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Pricing model and application of new materials in power transmission and transformation engineering

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Abstract: At present, the research and development and application of various new materials constantly revolutionize the construction of power transmission and transformation projects. The characteristics and pricing of such new materials are somewhat different from those of pain-producing materials, resulting in large errors in the pricing of power transmission and transformation projects. In combination with the construction characteristics of power projects, this paper studies the mechanism of disturbance of engineering cost caused by the application of new materials. The construction cost is to build an application pricing model that conforms to the characteristics of the new material, and the model construction and testing are carried out on the prefabricated optical cable, energy-saving wire. The test results show that the error between the estimation results and the actual cost of the pricing model is controlled within 10%, and the test results are reasonable.

1. Introduction

At present, the application of all kinds of new materials are in the initial promotion stage, and the price release often has a certain lag, resulting in a large or too general balance rate between the new material pricing and the actual cost of the power transmission and transformation engineering project, which could affect the use efficiency. Therefore, the construction of the application pricing model of new materials in power transmission and transformation engineering can clarify the application pricing standard of new materials and effectively calculate the periodic price of new materials, so as to solve the problem of difficult pricing and lack of basis in engineering review. This paper will build an application pricing model suitable for new materials by analyzing the influencing factors related to the application cost of new materials.

2. Literature review

Since Adam Smit put forward the theory of free economy, market pricing has become an important means of product pricing in mainstream economic theory. According to the market mechanism, the basic idea of product pricing is to establish a profit-maximizing price and output model according to its production function and market structure. From the perspective of foreign studies, Dewan and Jing et al. (2003)[1] applied the competition model of standard products and customized products to the network environment to analyse the optimal product mix of standard products and customized products, and how customization affects price competition. Xia and Rajagopalan (2009) [2] constructed a model to determine the variety, delivery time, and price of two commodities in a competitive environment. Zheng and Chiu et al. (2012) [3] analysed the optimal advertising and pricing strategies of luxury brands in the market and studied the optimal product strategies and pricing schemes by exploring different sales strategies.

From the perspective of domestic research, Cao Hong and Zhou Jiang (2004)[4] proposed that the pricing method of consumable products should not adopt the fixed pricing method of marginal cost or average cost. Liu Qing and Li Guifu (2006) [5] modified and improved the assumptions of the perfect competitive market of the hedonic model by analysing various features of the electronic product market. They introduce the functional form of the hedonic model under monopoly conditions and discuss the application of this model in the pricing of cable digital TV and the possible problems. Wang Zhao (2007) [6] took the pricing method and pricing model of reducer products as the research object, started from economic pricing theory and marketing theory, and proposed pricing models suitable for the characteristics of different reducer products according to the basic laws of price operation under different market and competition conditions. Weng Shichun and Huang Wei (2013) [7] used the chain store paradox model and KMRW reputation model to build a theoretical model suitable for analysing smartphone pricing strategies in non-cooperative games. Xu Jing (2016)[8] introduced the characteristic price model, clarified the basis, hypothesis and function form of the characteristic price model, and then took 317 computer samples as research objects to quantify the characteristic factors affecting the computer price, and established the computer characteristic price model. Zhang Jun (2018) [9] adopted game theory to build a product pricing model based on alliance partnership and analysed the impact of vertical partnership on alliance product pricing and pricing strategies from three aspects: cooperative relationship, market structure and bargaining power. Wei Yanfeng, Lv Fei et al. (2019) [10]analysed the cost components of cigarette decoration materials and built a pricing model of cigarette decoration materials based on main raw material price prediction and big data thinking. Wei Fajie, Lu Ping et al. (2020) [11]proposed a military pricing cost model based on material cost, starting with the pricing review method of military products in China. In the same year, Tang Biao and Yang Li (2020) [12] studied the equilibrium output and profit of Internet of Things enterprises under duopoly competition in the market environment of oligopoly competition by introducing a quadratic demand function model and using the two-stage Kurnot model of incomplete information through the formulation of discount pricing strategy.

Through the review of the existing domestic and foreign literature on electricity pricing model, it is found that the existing research has analysed the characteristics of various markets, explored different applicable conditions for different pricing methods, and indicated that it is necessary to formulate different pricing methods for different market backgrounds. Some literatures give market-based pricing competition models considering costs and benefits, and some literatures put forward new pricing methods based on the interaction between the market and users. However, although the above-mentioned methods add competition models or market linkage, they are more applicable to the pricing and sales of products under the market and cannot reflect the impact of the application of new materials on the project cost in power transmission and transformation projects. In view of the shortcomings reflected in the above literature, this paper analyses the disturbance mechanism of the new material cost, constructs the corresponding application pricing model, and feedback the pricing results into the engineering cost to improve the effectiveness of pricing.

3. Methodology

3.1. New material cost disturbance mechanism

The use of a new type of material will first affect the cost of a single project. Under the conditions of market economy, the price of new materials is not only affected by its own cost, but also affected by factors such as regional economic development level, industrial policy, industry monopoly and so on. Through the investigation of data and information related to material prices, the factors affecting material pricing are extracted from the aspects of factor price, market factor and policy standard, and the price formation mechanism is analysed. The new material cost disturbance mechanism of a single project is shown as follows:

$$Y_1 = Y_c + Y_j = Y_{PR} + (Y_M + Y_{PO}) = Y_{PR} + \alpha * Y_{PR} = (1+\alpha) * Y_{PR} \tag{1}$$

Where:
Y_1=The cost disturbance of a new material to a single project
Y_c=Cost disturbance = factor price disturbance
Y_j=Technical premium=disturbance of market factorsY_M+Perturbation of policy criteriaY_{PO}
Y_{PR}=Perturbations in factor prices
Y_M= Disturbance of market factors
Y_{PO}= Perturbation of policy criteria
α= Coefficient of technical premium

After determining the cost disturbance of a new material to a single project, multiplying it with the total number of projects using the new material, the cost disturbance of the new material to the whole company can be obtained. The disturbance mechanism is shown as follows:

$$Y = n * Y_1 \tag{2}$$

Where: Y= The cost disruption of a new material to the company as a whole, n= The number of projects using a new type of material.

Various types of domain perturbations are described in detail below:

Table 1: New material cost disturbance mechanism.

Factor class	Factor name	Index	Unit	Data source
Factor price domain	Labor cost	Average wages	yuan	The National Bureau of Statistics
	Raw material price	Unit price of raw material	yuan	Statistics of tenderers
Market factor domain	Product life cycle	Impact of life cycle on price	1	Statistics of tenderers
	Supply and demand	Supply demand ratio	1	Statistics of tenderers
	Inflation	CPI	1	The National Bureau of Statistics
	Industry monopoly	HHI	1	Statistics of tenderers
	Regional economic development level	GDP	trillion	Regional statistical office
Policy standard domain	Industrial policy	Device manufacturers proportion	%	Statistics of tenderers
	Monetary policy	Benchmark lending rate	%	The National Bureau of Statistics

3.2. New material pricing model construction

Commonly used pricing models can be divided into the following two categories. First, the traditional market pricing model is used to measure the price changes under the basic laws operating under different market and competition conditions. This kind of model is biased to mathematical research and lacks data support. The second is the use of computer means, based on the historical price, to predict the future price fluctuations, there are many methods, such as support vector machine, artificial neural network algorithm. Although support vector machine has excellent nonlinear fitting ability, it lacks efficient processing means for large-scale data. However, neural network algorithm not only has very strong nonlinear fitting ability, but also can self-learn based on a large number of data, and the learning rules are simple, which is convenient for computer implementation. With strong robustness, memory ability, nonlinear mapping ability and self-learning ability, Sun, W., and Huang, C. (2020)[13] proposed a new carbon price hybrid model based on BP neural network model, and innovatively introduced the quadratic decomposition algorithm into carbon price prediction. The empirical analysis of Hubei market proves that the proposed model is superior to other comparative models. The model also performed best in the complementary case of the Beijing and Shanghai carbon markets. Jiang Jinhu et al. (2022) [14] applied BP neural network to establish a price prediction model and forecast the price of building materials in order to strengthen cost control in the construction process and realize price trend prediction of building materials. The forecast result is basically in line with the actual price. Therefore, this paper will use BP neural network to construct and test the pricing model.

For new materials, the construction of application pricing model is based on cost analysis and technology premium. Combined with the study on the influencing factors of the cost disturbance mechanism on the pricing of new materials, the labor cost and material cost are taken as the cost disturbance model, and the other influencing factors are taken as the technology premium model. BP neural network is used to construct the technology premium model, and the technology premium coefficient is obtained. By combining cost disturbance and technology premium, the new material pricing model can be constructed.

BP neural network model adopts the error back propagation algorithm during training, which consists of two parts: information forward propagation and error back propagation. The role of neurons in the input layer is to receive data information sent from the outside world and transfer the data to neurons in the middle layer, and neurons in the middle layer convert and process the received information. When processing data, it should be realized in combination with user requirements. Different structures of one or more layers on the middle-hidden layer should be reset, and data should be transmitted to the output layer on the last hidden layer. The whole process above is the BP neural network forward propagation process. Currently, the ideal output is compared with the actual output, and if the difference between the two is higher than the expected value, the error backpropagation process is entered. The output layer is used as the initial end, error reduction method is used to correct the error weight on each layer, and then propagate to the hidden layer and the input layer in order. Combining information forward rebroadcasting and error back propagation to effectively adjust the weights on each layer, this process is called the learning training process on neural networks. When the output error is reduced to the expected degree or the number of learning iterations set in advance, the BP neural network ends the learning. The specific construction process of neural network is as follows:

(1)BP neural network forward input

Suppose that the net input of the neural network is:

$$n_i^m = \sum_{i=1}^{s^{m-1}} w_i^m, y_i^{m-1}, m = 1,2,\dots,M(M \geq 2) \tag{3}$$

Where: m represents the net input sum of the weight and deviation value of the i^{th} nerve of the m layer of the network, and M represents the number of layers of the neural network.

In the neural network, the output of layer m:

$$y^m = f^m(n^m) \tag{4}$$

Where: m is any layer on the neural network, f^m is the transfer function on this layer.

When m=1, y^1 represents the output information of neurons in layer 1, and its input information is determined by the input layer, so y^1 can be expressed as:

$$y^1 = f^1(W^1x + b^1) \tag{5}$$

At this time, the output of the neuron in the last layer on the network is the output of the BP neural network, that is:

$$y = y^M \tag{6}$$

(2)BP neural network backpropagation

The error function used by BP neural network algorithm is the mean square error function. The set that takes the input of the algorithm and the corresponding ideal or desired output as samples is:

$$\{X_1, t_1\},\{X_2, t_2\},\ldots,\{X_R, t_R\} \tag{7}$$

X_R represents the input of the neural network, and t_R represents the desired target output. For each input sample, the expected output of the neural network is compared with the actual output value. The BP neural network algorithm will iteratively modify the weight value to achieve the purpose of minimizing the mean square error. When the neural network has multiple outputs, the above process of minimizing the mean square error can be expressed as:

$$F(z) = E[e^Te] = E[(t-y)T(t-y)] \tag{8}$$

The above function is regarded as the network output error related to the weight, and the error can be reduced by modifying the weight. The modified weight can continuously reduce the error, so to achieve a positive proportional relationship between the degree of weight correction and the direction of error gradient reduction, the gradient descent method of approximate mean square error is as follows:

$$w_{I,j}^m(k+1) = w_{I,j}^m(k) - \eta \frac{\partial F}{\partial w_{I,\ j}^m} \tag{9}$$

$$b_{I,j}^m(k+1) = b_i^m(k) - \eta \frac{\partial F}{\partial b_i^m} \tag{10}$$

The symbol to the right of the equal sign above is used to represent the gradient reduction direction, η represents the learning rate, which is an intuitive representation of the network training speed.

To find the minimum value of the error function, usually use the gradient descent method, that is, to find the partial derivative of the function and calculate the partial derivative. After simplification, the following formula can be obtained:

$$\frac{\partial F}{\partial \omega_{I,j}^m} = \frac{\partial F}{\partial n_i^m} \times \frac{\partial n_i^m}{\partial \omega_{I,j}^m} \tag{11}$$

$$\frac{\partial F}{\partial b_i^m} = \frac{\partial F}{\partial n_i^m} \times \frac{\partial n_i^m}{\partial b_i^m} \tag{12}$$

The explicit function of the weight and bias values is usually the main function input to each layer of the neural network, so the second term of the above formula can be calculated.

If $S_i^m = \frac{\partial F}{\partial b_i^m}$ is defined as sensitivity, then the above equation can be simplified to:

$$\frac{\partial F}{\partial \omega_{I,j}^m} = S_i^m y^{m-1} \tag{13}$$

$$\frac{\partial F}{\partial b_i^m} = S_i^m \tag{14}$$

Back propagation of sensitivity. The sensitivity S_i^m is defined as $\boldsymbol{F}$ representing the true sensitivity of the net input *i* element variable on the *m* layer of the neural network. The recursion relation in the form of sensitivity matrix can be obtained by using Jacobian matrix to obtain the recursion relation of sensitivity matrix:

$$S^{m-1} = \frac{\partial F}{\partial n^{m-1}} = \left(\frac{\partial n^m}{\partial n^{m-1}}\right)\frac{\partial F}{\partial n^m} =$$

$$(F^{m-1}), (n^{m-1})(W^m)Ts^m \tag{15}$$

The sensitivity pathway is backpropagated to the first layer after the last layer of the neural network. After the error is backpropagated to the input layer, the weights between the hidden layer and the output layer and the weights from the hidden layer to the input layer are adjusted according to the values obtained from the adjustment formula. After repeated iterations, the neural network with the lowest mean square error can be obtained. The following is the adjustment weight formula taken between the output layer and the hidden layer of the neural network algorithm:

$$\omega_{I,j}^m(k+1) = \omega_{I,j}^m(k) - \eta S_i^m y_j^{m-1} \tag{16}$$

$$b_i^m(k+1) = b_i^m(k) - \eta S_i^m \tag{17}$$

3.3. Data processing principles for pricing factors

Factor indicators are usually divided into four types, very large indicators, very small indicators, intermediate indicators and interval indicators. In factor screening, different types of indicators need to be converted into the same type of indicators for evaluation and analysis. It is common practice to convert other types of indicators into very large indicators.

For very small indicators, you can use the reciprocal form or reverse form for processing, that is:

$$\tilde{x} = 1/x \ (x \neq 0) \tag{18}$$

Where: *M* is the upper bound of indicator *x*.

For intermediate indicators, let *m* be the lower bound value of indicator x, and *M* be the upper bound value of indicator *x*. If $x \in [m,(M+m)/2]$ then,

$$\tilde{x} = \frac{2(x-m)}{M-m} \tag{19}$$

If x∈((M+m)/2,M]，then

$$\tilde{x} = \frac{2(M-x)}{M-m} \tag{20}$$

For an interval type indicator, let the interval $[v_1, v_2]$ be the best interval of indicator *x*, *M* and *m* are the upper and lower bound values of indicator *x* respectively, then

$$\tilde{x} = \begin{cases} 1 - \dfrac{v_1 - x}{max(v_1 - m, M - v_2)} & x < v_1 \\ 1 & v_1 \le x \le v_2 \\ 1 - \dfrac{x - v_2}{max(v_1 - m, M - v_2)} & x > v_2 \end{cases} \tag{21}$$

Through the above methods, very small indicators, medium indicators, and interval indicators can be transformed into very large indicators. Then the normalized indicators are treated without dimension, usually the methods used are standardized treatment, linear proportion method, efficiency coefficient method and so on.

(1)Normalized treatment

Normalized treatment means subtracting the sample mean from the sample value and dividing by the standard deviation of the sample:

$$\tilde{x}_{ij} = \frac{(x_{ij} - \bar{x}_j)}{s_j} \tag{22}$$

Where, x_{ij} is the actual value of indicator sample *j*, $\bar{x}_i$ is the mean value of sample *j*, and s_i is the standard deviation of sample *j*. After normalization, the sample mean $\tilde{x}_{ij}$ is 0 and the standard deviation is 1. This method is suitable for the index samples with large amount of data and significant difference of actual values.

(2)Linear ratio method

$$\tilde{x}_{ij} = \frac{x_{ij}}{x_j^*} \tag{23}$$

Where, x_i^* is a specific value, which can be the maximum, minimum or average value according to the indicator characteristics. The method requires that $x_i^* > 0$, if the minimum value of the index value x_i^* is taken, then $\tilde{x}_{ij} \in [1, +\infty)$. If the maximum value x_i^* is taken, then $\tilde{x}_{ij} \in (-\infty, 1]$. If the average value x_i^* is taken, then $\tilde{x}_{ij} \in (-\infty, +\infty)$.

(3) Efficiency coefficient method

According to the principle of multi-objective programming, the satisfactory value and unacceptable value of all evaluation indicators are determined. The satisfactory value is taken as the upper limit and the unacceptable value is taken as the lower limit to obtain the satisfactory degree of each index value, and the score of each index is determined based on this, and the weighted average of the evaluation value of each index is synthesized to finally obtain the comprehensive status of the evaluated object. The power function is converted into measurable evaluation scores.

$$\tilde{x}_{ij} = p + \frac{x_{ij} - x_j^m}{x_j^M - x_j^m} \times q \tag{24}$$

Where, x_i^M is the satisfactory value of the index, x_i^m is the allowable value of the index and p,q is the known constant. The maximum value $\tilde{x}_{ij}$ is p+q and the minimum value is p.

4. Empirical analysis and application

In this paper, the lithium iron phosphate battery and prefabricated chamber will be used for example verification. Compared with conventional lead-acid batteries in the past, lithium iron phosphate batteries have a more stable voltage and are not easily affected by electricity. In addition, the lead and sulfuric acid used in lead-acid batteries are very harmful to environmental pollution. Lead is harmful to the environment and can be spread through the air, making it more polluting during production. Prefabricated cabin type is composed of prefabricated cabin body, secondary equipment screen cabinet (or frame), cabin body auxiliary facilities, etc., complete production, assembly, wiring, debugging and other work in the factory, and transported to the engineering site, which is located on the installation basis. The prefabricated cabin and its internal equipment realize the integration of the whole set of equipment by the manufacturer, realize the factory processing, reduce the site secondary wiring, reduce the design, construction, commissioning, workload, simplify the overhaul and maintenance work, shorten the construction cycle, and effectively support the rapid construction of the power grid. The model verification of the lithium iron phosphate battery and the prefabrication chamber will be carried out respectively in the following paragraphs.

4.1. Prefabricated optical cable

The prefabricated cable collected a total of 3000 samples, of which 2100 samples were used as the training set, 450 samples were used as the verification set, and 450 samples were used as the test set. The price of prefabricated cable is obtained through market inquiry, recent market retail price, recent price of the State grid and other channels, and the remaining parameters are obtained through the website of the National Bureau of Statistics. Since each parameter in the sample is of different orders of magnitude, to avoid the impact of dimension on the model, it is necessary to carry out normalization processing on each parameter, so that the value of each parameter is controlled between [0,1].

A BP neural network with 20 nodes is constructed and trained by training set and verification set samples. At the third iteration, the mean square error of the model is the smallest, so the model of the third iteration is taken as the final model.

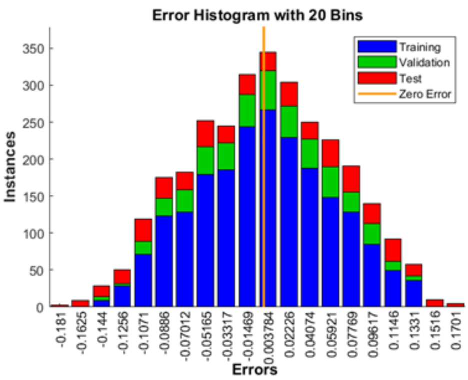


Figure 1: Mean square error of the model.

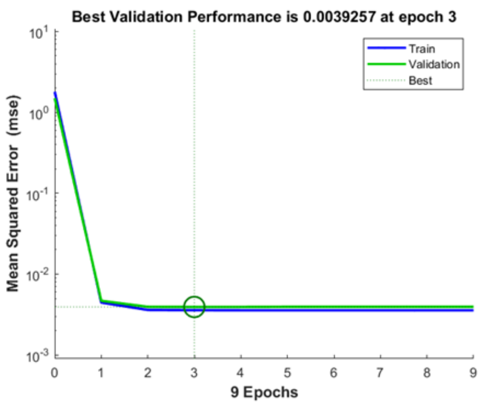


Figure 2: Model error.

Take the remaining samples as test samples, test the BP neural network, and substitute the output technical premium coefficient into the formula to get the predicted price of new equipment and new materials. By comparing the predicted price with the real price, the error rate of the pricing model can be obtained. Due to the large sample size of the test set, the following table only shows part of the test results.

Table 2: Sample test results.

	True value (yuan/km)	Predicted value (yuan/km)	Difference (yuan/km)	Error rate(%)
1	860	840	-20	-2.29%
2	990	1049	59	5.98%
3	900	941	41	4.57%
4	950	971	21	2.19%
5	1150	1128	-22	-1.91%
6	953	929	-24	-2.50%
7	1045	961	-84	-8.02%
8	1123	1094	-29	-2.61%
9	982	942	-40	-4.07%
10	970	955	-15	-1.55%
11	1063	1089	26	2.41%
12	1035	1078	43	4.15%
13	1135	1193	58	5.10%
14	1048	973	-75	-7.12%
15	950	930	-20	-2.11%

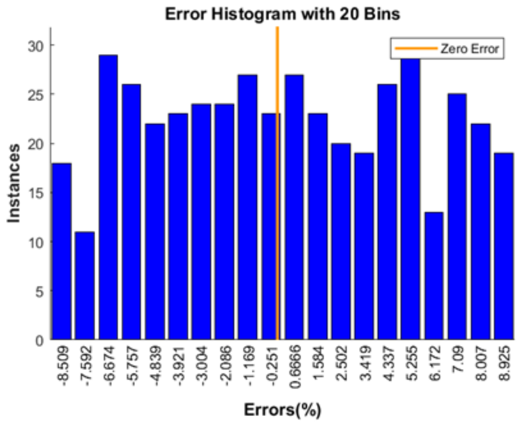


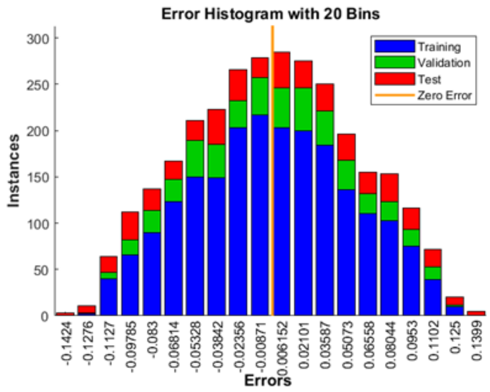
Figure 3: Test sample price error.

Through the analysis of the sample error of the test set, it can be seen that the average error of the model is 6.19%, and the control is less than 10%, which can accurately predict the price of prefabricated optical cable according to the input parameters.

4.2. Energy saving wire

Energy saving wire collected a total of 3000 samples, of which 2100 samples were used as the training set, 450 samples were used as the verification set, and 450 samples were used as the test set. The price of energy-saving wire is obtained through the market inquiry, the recent market retail price, the recent price of the State grid and other channels, and the remaining parameters are obtained through the website of the National Bureau of Statistics. Since each parameter in the sample is of different orders of magnitude, in order to avoid the impact of dimension on the model, it is necessary to carry out normalization processing on each parameter, so that the value of each parameter is controlled between [0,1].

A BP neural network with 20 nodes is constructed and trained by training set and verification set samples. At the second iteration, the mean square error of the model is the smallest, so the model of the second iteration is taken as the final model.



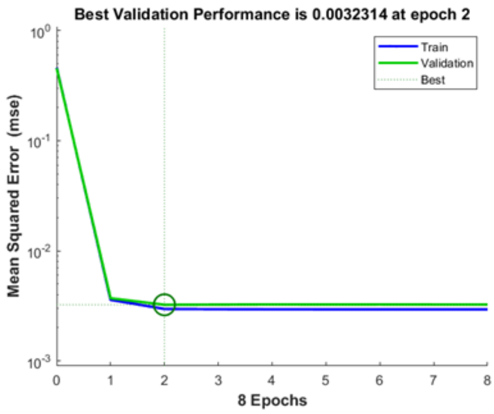


Figure 4: Mean square error of the model. Figure 5: Model error

Taking the remaining samples as test samples, test the BP neural network, and substitute the output technical premium coefficient into the formula listed in section 2.3.1 to get the predicted price of new equipment and new materials. By comparing the predicted price with the real price, the error rate of the pricing model can be obtained. Due to the large sample size of the test set, the following table only shows part of the test results.

Table 3: Sample test results.

	True value (yuan/t)	Predicted value (yuan/t)	Difference (yuan/t)	Error rate(%)
1	23300	25113	1813	7.78%
2	23100	21974	-1126	-4.87%
3	23540	22719	-821	-3.49%
4	25000	24727	-273	-1.09%
5	24809	23947	-862	-3.47%
6	22983	22131	-852	-3.71%
7	22525	21077	-1448	-6.43%
8	25044	23609	-1435	-5.73%
9	21561	20934	-627	-2.91%
10	23848	22195	-1653	-6.93%
11	21063	22821	1758	8.35%
12	24454	22852	-1602	-6.55%
13	23985	22430	-1555	-6.48%
14	24172	25006	834	3.45%
15	23819	24595	776	3.26%

Through the analysis of the sample error of the test set, it can be seen that the average error of the model is 5.01%, and the control is less than 10%, which can accurately predict the price of energy-saving wires according to the input parameters.

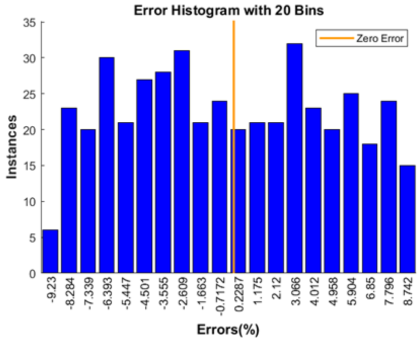


Figure 6: Test sample price error.

5. Conclusion

In this paper, the disturbance mechanism of new material cost is studied from the aspects of market factors and quota measurement factors, and the disturbance mechanism of various influencing factors is analyzed and sorted out to lay a foundation for the study of application pricing model. Based on BP neural network analysis, an application pricing model based on "cost analysis + technical premium" is constructed for new materials. Firstly, the pricing factors of new materials are analyzed in terms of data processing principles, and the models of lithium iron phosphate battery, prefabricated cabin, prefabricated optical cable, energy-saving wire and MMC converter valve tower are constructed and tested. The test results show that the error between the estimation results and the actual cost under the "four new" pricing model is controlled within 10%, and the test results are reasonable.

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