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Application of Artificial Intelligence Technology in Cost Control of Electric Power Project Cost Control

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SUMMARY: *The electric power sector occupies a key position in the national economy. To fulfill current cost-control requirements for power engineering projects, relevant personnel must adopt focused management strategies so that expenses can be controlled through more refined management. In this paper, the learning capability of BP neural networks is employed to refine the affiliation function of fuzzy rules and thereby strengthen the integration of the TS fuzzy system. An enhanced Bayesian classifier is introduced for evaluation, while a heuristic function is incorporated to reduce discretization problems in continuous values, thereby establishing a fuzzy neural network prediction model through K-Means clustering, with the training speed and effectiveness of the BP neural network further enhanced by the Levenberg-Marquardt optimization approach. The whole life-cycle cost of a power project is further classified by time, and model parameters are simultaneously applied in operational calculations to eliminate the price factor from the mathematical model. The evaluation scores of the three levels, general, good, and excellent, in relation to the cost management performance of electric power projects are 0.709, 0.731, and 0.69, respectively, and the performance evaluation in all models is close to 0.7, which indicates that artificial intelligence technology produces a meaningful effect on cost control. After these project cost management measures were carried out, the cost of an electric power project finally realized a balance of 4,395,400 yuan. By optimizing the construction plan, the expected cost-control target for the electric power project was ultimately achieved.*

KEYWORDS: *BP neural network; T-S fuzzy system; Levenberg-Marquardt; K-Means clustering; cost management; electric power project cost*

1 Introduction

Over the past few years, power enterprises in China have expanded rapidly and delivered notable results. Even so, behind this fast pace of development, a number of issues remain

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unresolved. One prominent problem is that the overall standard of cost governance in electric power projects is still not high, and existing practices in project cost regulation continue to lag behind broader market development trends, which has had a marked influence on the implementation of electric power projects [1, 2]. Cost management is one of the primary elements in the domain of engineering project management. In regard to the development of cost management, it has a long history that can be dated back to the early nineteenth century. At that time, project cost management was in its infancy; theoretical aspects had not been well-developed into systematic forms; and most construction organizations viewed project cost information as a resource for managerial purposes [3]. After a series of applications and developments, the PMI of America made the first attempt to introduce the concept of PMBOK based on experience gained and theoretical achievements in the late 1970s. This framework not only covers theoretical content associated with project management, but also includes systematic improvement methods, management tools, and cost-control practices relevant to project implementation [4, 5].

Tonchia [6] working from the project management knowledge framework developed by PMI, examined the background of cost control and cost budgeting, explained the related descriptive methods, and finally concluded that the scientific nature of project cost governance and cost activation should be strengthened. The study of project life-cycle cost management involves a variety of disciplines, including engineering economics, advanced mathematics, and engineering administration, with the goal of improving economic benefit assessment for engineering projects and achieving the dual objectives of shorter construction periods and lower costs [7, 8]. Through examining the contribution of BIM towards cost estimation of civil engineering projects in Kenya, Ninsmbe and others revealed several significant differences between BIM practitioners, and they concluded that BIM plays an important role in the cost management of civil engineering projects [9]. Elbeltagi and other researchers stated that modern cost control methods in enterprises are characterized by poor theory basis, lack of clarity in organizational implementation, lack of adequate expertise of cost controllers and deficiency in management tools. As a result, they recommended improving both project responsibility cost and target cost [10]. Zhou and Song analyzed cost budgeting and cost control of three cost items, including engineering design cost, construction cost, and material selection cost with the objective of improving cost control in green buildings [11]. Fernández-Valderrama and other researchers investigated engineering projects and costs and times risk factors, and they found that the construction phase poses the highest risk. The main risks identified were related to changes to the engineering designs, clients' request for changes, schedule delay, preparation of tender documents, inadequate scheduling and planning of work, shortage of skilled labor, and inadequate performance measurement [12]. For effective dynamic modeling, the proposed method includes project resources, project processes, schedule objectives, and cost objectives to estimate the overall cost overrun risk of construction projects [13].

Researchers outside China have proposed a range of methods for cost control, accurate prediction of cost overruns, and monitoring of engineering expenditure [14]. Moreover, Akinade et al. suggested that the use of BIM technology was expected to replace CAD technology in the engineering sector gradually. The researchers have outlined some motivations behind the substitution of BIM technology, described the benefits derived from BIM technology, and analyzed the value of BIM technology with regards to projects' lifecycle [15]. Youssefi and Celik suggested an approach towards the identification of the key reasons for cost overrun cases in the construction business field. Having identified 38 factors responsible for cost overruns in urban construction projects, the researchers prioritized factors which had the most effect on project expenses [16]. Park et al. designed a two-layer stacked heterogeneous integrated learning architecture for cost estimation in construction projects. Results showed that two-layer stacked integration model had greater efficiency than single integration model, hence improving objectiveness in participant selection in early stage of building construction [17]. Ramsey et al. noticed that PPP projects usually showed better cost management skills and had smaller cost variability range in comparison to DB projects [18]. Li et al. pointed to the significance of cost control as a factor ensuring successful project completion and value creating and presented the cost control process based on Analytic Hierarchy Process (AHP) and entropy weighting method [19]. The researchers highlighted the need for integration of BIM and Value Engineering (VE) to achieve improved functionality of construction projects before, during and after implementation.

Bringing management concepts into the costing field can make cost regulation more effective in electric power projects and can directly address problems caused by imperfect management procedures, thereby improving project efficiency and helping ensure the smooth and efficient completion of project tasks [20]. With the mathematical formalization of material costs in the transmission process of electric power communication systems as a key concern, Kuznetsov worked on quantifying construction costs that may arise in communication transmission systems and electric power engineering projects, and proposed several algorithms for solving the relevant model [21]. Through a detailed discussion of cost planning for transmission and substation network expansion projects under planning and control conditions, some studies identified practical cost-control methods for grid loads in traditional transmission and substation expansion network planning, incorporating blocking and risk costs into planning and cost-control research [22]. Murali and Kumar identified execution methods, worker management, equipment, schedules, and cost as some of the major elements influencing project cost governance. They further noted that these factors are closely linked to time overruns worldwide and identified the leading causes of both time and cost overruns in the construction sector by using a completed project [23]. Prasetyono et al. pointed out that project fluctuations are difficult to predict because cost variation is affected by a wide range of factors, including construction materials, human resources, and other project requirements used in construction. On this basis, they estimated the cost model using a regression approach, specifically linear regression, so as to obtain a formula for predicting the cost of project development [24].

The governing rules of the TS fuzzy system are defined in this paper, whereby the system output is computed as a function of the sum of all individual rule outputs with weights given by the degree of rule membership. Fuzzy rules are extracted while the membership (affiliation) functions are optimized using the learning ability of a neural network to enable better integration of the TS fuzzy system and neural network. In addition, Levenberg-Marquardt algorithm is utilized to optimize the training process and increase speed in the execution of operations carried out by the neural network. A cost model for whole-life cycle analysis in electric power engineering is developed in the framework of the TS fuzzy system coupled with LM-BP. To consider the influence of inflation on pricing, the fuzzy model is used in the arithmetic and design of the model, which undergoes evaluation through five-fold cross validation. The fuzzy model is then used in the actual estimation of costs in electric power engineering project cost budgeting through the life cycle.

2 T-S fuzzy system based on neural network integration

2.1 T-S fuzzy system based on neural network integration

2.1.1 T-S model structure

In this paper, the advantages of $T-S$ fuzzy system based on neural network integration in system modeling are utilized to construct a power project cost prediction model.

Let a multi-input, single-output $T-S$ fuzzy system has a total of n fuzzy rules, of which the first l fuzzy rule is expressed in the form:

$$\begin{aligned} &R^l : if \ x_1 \ is \ A_1^l, x_2 \ is \ A_2^l, \cdots x_m \ is \ A_m^l \\ &then \ y^l = p_0^l + p_1^l x_1 +, \cdots, + p_m^l x_m \end{aligned} \tag{1}$$

For a generalized input vector $\left(x_{10}, x_{20}, \cdots, x_{m0}\right)$, a weighted average of the outputs of all the rules gives the output of the system:

$$\hat{y} = \frac{\sum_{l=1}^{n} \mu^l y^l}{\sum_{l=1}^{n} \mu^l} \tag{2}$$

where μ^l is the affiliation of the generalized output vector to the lth rule:

$$\mu^l = \prod_{j=1}^{m} A_j^l(x_{j0}) \tag{3}$$

where $\prod$ is the fuzzy operator, usually using the take-small operation or the product operation.

Bringing the rule l into Eq. (2) can be obtained:

$$\hat{y} = \frac{\sum_{l=1}^{n} \mu^l y^l}{\sum_{l=1}^{n} \mu^l} = \sum_{l=1}^{n} \beta^l \left(p_0^l + p_1^l x_1 +, \cdots, + p_m^l x_m \right) \tag{4}$$

where $\beta^l = \mu^l \Big/ \sum_{l=1}^{n} \mu^l$.

2.1.2 BP Neural Networks

The fundamental element of a BP neural network is the BP neuron. The main distinction between a BP neuron and other types of neurons lies in its transfer function f , which is generally selected as a monotone increasing and differentiable function, such as the logarithmic Sigmoid function logsig, the tangent Sigmoid function tansig, or the linear function purelin. In most cases, the hidden layer adopts a Sigmoid-type transfer function, whereas the output layer more commonly applies a purelin-type transfer function. Figure 1 presents a representative BP neural network with a single hidden layer. Its input layer has m dimensions, the hidden layer includes n neurons using tansig as the transfer function, and the output layer consists of t neurons with purelin as the activation function. With this configuration, the network is able to approximate arbitrary output values.

It has been demonstrated theoretically that a BP neural network arranged in the form shown in Fig. 1 can approximate any nonlinear function with finite discontinuities to an arbitrary degree of precision, provided that the hidden layer contains a sufficiently large number of neurons. The training procedure adopted in BP neural networks is the error backpropagation algorithm, which plays a central role in ensuring the precision of nonlinear mapping.

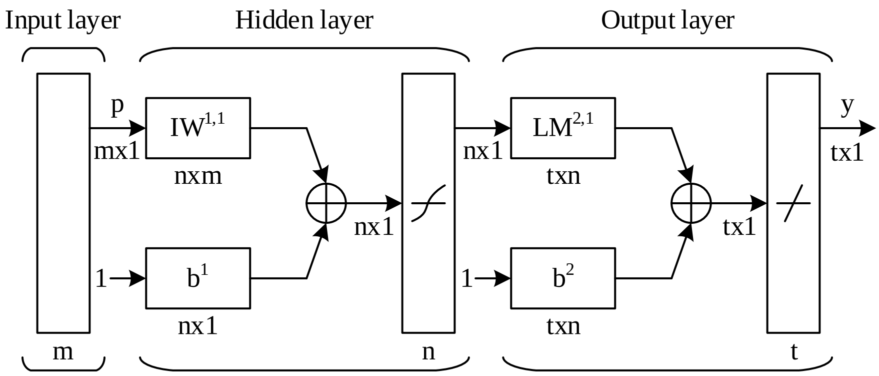

Figure 1: Neural Networks with single hidden layer

The actual output of neuron k at moment t is x_{out}^{k} and d_k denotes the desired output, the error can be expressed as:

$$e_k = d_k - x_{out}^{k} \tag{5}$$

The goal of an error correction learning algorithm is to minimize some e_k -based objective function such that the actual output of each output unit in the network approximates the desired output in some statistical sense. A commonly used objective function is the mean square error of e_k , which is the mean of the sum of squared errors:

$$J = E\left[\frac{1}{2}\sum_{k} e_k^2\right] \tag{6}$$

where E is the expectation operator. When applying J directly as the objective function, it is necessary to know the statistical properties of the whole learning process, and to solve this problem, the instantaneous value $\xi(k)$ of J at a certain moment is often used instead:

$$\xi(k) = \frac{1}{2}\sum_{k} e_k^2(k) \tag{7}$$

In order to satisfy the minimum storage requirement, the fastest gradient descent method is applied to derive the weight learning rule for any layer of the network:

$$\Delta w_{ji}^{(s)} = -\mu^{(s)} \frac{\partial \xi(k)}{\partial w_{ji}^{(s)}} \tag{8}$$

where s refers to the number of layers of the network and $\mu^{(s)} > 0$ is the corresponding learning rate parameter.

The modified equation for the network weights is:

$$w_{ji}^{(s)}(k+1) = w_{ji}^{(s)}(k) + \mu^{(s)} \delta_j^{(s)} x_{out,i} \tag{9}$$

2.1.3 Fuzzy neural network prediction modeling

In practical engineering applications, due to the large number of variables involved and the complexity of the situation, it is also difficult for domain experts to express the rules therein in a formalized way, which is often done with the help of intelligent computational methods to extract the rules directly from the data. The most commonly used way to automatically obtain fuzzy rules is to divide the data space into several fuzzy sets through clustering, and then adjust the affiliation function through the learning function of neural networks. Figure 2 shows a fuzzy system based on neural networks, along these lines, the model is constructed in the form of the network described in Figure 2 in the structure of the described fuzzy system. This is a multi-input, single-output model that can be easily generalized to the multi-input, multi-output case.

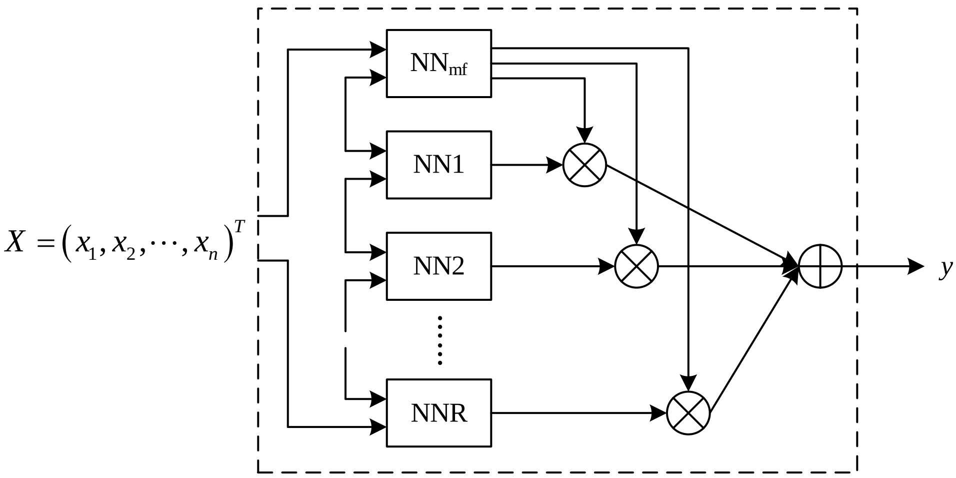

Figure 2: Neural networks with fuzzy system

The figure $NN_{mf}, NN_1, NN_2, \cdots, NN_R$ tables several relatively independent neural networks, which are BP neural networks using the error reversal algorithm. The network NN_{mf} accomplishes the parameter identification function of joint affiliation of each attribute, and its training data are all the records. The networks $NN_1, NN_2, \cdots, NN_R$ correspond to R fuzzy rules respectively, and the training data of each network is the data in the fuzzy set covered by the corresponding rule, and the weights of the network determined by the completion of the training of each neural network are able to embody all the fuzzy rules, and the outputs of the networks are synthesized according to Eq. (2) to obtain the model's The output of each network is synthesized by equation (2) to get the final output of the model.

2.2 Power project engineering cost prediction model construction

2.2.1 Optimizing Model Input Attributes

In power line engineering, historical data are mostly in the form of numerical attributes, and if a Bayesian classifier is to be used, it is necessary to discretize the continuous attribute values, which will produce a contradiction: a small number of discretizations will lead to serious information loss, while a large number of discretizations will lead to too long a computation time, too many branches of the decision tree, and ultimately it will be difficult to achieve the purpose of preferred attribute selection. Therefore, in this paper, the improved Bayesian classifier is used as the evaluation and heuristic function to avoid the discretization of continuous values.

When the attributes are continuous values, kernel density estimation is used to calculate the posterior probability, which becomes:

$$P\left(X \mid C_j\right)=\left(n_{C_j} h\right)^{-1} \sum_{X: C(X)=C_j} K\left(\frac{X-\mu_j}{h}\right) \tag{10}$$

where $h=\sigma$ is called the bandwidth of the kernel density, n_{C_j} is the number of samples of category C_j, and $K=g(X,0,1)$ is defined as a non-negative function, which is brought into the above equation to get the posterior probability of the Improved Bayesian Classification algorithm in the formula:

$$P\left(X \mid C_j\right)=\frac{1}{n_{C_j}} \sum_i g(X,0,1) \tag{11}$$

where $g(X,0,1)=\frac{1}{\sqrt{2\pi}} e^{-\frac{X^2}{2}}$ is a Gaussian density function with mean 0 and variance 1.

2.2.2 Fuzzy neural network prediction modeling

Clustering refers to an unsupervised pattern-recognition approach that partitions data records into several meaningful subsets according to the principle of maximizing intra-class similarity while minimizing inter-class similarity. Among clustering methods, k-means is a traditional algorithm that uses the sum of squared errors as its objective function. Suppose there are n samples $\left(x_1, x_2, \cdots, x_n\right)$, which are classified into k classes $\left(C_1, C_2, \cdots C_k\right)$, and the mean of each class is $\left(m_1, m_2, \cdots m_k\right)$, then the squared error sum expression is:

$$J=\sum_{k=1}^{K} \sum_{i=1}^{N_k}\left\|x_i-m_k\right\|^2 \tag{12}$$

where $\|\cdot\|$ denotes the paradigm expression, and the commonly adopted paradigm is the distance function, while N_k represents the number of samples included in the k th class.

Whereas in the case of past data related to construction of electric power engineering, an increase in the distance of transmission lines results in increases in other attributes such as distance traveled by automobiles and manual transport and number of towers. While using

Euclidean distance measure, more weight is given to the attributes associated with line length, thus making the clusters formed based on the attributes of the line length. The cosine-distance measure can be formulated as follows:

$$d\left(x,y\right)=\frac{\sum_{i=1}^{n}x_i y_i}{\sqrt{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}y_i^2}} \tag{13}$$

where x_i, y_i are the i th attribute of the project X and Y

The squared error sum of clustering results using the above cosine distance representation is expressed as:

$$J=\sum_{k=1}^{K}\frac{\left(\sum_{i=1}^{n}x_i m_k\right)^2}{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}m_i^2} \tag{14}$$

2.2.3 Neural network optimization

To enhance the speed and overall efficiency of network training, the Levenberg–Marquardt optimization method is adopted. The L-M algorithm can be regarded as an improved Newton-type method. It treats the network output error as the expected function and employs the iterative mechanism of Newton's method to continuously adjust network weights so that the expectation function can be minimized. If the network is configured as a BP neural network with a single hidden layer, the energy function may be expressed as:

$$E(w)=\frac{1}{2}\sum_{q=1}^{Q}\left(d_q-x_{out,q}^{(3)}\right)^T\left(d_q-x_{out,q}^{(3)}\right)=\frac{1}{2}\sum_{q=1}^{Q}\sum_{h=1}^{n_s}\left(d_{qh}-x_{out,qh}^{(3)}\right)^2 \tag{15}$$

where Q is the total number of training patterns, w denotes the vector containing all the weights in the network, d_q is the desired output, and $x_{out,q}^{(3)}$ is the actual network output of the q th training pattern. The iterative formula for the weights that minimize the energy function can be expressed as:

$$w(k+1)=w(k)-H_k^{-1}g_k \tag{16}$$

Among them:

$$H(k)=\nabla^2 E(w)\big|_{w=w(k)} \tag{17}$$

$$g(k)=\nabla E(w)\big|_{w=w(k)} \tag{18}$$

The $L-M$ algorithm improves on the problem of pathological matrices that can occur in Newton's algorithm by obtaining an expression for updating the network weights:

$$w(k+1) = w(k) - \frac{1}{\mu_k} J_k^T e_k \tag{19}$$

where μ_k is the learning rate parameter and J is the Jacobi matrix:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} & \frac{\partial e_1}{\partial w_2} & \cdots & \frac{\partial e_1}{\partial w_N} \\ \frac{\partial e_2}{\partial w_2} & \frac{\partial e_2}{\partial w_2} & \cdots & \frac{\partial e_2}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_p}{\partial w_1} & \frac{\partial e_p}{\partial w_2} & \cdots & \frac{\partial e_p}{\partial w_N} \end{bmatrix} \tag{20}$$

can be calculated for each element of the matrix using a simplified calculation that

$$J_{i,j} \approx \frac{\Delta e_i}{\Delta w_j} \tag{21}$$

3 Component analysis and application of computational models

3.1 Whole Life Cycle Costs for Power Projects

Figure 3 for the project's full life cycle cost by time detailed division, the cost of the various stages of the power project can be directly used to add the cost, which is more special is the penalty cost, penalty cost is mainly due to the project's power network failure, resulting in insufficient power supply or interruption of the supply of power, the loss caused by the number of substation results of the power grid power supply reliability level of the most direct reflection of the size of the penalty cost is closely related to the probability of grid outage duration of the power grid average outage power and maintenance costs after the grid outage. It is the most direct reflection of the level of reliability of the power grid power supply of the number of substation results, the specific size of the penalty cost and the probability of grid outage, the duration of grid outage, the average power grid outage and the power grid outage after the maintenance costs are closely related to the specific calculation of the penalty cost is as follows:

$$CF_i = \sum_j k\lambda_j \left(a \times W_j \times T_j \times RC_j \times MTTR_j \right) \tag{22}$$

where: k is the failure rate adjustment factor, λ_j is the j average annual failure rate of the equipment, T_j is the j annual time of interruption of power supply due to equipment failure, W_j is the power of interruption of power supply due to j equipment failure, RC_j is the average cost of repairing j equipment failures, $MTTR_j$ is the average time of repairing the equipment, and a is the value of the average interruption of power supply of the relevant user.

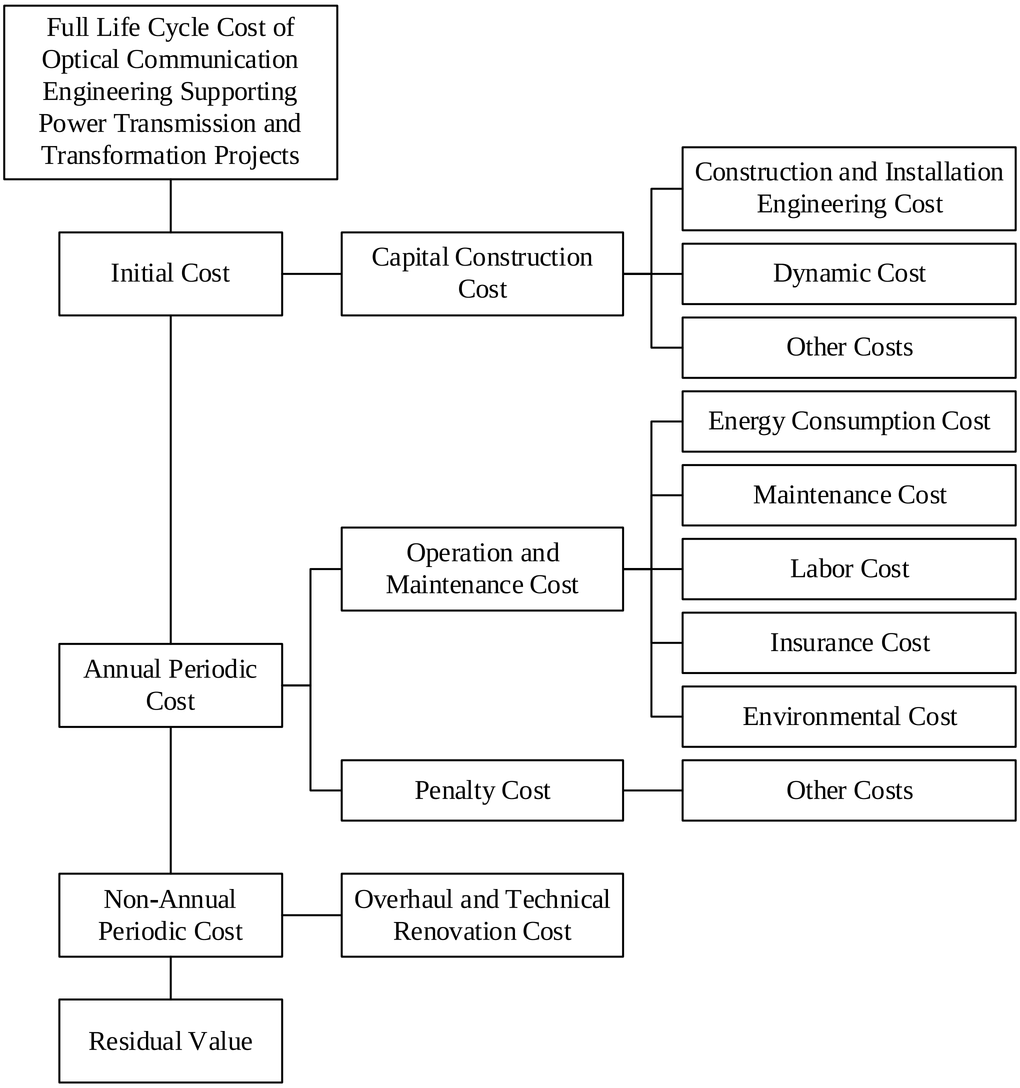

Figure 3: The full life cycle cost of the project is detailedly divided by time

The next step is to establish the whole life cycle cost analysis model of the transmission and substation project supporting optical communication project.

In order to deal with the uncertainty factors of the transmission and substation project, this topic is based on the trapezoidal affiliation function of fuzzy logic, because the trapezoidal affiliation function, compared with the triangular affiliation function and the Gaussian affiliation function, has a wider scope of application and a better ability of describing the actual problem.

Take the cost value of the annual cycle of the transmission and substation project supporting optical communication project as an example, the highest cycle cost of a certain year will not be less than d or greater than a, and the most likely is between b and c. Therefore, this cost fuzzy uncertainty can be described by a trapezoidal subordination function, as shown in Fig. 4:

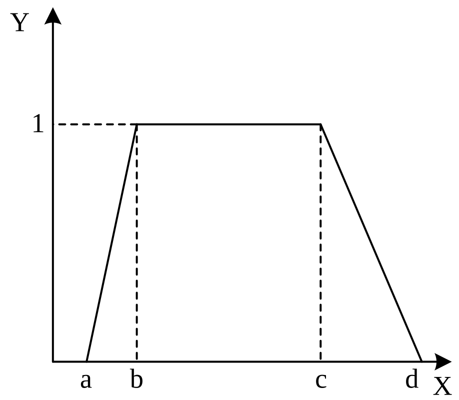

Figure 4: Membership function of trapezium

Let a transmission and substation project has a total of M options, and the net present value of the i th option is NPV_i. The formula for the whole life cycle cost analysis of a transmission and substation project is as follows:

$$NPV_i = C_{0i} + PMW \times CO_i + PWN_{im} \times CM_i + PWA \times CF_i - PWS \times S_i \tag{23}$$

$$PWA = \frac{1}{r}\left(1-(1+r)^{-T}\right) \tag{24}$$

$$PWS = \left(1+r\right)^{-T} \tag{25}$$

$$PWN_{im} = \frac{1-(1+r)^{-n_{im}/f_{im}}}{(1+r)^{1/f_{im}}} \tag{26}$$

where C_{0i} is the initialized construction cost of scenario i, CO_i is the annual cycle cost of scenario i, CM_i is the overhaul cost of scenario i (costs incurred in the non-annual cycle), CF_i is the penalty cost of scenario i, S_i is the salvage value of scenario i at the end of the period of analysis, r is the discount rate, T is the analysis period, f_{im} is the frequency of the non-annual cycle costs of scenario i, and n_{im} is the number of times the non-annual cycle costs of scenario i are incurred, which is computed as follows:

$$n_{im} = \begin{cases} \operatorname{int}\left(\dfrac{T}{f_{im}}\right), & if \quad rem\left(\dfrac{T}{f_{im}}\right) \neq 0 \\ \dfrac{T}{f_{im}} - 1, & if \quad rem\left(\dfrac{T}{f_{im}}\right) = 0 \end{cases} \tag{27}$$

3.2 Mathematical model solving

3.2.1 Elimination of price influencing factors

For engineering projects, as time moves forward, the construction cost of the project will occur more obvious changes, mainly because of changes in the purchase of construction materials prices, and such changes will further affect the effect of comparison between different programs. Therefore, this paper needs to do some operations on the model parameters to eliminate the price factor, as follows:

First, the initialized cost of scheme i is used to normalize the other costs in the formula, and the following equation is assumed to hold:

$$C_{0i}\overline{CO}_i = CO_i \tag{28}$$

$$C_{0i}\overline{CF}_i = CF_i \tag{29}$$

$$C_{0i}\bar{S}_i = S_i \tag{30}$$

$$C_{0i}\overline{NPV}_i = NPV_i \tag{31}$$

After normalization, the original formula becomes:

$$\overline{NPV}_i = 1 + PMW \times \overline{CO}_i + PWN_{im} \times \overline{CM}_i + PWA \times \overline{CF}_i - PWS \times \bar{S}_i \tag{32}$$

It can be further rewritten as:

$$\overline{NPV}_i = 1 +^d ARCO_i +^d NRCM_i +^d ARCF_i -^d SAV_i \tag{33}$$

The cost of the original initial i th scenario is then used to normalize the cost of all other scenarios, which in turn defines a factor for the initial cost after normalization:

$$C_{01}\hat{I} = C_{0i} \tag{34}$$

The following equation is obtained:

$$N\hat{P}V_i = I +^d AR\hat{C}O_i +^d NR\hat{C}M_i +^d AR\hat{C}F_i -^d S\hat{A}V_i \tag{35}$$

3.2.2 Defining fuzzy function solutions

For a fuzzy set A, RA is defined as:

$$R_A = \frac{1}{2}\int_0^1 {}^a\alpha_1 +^a \alpha_r d\alpha = \frac{1}{2}\left(A_l + A_r\right) \tag{36}$$

3.2.3 Defining the Confidence Test Arithmetic

$$CI_1 = \frac{A_2}{2A_2 + A_2 + A_3} \tag{37}$$

$$CI_2 = \frac{A_1 + A_2}{2A_1 + A_2 + A_3} \tag{38}$$

$$0 \le CI_1 \le 1 \tag{39}$$

$$0 \le CI_2 \le 1 \tag{40}$$

CI_1 indicates confidence that option A is better than option B, and CI_2 indicates confidence that option A is at least as good as option B. At this point, the whole life cycle cost analysis model and its solution process for power projects are completed.

4 Empirical study of cost forecasting for power projects

4.1 Project Status

For the present research, the process through which data were collected has been sufficient enough to capture the price cuts that have been witnessed in wind turbines and wind-powered machinery. To enable better comparability between different data sets, one data set covering the years from 2019-2023 has been used. To maintain data integrity, the collected data have been cleaned and processed.

4.2 Subgroup comparison validation

4.2.1 Model grouping

To examine whether the L-M algorithm can effectively improve the neural-network prediction model, a comparative analysis involving several groups is carried out in this paper. The computing environment used for the program consists of a 2.2GHz 4-core Intel Corei5-5200 CPU, 4G RAM, a 64-bit operating system, and MATLAB R2016a as the programming platform.

To preserve consistency and comparability in the dataset, 20 samples were randomly selected as testing samples at the beginning of each round of model comparison, while the remaining data were used as training samples. The predicted values were then compared with the observed values so as to test the predictive performance of the model.

In the first group of model comparison, with a focus on neural-network optimization, the genetic-algorithm-based optimization method widely used in electric power engineering cost prediction is taken as a benchmark. Accordingly, the BP neural network algorithm, the GA-BP neural network algorithm, and the L–M neural network algorithm are compared and tested in this study to verify how effective the L–M algorithm is in optimizing neural networks.

4.2.2 Performance evaluation indicators

To assess the accuracy of the algorithmic model, this study chooses mean absolute error (MAE) and mean absolute percentage error (MAPE) as stability indicators, and uses mean square error (MSE), root mean square error (RMSE), and accuracy-related indices to evaluate the BP model, the GA-BP model, and the LSSA-BP model. Mean Absolute Error (MAE) reflects the average magnitude of absolute error and directly indicates the actual prediction deviation. Mean Absolute Percentage Error (MAPE) represents the average ratio between the absolute deviation of the predicted value and the actual value, which reduces the influence of scale magnitude and is therefore suitable for the objective assessment of deviation. Mean Square Error (MSE) is defined as the ratio of the sum of squared deviations between predicted values and actual values to the total number of samples. Root Mean Square Error (RMSE) is the square root of that ratio and further reflects the overall extent of prediction error. The specific formula is given below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - Y_i'\right| \tag{41}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_i'\right)^2 \tag{42}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_i'\right)^2} \tag{43}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - Y_i'}{Y_i}\right| \tag{44}$$

where: n denotes the number of test samples, Y_i denotes the actual value, and Y_i' denotes the model predicted value.

4.3 Comparative analysis of neural network optimization

4.3.1 Optimization algorithm model parameter setting

In order to make comparisons more accurate, the iteration number for both the L-M and genetic algorithms is set as 1000, and the population size is set as 100. Mean squared error (MSE) is adopted as the fitness function. A smaller MSE implies better training accuracy of the model, which means that the predictive performance of the model will be improved as well. Considering that the multi-layer neural network is usually used to handle the nonlinear problem, a three-layer neural network is used as the prediction model, including the input layer, the hidden layer, and the output layer. According to the selected input/output indicator, the number of the input node is set as 7, while the number of the output node is set as 1.

If the hidden layer has too few nodes, the predictive ability of the network will be reduced. However, if the number of the hidden nodes is too large, there will be the risk of overfitting, and the possibility of converging to the local optimum point will also increase. Experiments show that the best predictive performance can be achieved when the hidden layer has 7 nodes. Therefore, the structure of the network is 7-7-1.

4.3.2 Experimental results and analysis

Figure 5 presents a comparison between the actual values and the predicted values generated by the BP, GA-BP, and LM-BP models, while Figure 6 illustrates the error comparison among these three models. The results show that all three models produce relatively satisfactory prediction performance. However, compared with the GA-BP and LM-BP models, the BP model exhibits substantial deviation in Samples No. 5 and No. 16, suggesting weaker prediction accuracy and lower stability. In practical engineering projects, the cost-prediction error during the investment decision-making stage of power projects should generally remain within 10%. The LM-BP model performs better in this respect, with the relative error at each point remaining below 10%, and the mean absolute error reaching 0.9905, which is a favorable outcome. Even so, these findings alone are not sufficient to fully evaluate the predictive accuracy and stability of each model quantitatively, so a further analysis of model error comparison is still required.

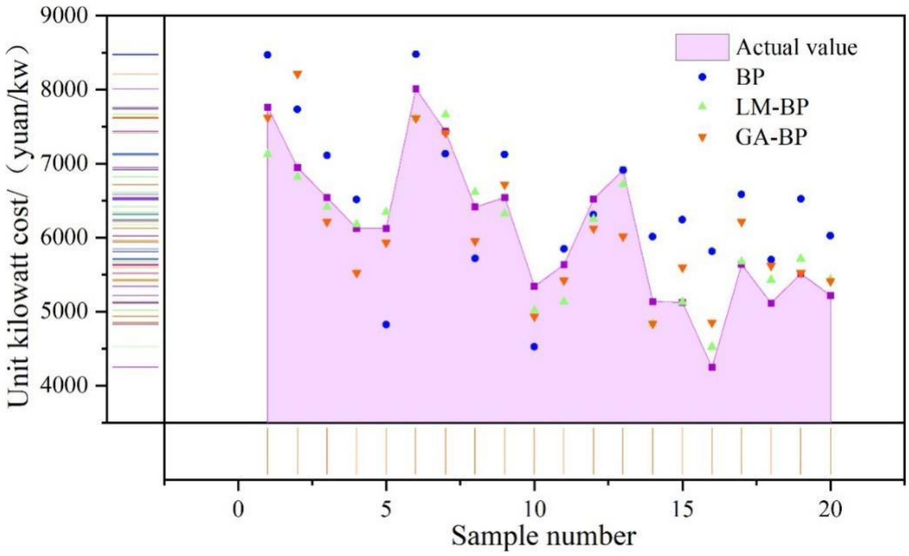

Figure 5: Comparison of the predicted values of the three models with the actual values

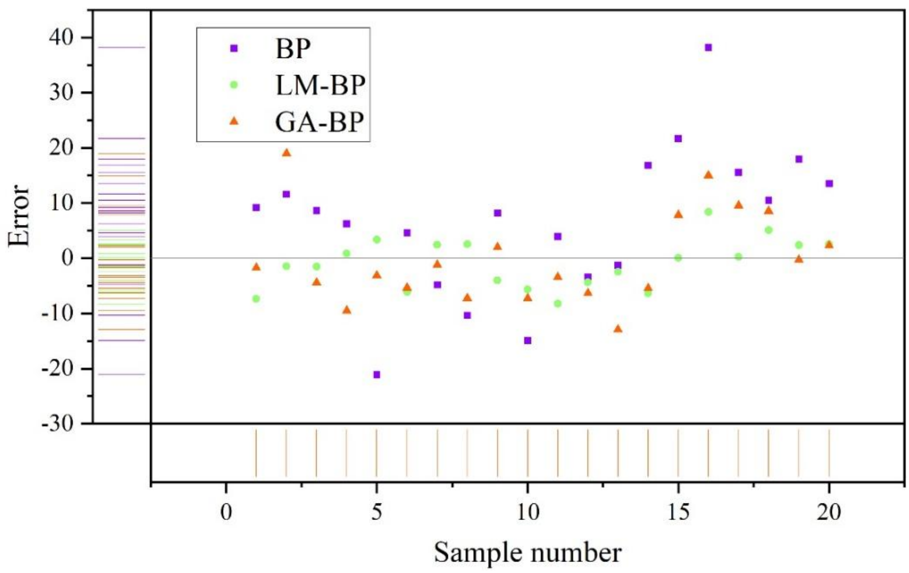

Figure 6: Comparison of errors among the three models

5 Costing and evaluation of engineering costs for power projects

5.1 Evaluation of cost management performance

Figure 7 shows the evaluation of cost management performance of electric power project, which is different in different modes. Overall, the evaluation scores for the three levels of average, good and excellent cost management performance are 0.709, 0.731 and 0.69, respectively, and the ratings of all the modes are close to 0.7, indicating that the artificial intelligence technology is effective for cost control.

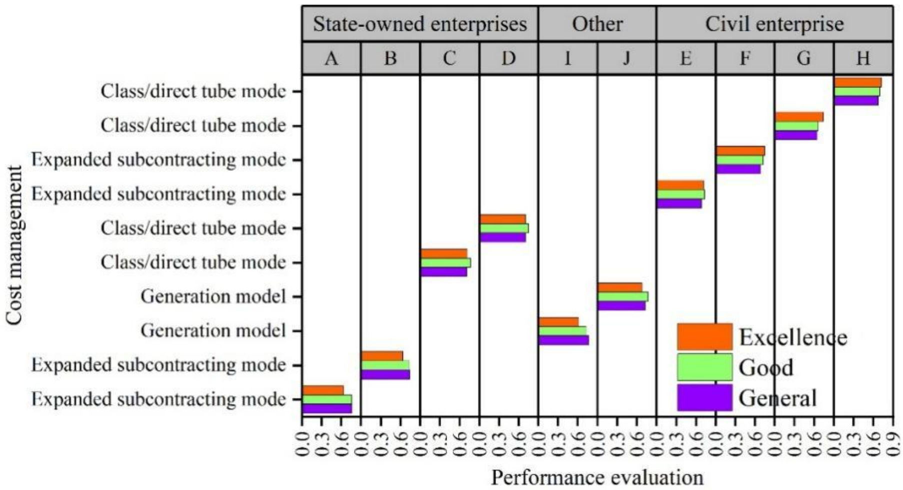

Figure 7: Evaluation of cost management performance of power engineering project

5.2 Whole Life Cycle Cost Analysis of Electricity Projects

5.2.1 Effectiveness of cost management implementation in power engineering projects

The application of the TS fuzzy system in combination with LM-BP enables the evaluation of the earned value analysis (EVA) method based on three graphs: ACWP, BCWS during the planning phase of the project, and BCWP. Through the EVA approach, these three curves demonstrate the interconnection between the project costs, schedule performance, and budgeting process.

The cost management strategies adopted for the construction of this power plant significantly improved the efficiency and performance of the project implementation process. The budgeted costs of the project phases achieved up until May 2023, according to the project schedule and earned value analysis, are shown in Table 1. The budgeted cost of completed work for the first, second, third, and fourth phases is 14,526,900 yuan, 24,816,200 yuan, 30,941,700 yuan, and 19,078,000 yuan, respectively.

Table 1: Project Schedule and BCWP Correspondence Table (Unit: ten thousand yuan)

Project progress	Time	BCWP
Project commencement and construction preparation	Mar-22	332.15
	Apr-22	723.49
	May-22	1452.69
Assumption of low-voltage lines and installation of electrical equipment	Jun-22	1826.36
	Jul-22	2542.36
	Aug-22	2863.36
	Sep-22	3315.36
	Oct-22	3934.31
Electrical test and completion	Nov-22	5015.96

	Dec-22	6425.63
	Jan-23	7028.48
Completion acceptance	Feb-23	7636.66
	Mar-23	8215.69
	Apr-23	8755.69
	May-23	8936.36

5.2.2 Earned value analysis of power engineering projects

The earned value analysis table for its specific implementation effects is shown in Table 2, and by May 2023, the known data are shown below:

BCWS (the budgeted cost for completing the tasks at this stage) = 103,873,200 yuan

BCWP (the actual budgeted cost for completing the tasks of this stage) = 89.3636 million yuan

ACWP (the actual cost of completing the tasks at this stage)= 84.9682 million yuan

The calculation of project cost differences is as follows:

CV=BCWP-ACWP= 89.3636-84.9682 = 4.3954 million yuan

CV= 4.3954 million yuan >0, cost balance.

CPI=BCWP/ACWP=8936.36/8496.82=1.052>1, cost balance

The calculation of project progress differences is as follows:

SV=BCWP-BCWS= 89,363,600-103,873,200 = -14.5096 million yuan

SV= -14.5096 million yuan <0, progress delay.

SPI=BCWP/BCWS=8936.36/10387.32=0.86<1, progress delay.

Table 2: Earned Value Analysis for Project (Unit: ten thousand yuan)

Time	Current value			Cumulative value				
	BCWS	BCWP	ACWP	BCWS	BCWP	ACWP	SPI	CPI
Mar-22	174.69	332.15	334.25	174.69	332.15	334.25	1.90	0.99
Apr-22	223.36	391.34	258.26	398.05	723.49	592.51	1.82	1.22
May-22	652.45	729.2	752.36	1050.5	1452.69	1344.87	1.38	1.08
Jun-22	952.15	373.67	534.65	2002.65	1826.36	1879.52	0.91	0.97
Jul-22	593.15	716	722.36	2595.8	2542.36	2601.88	0.98	0.98
Aug-22	594.15	321	485.69	3189.95	2863.36	3087.57	0.90	0.93
Sep-22	593.12	452	264.58	3783.07	3315.36	3352.15	0.88	0.99
Oct-22	740.96	618.95	612.58	4524.03	3934.31	3964.73	0.87	0.99
Nov-22	715.25	1081.65	1125.36	5239.28	5015.96	5090.09	0.96	0.99
Dec-22	1826.36	1409.67	1425.36	7065.64	6425.63	6515.45	0.91	0.99
Jan-23	748.25	602.85	828.36	7813.89	7028.48	7343.81	0.90	0.96
Feb-23	425.18	608.18	512.36	8239.07	7636.66	7856.17	0.93	0.97
Mar-23	963.85	579.03	158.48	9202.92	8215.69	8014.65	0.89	1.03
Apr-23	1054.25	540	372.69	10257.17	8755.69	8387.34	0.85	1.04
May-23	130.15	180.67	109.48	10387.32	8936.36	8496.82	0.86	1.05

Figure 8 shows the earned value curve of the project. During the first period, the Budgeted Cost for Work Scheduled (BCWS) or the budgeted cost for the execution of activities during this period was less than the Budgeted Cost for Work Performed (BCWP) or budgeted cost for the completion of work and the Actual Cost of Work Performed (ACWP) or actual cost incurred for completing the activities. The respective figures are BCWS = 1.7469 million yuan, BCWP = 3.3215 million yuan, and ACWP = 3.3425 million yuan. As the project proceeded, the sum of BCWS kept increasing beyond both BCWP and ACWP. At the completion of the project, the BCWS figure became 103.8732 million yuan.

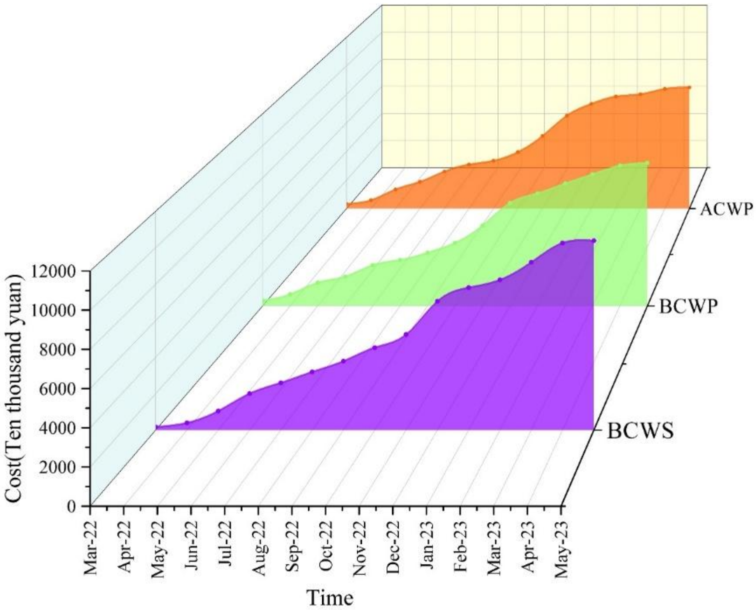

Figure 8: Project Earned Value Curve

Based on the calculation results in Table 2, the CV, SV, SCI and CPI of a power project are calculated and analyzed below, and the results are shown in Table 3.

Before May 2022, the index evaluation indicators SPI and CPI are above 1, indicating that the cost is within budget and the schedule is ahead of schedule. However, after May 2022/May, the index evaluation indicators appear to be less than 1, indicating cost overruns and schedule delays.

Table 3: The index of deviation of the power project

Time	Difference index		Index evaluation index		Specific analysis
	SV	CV	SPI	CPI	
Mar-22	157.46	-2.1	1.9	0.99	The cost is within the budget and the progress is ahead
Apr-22	325.44	130.98	1.82	1.22	The cost is within the budget and the progress is ahead
May-22	402.19	107.82	1.38	1.08	The cost is within the budget and the progress is ahead
Jun-22	-176.29	-53.16	0.91	0.97	Cost overruns and delays
Jul-22	-53.44	-59.52	0.98	0.98	Cost overruns and delays

Aug-22	-326.59	-224.21	0.9	0.93	Cost overruns and delays
Sep-22	-467.71	-36.79	0.88	0.99	Cost overruns and delays
Oct-22	-589.72	-30.42	0.87	0.99	Cost overruns and delays
Nov-22	-223.32	-74.13	0.96	0.99	Cost overruns and delays
Dec-22	-640.01	-89.82	0.91	0.99	Cost overruns and delays
Jan-23	-785.41	-315.33	0.9	0.96	Cost overruns and delays
Feb-23	-602.41	-219.51	0.93	0.97	Cost overruns and delays
Mar-23	-987.23	201.04	0.89	1.03	Cost overruns and delays
Apr-23	-1501.48	368.35	0.85	1.04	Cost overruns and delays
May-23	-1450.96	439.54	0.86	1.05	Cost overruns and delays

At the same time, the difference index and index evaluation index are drawn from the data in Table 3, as shown in Fig. 9 and Fig. 10.

According to the earned value analysis, after the implementation of project cost management measures, an electric power project finally realized a balance of 4,395,400 yuan, the main reason for this achievement is that in the process of project construction, timely adjustment of the construction strategy, the replacement of strong skill level, high comprehensive quality of the operating personnel, and the use of construction materials to strictly manage the reduction of additional cost expenditures, so that finally Achieved the expected cost management objectives of an electric power project.

However, the project duration due to some construction personnel changes, midway design changes, a power company's overall project management level is limited for a number of reasons, compared with the original plan completion time in early May 2023 there is a certain lag, the final acceptance of the completion of the time for the end of May 2023.

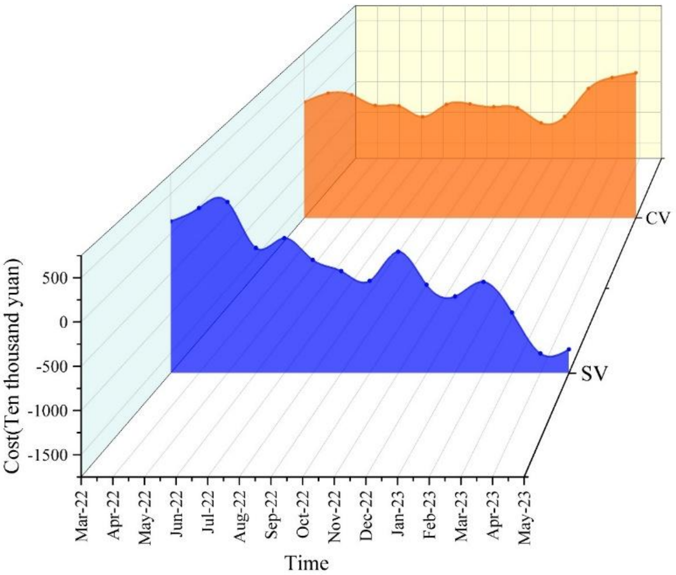

Figure 9: Difference indicator

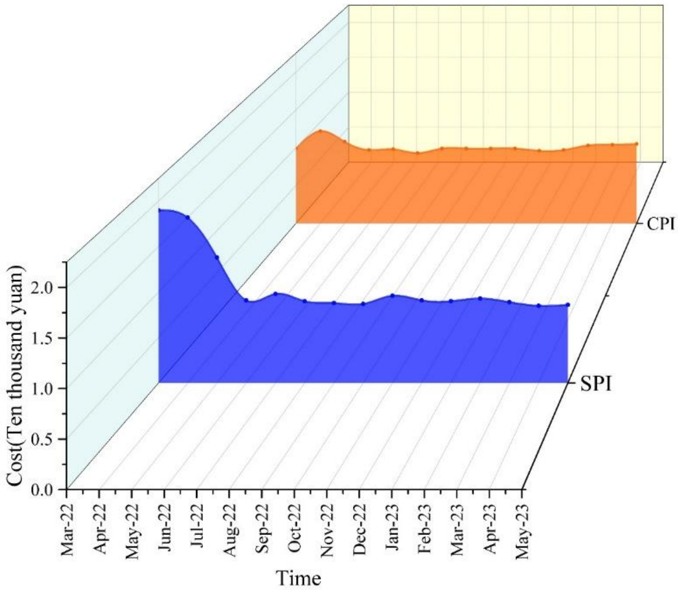

Figure 10: Exponential evaluation

6 Conclusion

In this research, a model for predicting the costs of power projects using a combination of TS fuzzy system and neural network architecture is developed. Using artificial intelligence techniques, rules are generated from the data, the input domain is divided into several fuzzy domains through clustering, and the learning ability of neural networks is used to improve the membership functions. In addition, the L-M enhanced Newton method is used to optimize the neural network. The optimized model is then used to calculate and evaluate the whole-life cycle cost of a practical electric power project based on the mathematical model. It is found that the LM-BP model has better prediction results, with a relative error of each point being controlled within 10% and the mean absolute error being 0.9905. For the cost-management practice of this electric power project, the TS fuzzy system combined with LM-BP is further applied to evaluate the whole-life-cycle cost. The budgeted cost of completed work (BCWP) for the four project phases is 14,526,900 yuan, 24,816,200 yuan, 30,941,700 yuan, and 19,078,800 yuan, respectively. The index values of SPI and CPI are also calculated. Before May 2022, both SPI and CPI remain above 1, indicating that the project cost stays within the planned budget. Eventually, the electric power project achieves a balance of 4,395,400 yuan and reaches the expected cost-control objective.

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