# Research on Cost Determination Technology for Power Grid Engineering Based on Bayesian Deep Learning Network Potential Impact Factor Mining

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**Abstract.** The cost of power grid project is a multivariable and highly nonlinear problem. With the continuous expansion of the investment scale, the factors affecting the project cost are complex, diversified, volatility and other characteristics, and the single prediction model is often not comprehensive enough. In view of this, this paper excavates out the potential impact factor of project cost based on artificial neural network learning, which has a certain self-learning, adaptive ability, is a high accuracy, wide applicability of power grid engineering cost determination model, has high value, can further improve the efficiency of power grid enterprises.

**Keywords:** Power grid engineering · Bayesian deep learning network · cost determination technology

## 1 Introduction

At present, the analysis of cost influencing factors at home and abroad only stays in a single control stage, without building a scientific and complete factor library, and has not yet achieved quantitative analysis of the mechanism and degree of factor influence. Regarding the characteristics of different types of power grid projects, research on power grid cost determination techniques that consider the impact of uncertainty factors is even rarer.

Reference [1] constructed a static cost indicator value prediction model GRA-PSO-SVR and a dynamic cost indicator value prediction model GM (1, 1) - BP. Based on this, a transmission engineering cost control system based on cost lean management objectives was constructed, and multiple empirical studies were conducted. Reference [2] uses the ARIMA model prediction method to train and test historical engineering data, and ensure that the error is within a reasonable range. Reference [3] used existing distribution network engineering data to validate the proposed BP neural network prediction model. The experimental results showed that the proposed prediction model had high accuracy, good practicality, and feasibility. Literature [4] uses statistical analysis method to prove


S. H. B. D. M. Zailani et al. (Eds.): ICMSEM 2023, 259, pp. 840–847, 2024.
https://doi.org/10.2991/978-94-6463-256-9_84

that the probability distribution of unit cost of final settlement of substation project is similar to normal distribution, and the probability distribution of unit cost of final settlement of line project is similar to normal distribution. Reference [5] based on actual cost data of power grid overhead line engineering, proves that the improved PSO-SVM model can effectively predict the cost of power grid overhead line engineering, with an average error rate of only 1.23%.

## 2 The Main Research Ideas of This Article

The power grid engineering cost simulation and determination technology based on improved Bayesian deep learning network proposed in this article is significantly superior to other models in terms of cost prediction skills and reliability, and can provide effective uncertainty estimation and prediction results. The main research ideas of this article are shown in Fig. 1.

From Fig. 1, it can be seen that in this article, the cost related data of the engineering estimate is taken as the input value and input into the LSTM deep learning network model; Then, based on random gradient Hamiltonian Monte Carlo sampling, the expected settlement cost control indicators are obtained.

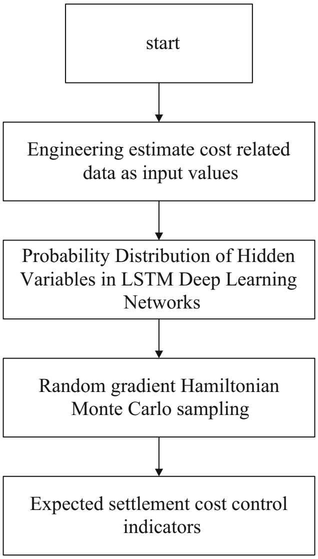


**Fig. 1.** The main research ideas of this article.

# 3 Construction of Technical Model of Power Grid Engineering Cost Simulation Determination Based on Improved Bayesian Deep Learning Network

This proposed grid engineering cost simulation technology based on improved Bayesian deep learning network, the model construction process is as follows:

1) Based on the engineering cost database, select the pre estimate cost data x and settlement cost indicator y to form a new training sample database, represented as $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where the cost data is constantly updated over time. When new cost data $x_{n+1}$ is given, the target obtains the settlement cost control indicator $p(y_{n+1}|x_{n+1}; D)$.

For $x_1, y_1, x_2, y_2, x_n, y_n$ represent the input (cost data before estimate) and output (settlement cost index) in the training sample data respectively. The $y_{n+1}$ indicates the corresponding output settlement cost index given the new cost data $x_{n+1}$.

2) The cost index prediction model based on the LSTM deep learning network is adopted to process the cost control index data in a nonlinear way.

## 3.1 Construction Based on the Bayesian Deep Learning Network Model

In many deep learning models, Long Short Term Memory Network (LSTM) can model nonlinearly and process data with multiple dimensions in a nonlinear way. The introduced gating mechanism can effectively solve the problem of gradient explosion or disappearance. Among them, the sender gate $i^{(t)}$ controls how much information of the candidate state at the current moment needs to be saved, the forgetting gate $f^{(t)}$ controls the internal state of the previous moment $c^{(t-1)}$ how much information needs to be forgotten, and the output gate $o^{(t)}$ controls the internal state of the current moment $c^{(t)}$ how much information needs to be output to the external state. The path to control information transmission is calculated as follows:

$$i^{(t)} = \sigma(W^{(i)}x^{(t)} + U^{(i)}h^{(t-1)} + b^{(i)}) \tag{1}$$

$$f^{(t)} = \sigma(W^{(f)}x^{(t)} + U^{(f)}h^{(t-1)} + b^{(f)}) \tag{2}$$

$$o^{(t)} = \sigma(W^{(o)}x^{(t)} + U^{(o)}h^{(t-1)} + b^{(o)}) \tag{3}$$

where $\sigma(\bullet)$ is the sigmoid function, its output interval is (0, 1), $x^{(t)}$ is the input of the current moment, and $h^{(t-1)}$ is the external state of the previous moment, namely the hidden layer state at time $t - 1$. $W^{(i)}$, $W^{(f)}$, and $W^{(o)}$ are the corresponding input weights of the input gate, forgetting gate, and output gate respectively. $U^{(i)}$, $U^{(f)}$, $U^{(o)}$ are the weights of the input gate, forgetting gate, and output gate corresponding to the previous moment. The words $b^{(i)}$, $b^{(f)}$ and $b^{(o)}$ are the deviations corresponding to the input, forgotten and output gates respectively.

The dependency relationship of the entire network is represented as:

$$\tilde{c}_t^{(t)} = \tanh(W^{(c)}x^{(t)} + U^{(c)}h^{(t-1)} \tag{4}$$

$$c^{(t)} = f^{(t)} \otimes c^{(t-1)} + i^{(t)} \otimes c^{(t)} \tag{5}$$

$$h^{(t)} = o^{(t)} \otimes \tanh(c^{(t)}) \tag{6}$$

wherein, $\otimes$ is the product of vector elements, $c^{(t)}$ represents the long-term memory state at time t, which is a candidate state obtained through nonlinear functions, and $h^{(t)}$ represents the hidden layer state.

### 3.2 Optimization of Bayesian Deep Learning Network Model Based on Stochastic Gradient Hamilton Monte Carlo Probability Method

After training the model in Sect. 3.1, there is a hidden relationship between the cost control sample data and the control index, which is expressed by the hidden variable z. The probability prediction of the cost control index in the settlement link can be expressed as follows:

$$p(y|x) = \int p(y|x, z)p(z|D)dz \tag{7}$$

where: $z = \{\omega, b\}$, $\omega = \left[\omega^1, \omega^2, \ldots, \omega^L\right]$ is the weight vector of each layer of the multilayer neural network, $b = \left[b^1, b^2, \ldots, b^L\right]$ is the bias of each layer of the multilayer neural network. The project settlement cost control index of to network output is $y = f_z(x, \omega, b)$.

The result of stochastic gradient Hamiltonian Monte Carlo sampling is designed to obey the $p(z|D)$ distribution of the LSTM deep learning network, which is difficult to achieve in practice. Therefore, the approximate distribution $q(\omega, b)$ is adopted, and the sampling results are indicated as follows:

$$\left[(\overset{\frown}{\omega}^1, \overset{\frown}{b}^1), (\overset{\frown}{\omega}^2, \overset{\frown}{b}^2), \ldots, (\overset{\frown}{\omega}^m, \overset{\frown}{b}^m)\right] = q(\omega, b)_{SGHMC} \tag{8}$$

$$\left[y^1, y^2, \ldots, y^M\right] = f_z^{\left[(\overset{\frown}{\omega}^1, \overset{\frown}{b}^1), (\overset{\frown}{\omega}^2, \overset{\frown}{b}^2), \ldots, (\overset{\frown}{\omega}^m, \overset{\frown}{b}^m)\right]} \tag{9}$$

Formula (8) represents a set of weights and bias parameters used for random gradient Hamiltonian Monte Carlo sampling $(\overset{\frown}{\omega}^1, \overset{\frown}{b}^1), (\overset{\frown}{\omega}^2, \overset{\frown}{b}^2), \ldots, (\overset{\frown}{\omega}^m, \overset{\frown}{b}^m)$.

Formula (9) represents the corresponding sampled output $y^1, y^2, \ldots, y^M$.

Based on formulas (8) and (9), the predicted power grid cost control indicators are:

$$E(\hat{y}) \approx \frac{1}{M}\sum_{n=1}^{M} Y^n \tag{10}$$

In the formula, M is the number of samples, and $Y^n$ is the output corresponding to the sampled $(\overset{\frown}{\omega}^n, \overset{\frown}{b}^n)$.

Build a deep learning network, and assume that the maximum likelihood function of the network output obeys the Gaussian distribution, its mean value is related to D, determined by determining the trained network, and its variance is $\sigma_y^2$.

$$p(y|f_z(x, \omega, b) = N(y|f_z(x, \omega, b), \sigma_y^2) \tag{11}$$

where $p(y|f_z(x, \omega, b))$ in the cost control index for $f_z(x, \omega, b)$, the probability distribution of the output y, the output y obey mathematical expectation for $f_z(x, \omega, b)$ variance for the Gaussian distribution.

Similarly, the prior probability distribution for setting the weights w and the prior probability distribution of the paranoid b are chosen as Gaussian, in the form of:

$$p(\omega) = N(\omega\Big|0, \sigma_\omega^2 I) \tag{12}$$

$$p(b) = N(b\Big|0, \sigma_b^2 I) \tag{13}$$

In the formula, $N(\omega\big|0, \sigma_\omega^2 I)$ and $N(b\big|0, \sigma_b^2 I)$ represent Gaussian distribution, and I represent identity matrix.

For N independent identical distribution, the likelihood function is:

$$p(D|z) = \prod_{n-1}^{N} p(y_n|f_z(x_n, w, b)) \tag{14}$$

where, $f_z(x_n, w, b)$ is the corresponding cost control index when the input is $x_n$, and $p(y_n|f_z(x_n, w, b)$ is the conditional probability when the output is $y_n$ under this condition.

The variational Bayes approximation of the prior distribution, according to the Bayesian formula, the probability density of hidden variables $p(z|D)$ is expressed as follows:

$$p(z|D) = \prod_{n-1}^{N} p(y_n|f_z(x_n, w, b)) \tag{15}$$

$$p(z|D) = \frac{p(z)p(D|z)}{\int p(D)d(D)} \tag{16}$$

where $p(z)$ represents the prior probability of the hidden variable, $p(D|z)$ represents the probability of the sample being D when the hidden variable is z, and $p(D)$ represents the prior probability of the sample D.

The integration function is very difficult to solve. Variational inference is used to find a simple distribution $q^*(z)$ to approximate the conditional probability density $p(z|D)$. In this way, the inference problem transforms to a functional optimization problem.

$$q^*(z) = \underset{q(z)\in\Omega}{\arg\min}\, KL(q(z)\|p(z|D)) \tag{17}$$

The $KL(q(z)\|p(z|D))$ divergence is the relative entropy, which is used to measure the difference between the two probability distributions, $q(z)$ and $p(z|D)$. $\Omega$ Is the family of the probability distribution of the candidates. Where $\Omega$ is the family of probability distributions of the candidates. KL divergence cannot be directly optimized, the log marginal likelihood function logp (D) is decomposed:

$$q^*(z) = \arg\min_{q(z)\in\Omega} KL(q(z)\|p(z|D)) \tag{18}$$

The optimal $q^*(\omega, b)$ can be used to approximate the posterior probability distribution. When given with a new input, the probability of a new cost control index is

$$q^*(z) = \arg\min_{q(z)\in\Omega} KL(q(z)\|p(z|D)) \tag{19}$$

The optimal $q^*(\omega, b)$ can be used to approximate the posterior probability distribution. When given a new input, the probability of a new cost control indicator is:

$$\begin{aligned} p\left(\widehat{y}|x\right) &= \int p(y|z(x_D^n, \omega, b))p(\omega, b|D)d\omega \\ &= \int p(y|z(x_D^n, \omega, b))q^*(\omega, b)d\omega \end{aligned} \tag{20}$$

## 4 Empirical Analysis

This example uses the cost database of a certain provincial power grid company to select 240 representative new substation project data; 200 of them will be used as the training sample set, and 40 of them will be used as the test set for monitoring and verifying the accuracy of the model.

In order to verify the accuracy of the prediction model, the root mean square error (RMSE) and the absolute mean error (MAE) are used. The RMSE root mean square error is the arithmetic square root of the mean square error, and the mean square error (MSE) is the expected value of the difference between the estimated estimate and the true value; MSE can evaluate the degree of change of the data, the smaller the value of MSE, the better accuracy of the prediction model to describe the experimental data. The mean absolute error (MAE) is the mean of the absolute error; the mean absolute error can better reflect the actual situation of the prediction value error. The RMSE and MAE are calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{t=N}(\widehat{y}_t - \widehat{y})^2}{N}} \tag{21}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{t=N}\left|\widehat{y}_t - \widehat{y}\right| \tag{22}$$

where N is the number of samples and is the output value. Training samples of different sizes are used for learning, and then the settlement cost of the test set is predicted. The errors of the prediction results are shown in Table 1.

From the prediction results in Table 1, it can be seen that a suitable training set sample size is very important. To ensure prediction accuracy, it is necessary to use 60 or 200 samples for learning to achieve good prediction accuracy.

**Table 1.** RMSE and MAE indicators.

| Error indicator | Countable learning samples | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 20 | 40 | 60 | 90 | 120 | 150 | 180 | 200 |
| RMSE | 0.338 | 0.0337 | 0.0083 | 0.0619 | 0.0286 | 0.0362 | 0.041 | 0.0162 |
| MAE | 0.465 | 0.162 | 0.0866 | 0.0178 | 0.0157 | 0.0355 | 0.0162 | 0.1002 |

## 5 Conclusion

This paper proposes the technical method of power grid engineering cost determination based on variational Bayesian deep learning. This method uses Bayesian probability theory to consider the uncertainty of parameters in deep learning, which makes the prediction model uncertain and more in line with the real engineering situation. According to the characteristics of high-dimensional small sample of the cost data of power transmission and transformation projects, the model can provide effective estimation and prediction results of the uncertainty index of power grid project cost control, and the error between the settlement cost and the actual cost through the model pre-prediction is small, which can meet the needs of the actual project cost evaluation. It can strive for active time for power engineering construction, improve the review efficiency of project capital investment and the quality of the project, and guide the cost of new power construction project.

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