artificial neural network (ANN) [9]. Three independent 2D views of the passenger car (front, lateral, rear) were the input, and the scores given to each view were the output. Thus the primary layer of the neural network was constructed. The independent scores given by the experts to the 3 views were the input, while the scores of experts' overall impression about the passenger car based on the 3 views and the 3D projection of the car were the output. Thus the ANN-based model was obtained. W. Q. Zhao used a design proposal of a product as the sample and analyzed the product design evaluation indicators [10]. The evaluation results about the lower-layer indicators were the input, while the comprehensive evaluation about the product design was the output. Then the BP ANN network was established and the results of model training and testing were satisfactory. H. Tan *et al*. took the design of semi-fitting skirt as the research subject and proposed the indicators of subjective design evaluation [11]. The mechanical performance indicators of the fabrics measured by FAST system were the input and the overall design score obtained from group decision making was the output. The BP ANN-based evaluation model was built for the semi-fitting skirt and the model exhibited high accuracy according to linear regression analysis.

BP neural network algorithm is generally used for product design evaluation, which can achieve better effect as compared with conventional quantitative method. However, BP neural network algorithms still have the defects of slow convergence, getting stuck in local minima and sensitive to initial value configuration. With RBF network, the mapping from input to output is non-linear and the network output is linear in the sense that parameters are adjustable. Therefore, the weights can be directly solved using linear equations, thereby accelerating the learning speed and preventing being stuck in local minimum. Due to these advantages, we apply RBF network for building the design evaluation model for sowing machines.

2. Evaluation Indicator System for Sowing Machine Design

2.1. Evaluation Indicators

Sowing machines can be classified in different ways. By sowing method, there are broadcast sower, drill sower, bunch planting machine and precision sowing device. In this work, bunch planting machine is studied and the important components of the bunch planting machine are as follows: frame, plating device, fertilizer applying device, soil tillage device and coping device. Some are equipped with pesticide and herbicide applying device [12]. Like general machinery, sowing machines are designed based on the functions to be performed. Therefore, the design evaluation indicators are selected based on the following principles [13].

Table 1. Evaluation Indicator System of Sowing Machine Design

No	Primary indicator	Secondary indicator
1	Overall design	Consistence of local and overall design style x1
		Equilibrium and coordination of spatial volume of different parts with reasonable transition x2
		Compatibility between texture, functionality and environment x3
2	Man-machine interface	Design of operating mechanism that conforms to force application rules x4
		Comfortable height of operating mechanism x5
		Installation of operating mechanism to the most proper region x6
3	Form	Unification of form and functionality x7
		Right proportions x8
		Smooth appearance, distinct planes and edges, with proper connections x9
		Necessary protection for the interior structure x10
4	Color	Coordination between color tone, functionality and environment x11
		Visual stability of color x12
		Coordinated contrast x13
		Recognizability x14
5	Exterior decoration	Exquisite surface coating and reasonable layout x15
		Reasonable layout of logo x16
6	Exposed parts	Consistence of style of exposed parts and main body, with proper configuration x17
7	Other	Use of new technology, process and material and proper cost x18

(1) Practicability: The product should be functional, safe and reliable and in the sense of man-machine engineering, it is expected to be highly efficient and comfortable.

(2) Scientificity: Product design is an embodiment of advanced manufacturing and processing technology, and material selection and mechanism design should be standardized and generalized.

(3) Aesthetics: Form constitution of the product should obey the aesthetic principles of proper scale, equilibrium & stability, unification and variation. Both the color and the decoration should keep up with the trend and the general aesthetic standards.

(4) Innovation: Innovation not only consists in the appearance and the concept, but also in the functionality of the product.

(5) Economy: The design proposal should be chosen with the consideration of cost.

2.2. Evaluation Indicators

Except a higher requirement on working conditions, the design requirements for agricultural machinery are similar with those of other electromechanical products. In the case of sowing machine, method of design evaluation for electromechanical products [14] and general rules of structural and functional design of sowing machines are referred to. Seven primary indicators are identified, including overall design, man-machine interface, form, color, exterior decoration and exposed parts. These primary indicators are subdivided into 18 secondary indicators as lower evaluation layer.

3. Building Comprehensive Design Evaluation Model Based On RBF Network

3.1. An Introduction of RBF Network

Powell put forward radial basis function (RBF) for multivariable interpolation in 1985. Later Moody and Darken proposed RBF network in 1988, which belongs to forward propagation neural network and can approximate any continuous function at any precision. This algorithm is particularly fit for classification[15]. With hidden neurons forming an arbitrary basis for the input, the input vectors are directly mapped to the hidden space. Once the center point of RBF is determined, the mapping relation is determined as well. The mapping from the hidden space to the output space is linear, which means the output is the linear weighted sum of the hidden unit output. Here weight is the adjustable parameter.

3.2. Principle of RBF Network

The RBF-based model consisting of input layer, hidden layer and output layer is shown in Figure. 1.

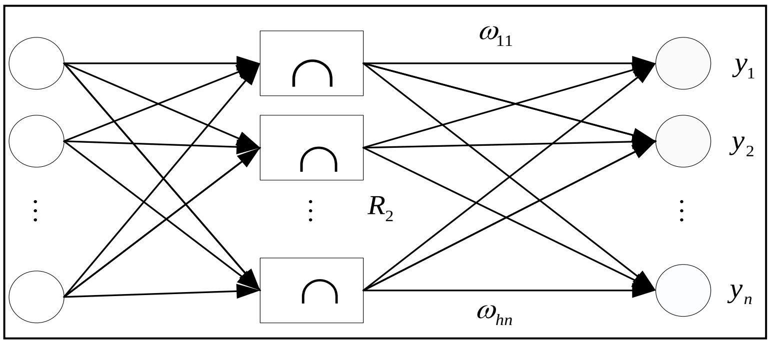

Figure 1. RBF-Based Model

Gaussian-shaped RBF is usually used, and the RBF activation function is expressed as

$$R(x_p - c_i) = \exp\left(-\frac{1}{2\sigma^2}\left\|x_p - c_i\right\|^2\right) \tag{1}$$

where $\left\|x_p - c_i\right\|$ is Euclidean norm;

c is the center of Gaussian function;

σ is the variance of Gaussian function.

From Figure 1, the network output is calculated as

$$y_j = \sum_{i=1}^{h} \omega_{ij} \exp\left(-\frac{1}{2\sigma^2}\left\|x_p - c_i\right\|^2\right) \tag{2}$$

where x_p is input sample p;

$p = 1,2,\cdots,P$ is sample size;

c_i is center of neuron of the hidden layer;

ω_{ij} is the connection weight between hidden layer and output layer; $i = 1,2,\cdots,h$ is the neuron number of the hidden layer;

y_j is the actual output of the output node j corresponding to the input sample.

Let d between the expected output value of the sample, then the variance of RBF is

$$\sigma = \frac{1}{p}\sum_{j}^{m}\left\|d_j - y_j c_i\right\|^2 \tag{3}$$

3.3. RBF Network Learning

The center c of RBF is solved using K-means clustering:

(1) Initialization: h training samples are randomly selected to form the cluster center $c_i(i = 1,2,\cdots,h)$;

(2) The training samples are clustered by nearest neighbor rule: Based on the Euclidean distance between x_p and center c_i, x_p is allocated to the cluster set $\vartheta_p(p = 1,2,\cdots,P)$ for the input samples.

(3) Readjusting the cluster center: The means of the training samples in each set of clusters ϑ_p are calculated as the new cluster center c_i. If the cluster center no longer changes, the resulting c_i will be the final center of the RBF. If not, return to step 2 to start another round of center calculation.

Calculation of variance σ_i:

If the RBF is Gaussian-shaped, the variance σ_i is calculated as follows:

$$\sigma_i = \frac{c_{\max}}{\sqrt{2h}} \qquad i = 1,2.\cdots.h \tag{4}$$

where $c_{\max}$ is the largest distance between the selected centers.

(4) Calculating the connection weight between hidden layer and output layer

Connection weight between hidden layer and output layer is estimated by least-squares method:

$$\omega = \exp\left(\frac{h}{c_{\max}^2}\left\|x_p - c_i\right\|^2\right) \qquad p = 1,2,\cdots,P; i = 1,2.\cdots.h \tag{5}$$

3.4. RBF-Based Evaluation Model

First the node numbers of the three layers of the RBF network are determined. The scores of the 18 secondary indicators are the input, so the node number of the input layer is 18. The results of comprehensive design evaluation obtained by image scale method are the output, and the node number of the output layer is 1.

4. Simulation using RBF-Based Model

4.1. Sample Data

Designs of several sowing machines of different brands are classified and compared and 26 representative design samples are selected. All evaluators have been educated in mechanical design, agricultural machinery design or industrial design. They are asked to score the 18 evaluation indicators for 26 samples using the 5-point Likert scale, with 1 point indicating very poor, 5 point very good, and 3-point moderate. The scoring results are shown in Table 2.

Table 2. Scoring Results of 26 Design Samples

Samples	1	2	3	4	5	6	7	8	9	10	11	…	22	23	24	25	26
X1	3.5	1.2	4.5	1.9	2.6	3.8	2.5	1.9	2.2	3.5	2.8	…	3.5	3.0	1.1	4.5	2.9
X2	4.7	2.1	4.6	2.0	3.0	4.0	2.9	2.1	2.3	3.8	2.5	…	4.6	3.8	1.0	4.7	2.2
X3	3.8	1.8	3.9	1.5	2.9	3.9	3.0	1.8	2.0	4.1	3.0	…	3.2	4.2	1.2	4.6	2.4
X4	3.3	1.9	4.4	1.7	3.2	4.2	2.6	2.2	2.8	3.9	2.6	…	3.4	4.1	1.5	4.8	2.3
X5	3.9	1.3	4.7	1.8	2.8	4.1	2.7	2.3	2.5	4.4	2.4	…	3.3	3.4	1.2	4.4	1.9
X6	3.5	1.5	4.6	1.9	2.7	2.9	3.1	1.7	1.8	4.0	3.1	…	3.7	3.7	1.3	4.1	1.9
X7	4.1	1.4	4.8	2.1	3.4	4.4	2.8	1.8	2.3	3.6	3.2	…	3.5	3.9	1.0	4.3	2.4
X8	4.2	1.8	4.2	2.2	3.5	4.6	3.2	2.4	2.6	3.7	3.5	…	3.9	4.0	1.4	4.7	1.8
X9	4.3	1.6	4.3	2.3	2.2	3.7	1.9	2.5	2.1	4.5	3.4	…	2.9	3.6	1.2	4.5	2.0
X10	4.5	1.2	4.0	1.6	3.6	4.1	2.9	1.9	2.2	4.2	2.7	…	2.7	3.9	1.6	4.9	2.7
X11	4.2	1.4	4.5	1.3	2.1	3.5	3.4	2.7	1.8	2.6	2.9	…	3.5	2.8	1.3	4.2	2.3
X12	3.6	1.9	4.2	2.6	2.5	3.6	3.5	2.4	2.0	3.3	3.3	…	3.6	2.9	1.6	3.9	2.6
X13	3.5	2.3	4.6	1.4	3.7	3.7	2.1	1.5	2.4	4.3	3.1	…	3.8	3.1	1.2	4.8	2.2
X14	2.8	1.1	3.7	2.3	1.9	3.4	2.2	2.0	2.7	4.8	3.6	…	2.9	3.7	1.1	4.7	2.7
X15	3.4	1.6	2.9	1.9	3.1	4.0	3.6	2.6	1.9	4.5	3.7	…	2.8	3.2	1.5	4.6	1.9
X16	3.5	1.9	4.8	2.4	3.3	3.9	3.3	1.4	2.4	3.2	2.3	…	3.1	4.5	1.4	4.5	2.2
X17	3.2	1.0	4.7	2.6	3.5	2.8	3.1	2.1	1.6	4.1	3.4	…	4.1	4.0	1.3	4.3	2.9
X18	3.7	1.7	3.8	1.8	3.6	4.3	2.0	2.4	2.5	4.3	3.6	…	2.8	3.9	1.7	4.4	2.8

4.2. Simulation and Verification

Of 26 samples, 20 samples are used for training, and the remaining 6 for testing. The node number of input layer and output layer hidden layer is 18 and 1, respectively. The RBF-based evaluation model is built. With speed=4, the RBF network is trained. The predicted values and the actual values of the training samples based on RBF are shown in Figure. 2. The predicted values and the actual values of the testing samples based on RBF are shown in Figure. 3.

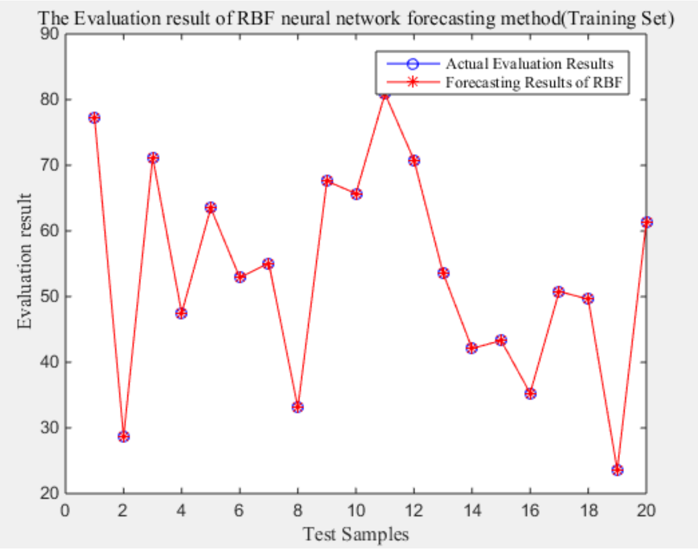

Figure 2. Comparison of Predicted Values and Actual Values of Training Samples with RBF-Based Model

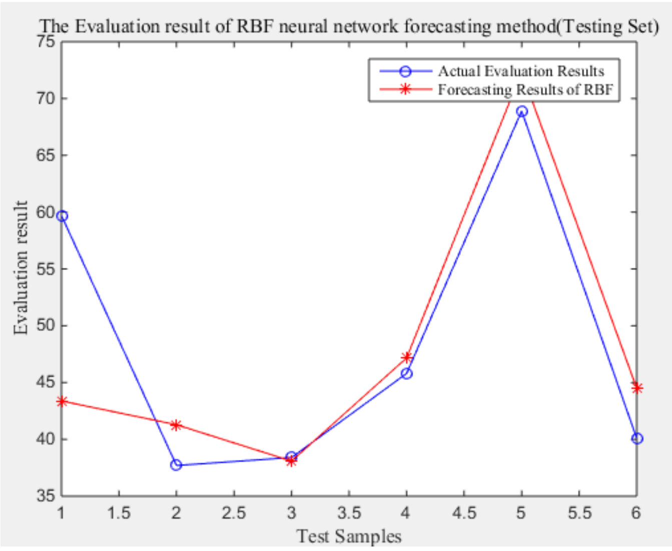

Figure 3. Comparison of Predicted Values and Actual Values of Testing Samples with RBF-Based Model

BP neural network model is also built, and node numbers of the input and output layers are the same as in RBF-based model. The learning rate is 0.1, the target value of error is 0.0000001, and the network is trained for 200 times. The predicted values and the actual values of the training samples with BP neural network model are shown in Figure 4. The predicted values and the actual values of the testing samples with BP neural network model are shown in Figure 5.

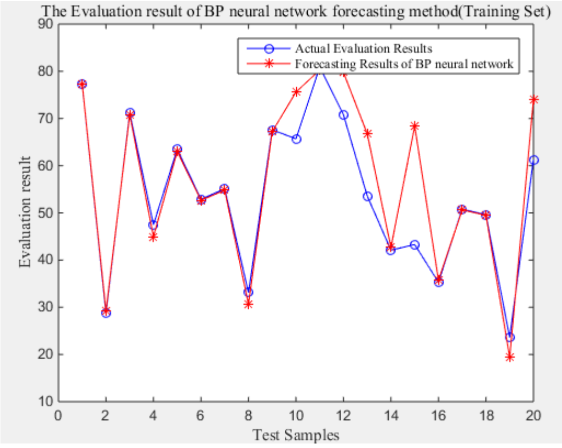

Figure 4. Comparison of Predicted Values and Actual Values of Training Samples with BP-Based Mode

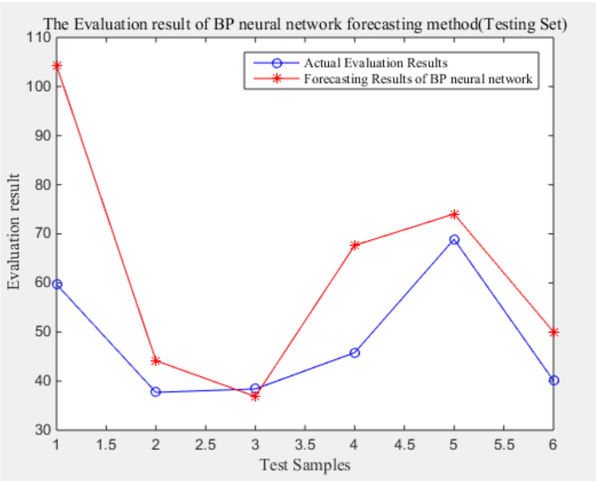

Figure 5. Comparison of Predicted Values and Actual Values of Testing Samples with BP-Based Model

Comparing Figure. 2 and 4, 3 and 5, it can be found that the RBF-based model has a much smaller error than the BP-based model. Table 3 is the comparison of the two models from testing samples.

Table 3. Comparison of Predicted Values and Errors with RBF-Based Model and BP-Based Model Using the Testing Samples

Output values of test samples	Output values of the RBF-based model	Output values of the BP-based model	Relative error of the RBF-based model	Relative error of the BP-based model
59.7	43.3814	104.2725	27.3343	74.6608
37.7	41.2882	44.1574	9.5178	17.1284
38.4	38.0859	36.8735	0.8181	3.9753
45.8	47.1715	67.6511	2.9945	47.7099
68.9	72.3356	74.0442	4.9863	7.4662
40.1	44.5019	50.0370	10.9774	24.7805

5. Conclusion

Based on the features of sowing machines and the general method for design evaluation of mechanical products, 7 primary indicators and 18 secondary indicators are evaluated. The scores of the evaluation indicators are the input, and the results of comprehensive design evaluation using image scale method are the output. Thus the RBF-based evaluation model is built. Simulation shows that the prediction error with the RBF-based model is far smaller than that with BP-based model.

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