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STUDY ON COST-SHARING METHOD OF POWER GRID ENGINEERING OPERATION AND MAINTENANCE BASED ON DEMATEL METHOD AND RANDOM FOREST *

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Abstract. The transmission and distribution (T&D) tariff reform raises higher requirements for the control of operation and maintenance (O&M) cost in power grid engineering. By constructing a model analyzing the O&M cost influencing factors, the paper uses an elastic regression analysis and verifies the key influencing factors on O&M cost, including 14 items such as population size, electricity consumption, gross regional product (GRP). And the subjective and objective weights of each influencing factor are analyzed using the DEMATEL method and random forest. Finally, by calculating the combined weight of factors affecting the power grid O&M cost of each local municipal company, the method of O&M cost-sharing is proposed, which can effectively improve the efficiency of operation and maintenance and make the cost-sharing more balanced and reasonable. Through the empirical analysis, the feasibility of this method is proved, which provides an effective reference for the cost-sharing and control of power grid O&M.

Key words: operation and maintenance (O&M); DEMATEL method; Random forest; combination weight; cost-sharing

1. Introduction. In recent years, artificial intelligence algorithms, including random forest algorithm, logistic regression, SVM, neural network, etc., have been widely used in all walks of life. How to make better use of artificial intelligence algorithms to do a good job in enterprise cost management has gradually attracted the attention of experts and scholars. In order to implement the relevant requirements for deepening the reform of the electric power system, improve the depth and breadth of the reform, and continuously improve the reasonableness of the T&D tariffs, the National Development and Reform Commission (NDRC) issued a "Provincial Grid Transmission and Distribution Tariff Pricing Measures" in January 2020, which stipulates that provincial grid T&D tariffs should be approved in accordance with the "approved costs with reasonable returns", and puts forward the requirement of imposing a rate cap on the O&M cost. There are many provinces and regions with large differences in topography, natural environment and resource endowment in China. In particular, some regions have long transmission distances for power grids, which makes power grid operation difficult and O&M cost high. However, under the premise of the national control on provincial O&M cost, the way to make reasonable O&M cost-sharing so as to maximize the cost-effectiveness not only meets the requirements of the control, but also plays a maximum role in the stable operation of grids and the sustainable development of the region, which becomes the focus direction of the study.

At present, there are many studies on O&M cost-sharing and O&M cost influencing factors. Among the studies on O&M cost-sharing, Reference [1] used Lasso regression algorithm for the influencing factors of O&M cost, and then allocates cost to each individual project based on key performance criteria. Reference [2] put forward the analytic hierarchy process (AHP) -entropy weight method based on distribution network equipment asset operation and maintenance cost optimization allocation mode. Reference [3] used elastic network algorithm to screen the influencing factors of operation and maintenance cost, and the efficiency standards of key factors are determined. Secondly, the CRITIC method is selected for weight side calculation, and the cost allocation coefficient of a single project is obtained. Reference [4] studied the direct costs, indirect costs and other related

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costs incurred during the life cycle of assets and equipment, optimized the cost composition during the life cycle of assets, and thus improved the cost collection and allocation method. Reference [5] combined with the application mechanism of power grid operating standard cost, determined the differentiated allocation algorithm of operating standard cost based on DEMATEL and combined weighting method. Taking substation maintenance service as an example, the differentiated allocation of operating standard cost was realized. And among the studies on O&M costs influencing factors, Reference [6] proposes to use Bayesian Model Averaging (BMA)-improved Grey Relation Analysis in terms of economic factors, equipment factors, environmental factors, and network structure for the O&M cost influencing factors and finally identifies nine key factors. Reference [7] studies and determines the direct and indirect O&M cost influencing factors on extra-high voltage equipment, and then quantifies the influencing factors using correlation analysis, percentage analysis and other methods. In addition, some scholars have calculated and predicted the whole life cycle cost of power grid by means of least square method and principal component analysis method [8], and proposed the use of cloud mass movement technology to deepen the role of physical data chain, collect technical and value information at each stage of the whole life cycle of equipment, and form a security, efficiency and cost optimization control strategy in line with the staged goals of enterprises [9].

The current studies on O&M cost-sharing and the analysis of influencing factors are relatively limited, and the cost-sharing studies focus on a single project itself or a single equipment without the perspective of actual O&M management on local municipal companies. On this basis, from the perspective of management, we establish an influencing factor analysis model on O&M cost, and uses elastic regression analysis to identify the key O&M cost influencing factors, and then calculate the subjective and objective weights of the influencing factors based on DEMATEL method and random forest, and finally calculate the combination weight, and put forward the cost-sharing method on O&M for local municipal companies.

2. Analysis of the power grid O&M cost influencing factors.

2.1. Influencing factor recognition. China has issued a “Measures for the Supervision of T&D Tariff” and qualified the T&D tariff cost components, including depreciation expense and O&M cost (i.e., operation, maintenance and repair costs). From the level of T&D pricing, grid O&M cost is mainly composed of material cost, repair cost, labor cost and other operation costs; from the level of cost types, there are mainly composed of operation cost, maintenance cost and repair cost; and from the level of basic cost components, they are mainly composed of labor cost, material cost, machinery cost as well as other costs. O&M cost of power grid equipment are influenced by many different factors. Brainstorm method is used to collect and summarize the most extensive factors affecting the cost of power grid operation and maintenance by inviting experts from all aspects of power grid operation and maintenance to discuss. Besides, considering the availability of data, the factors are sorted out and summarized to determine the influencing factors that need further analysis and research, as shown in Table 2.1. O&M cost influencing factors mainly include social, technical, environmental factors.

2.2. Influencing factor analysis model construction. In the last century, American experts such as Ehrlich first proposed IPAT model to study the impact of social and economic conditions on the environment, including social, economic, population, technology and other factors on harmful gas emissions and various energy consumption. However, the basic logic of this model is that the contribution of the influencing factors to the impact on environment is the same [10]. Obviously it is impossible to be the same in practice, so many scholars at home and abroad have conducted more in-depth studies on it, and then optimized model was proposed, namely the STIRPAT model [11],[12]. The premise of the establishment of the multiple line regression model is a roughly linear relationship between the independent variables and the dependent variables, but based on the analysis on the O&M cost of the various influencing factors, some of the influencing factors and the O&M cost do not show a conventional linear relationship, and there is an obvious multicollinearity problem among the factors. Considering that O&M cost is similar to the principle of energy consumption in the STIRPAT model, the grid O&M cost influencing factor analysis model is constructed with reference to the STIRPAT model as shown in the following equation:

$$I = aP1^{b}P2^{c}A1^{d}\cdots E4^{s}t \tag{2.1}$$

Table 2.1: Elastic regression analysis results.

No	1st level influencing factor	2nd level influencing factor
1	Social factor	Population size
2		Urbanization rate
3		GRP
4		Consumer price index
5		Power supply area
6		Electricity consumption
7	Technical factor	Substation capacity
8		Line length
9		Average equipment running time
10		Average annual outage time
11		Average annual outage number
12		Equipment failure rate
13		Comprehensive line loss rate
14		Substation capacitance to load ratio
15	Environmental factor	Average temperature
16		Topographic situation
17		Population density

Where I is grid O&M cost; a is the model coefficient; t is the random error term; b, c, d, ..., s represent the model elasticity coefficients for each influencing factor, respectively. If we put logarithms in the model, it can be converted into a line regression model, and then the regression analysis can be utilized for an in-depth study on the influencing factors.

2.3. Influencing factor analysis. Generally, linear regression models is applied to analyze the influencing factors and Ordinary Least Squares (OLS) is usually used to calculate the parameters of the regression model, but this cannot solve the multicollinearity problem among the influencing factors. Elastic Net Regression (ENR) can both reduce the coefficients as in Ridge Regression and select features as in Lasso Regression [13]. The advantages of ENR over Ridge and Lasso Regressions are that ENR can automatically select features when the data is highly correlated, reduces the effect of matrix singularity, and can handle high-dimensional small sample data [14], [15]. Therefore, ENR is used to solve the multicollinearity among various influencing factors, and modeling analysis is carried out to determine the key influencing factors. The expression of the elastic network regression model is as follows:

$$\widehat{\beta}(Elasticnet) = \arg\min_{\beta} \left\{ \|Y - X\beta\|^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| + \lambda_2 \sum_{j=1}^{p} {\beta_j}^2 \right\} \tag{2.2}$$

If set $\alpha = \frac{\lambda_1}{\lambda_1+\lambda_2}, \lambda = \lambda_1 + \lambda_2$, then

$$\widehat{\beta}(Elasticnet) = \arg\min_{\beta} \left\{ \|Y - X\beta\|^2 + \lambda \left[\alpha \sum_{j=1}^{p} |\beta_j| + (1-\alpha) \sum_{j=1}^{p} {\beta_j}^2 \right] \right\} \tag{2.3}$$

where $\alpha \sum\limits_{j=1}^{p} |\beta_j| + (1-\alpha) \sum\limits_{j=1}^{p} {\beta_j}^2$ is called the penalty term of the Elastic net.

3. Grid O&M cost-sharing model.

3.1. Influencing factor subjective weights determination. Graph theory and matrices are used in DEMATEL method, whose basic principle is to identify the logical relationships between the influencing factors in the system, and then calculate the degrees of influence and the degrees of being influenced between them

[16], [17], [18]. The method fully considers the impact of the influencing factors, and a more comprehensive and in-depth determination of the relationship between them. It can also evaluate and analyze the interrelationships between different factors and the extent to which they affect the outcome of the decision. Compared with other methods, DEMATEL method has higher accuracy and reliability. Therefore we use it to get the subjective weights between the influencing factors. The specific steps are as follows:

(1) The O&M cost influencing factors that need to be analyzed are identified firstly. Based on the results of the influencing factor analysis in Section 2, the influencing factors are expressed as followed:

$$F_1, F_2, \cdots, F_n \tag{3.1}$$

(2) A five-level scale method is used to represent the relationships between each influencing factor and different values are assigned. When there is no influence between two influencing factors, the value is 0; when weak influence, the value is 1; when medium influence, the value is 2; when strong influence, the value is 3, and when very strong influence, the value is 4. Thus we can determine the relationships between the influencing factors and O&M costs.

(3) The influence degrees between the influencing factors are represented by constructing matrices, and an n-order matrix is used as the direct influence matrix $C = (a_{ij})_{n \times n}$.

(4) Then we regularize the direct influence matrix N. N = S × C. The calculation formula of S in the above equation is

$$S = \frac{1}{\max\limits_{1 \le t \le n} \sum\limits_{j=1}^{n} A_{ij}} \tag{3.2}$$

(5) The comprehensive influence matrix T is calculated.

(6) Finally we calculate the influence degree and the degree of being influenced by the O&M cost influencing factors, from which the weights are then calculated.

3.2. Influencing factor objective weights determination. In order to make the weights calculated in a more reasonable way, Random Forest Intelligent Algorithm is introduced, which is an integrated learning algorithm based on decision tree as a base learner [19], [20], [21]. The method is used for the importance assessment to determine the objective weights. The random forest model is constructed as follows:

(1) The first training set is obtained by taking M1 samples from the training sample set of the feature metrics by put-back sampling method. And the number of samples in the training sample set of the feature indicator is M, M1<M.

(2) D1 feature indicators are randomly selected from the feature indicators and a feature indicator set is formed. Then the feature indicator with the optimal classification ability is selected from the feature indicator set and split.

(3) A training set and feature metrics are used to generate a decision tree.

(4) Repeat the above steps I times to obtain a random forest model consisting of I decision trees.

(5) The importance of the feature indicators is assessed through the Gini index. The main process of assessment is as follows:

   1) The number of feature indicators in the training sample is set as n; the number of decision trees is I, and the number of categories of evaluation results is C.

   2) The Gini index of node q of the ith decision tree is calculated.

$$Gini_q^{(i)} = \sum_{C=1}^{C} (p_{qc}^{(i)})^2 \tag{3.3}$$

   where $p_{qc}^{(i)}$ is the proportion of categories c of evaluation results in node q.

   3) The importance $VIM_{jq}^{(i)}$ of the feature indicator at node q of the ith decision tree is calculated.

$$VIM_{jq}^{(i)} = Gini_q^{(i)} - Gini_l^{(i)} - Gini_r^{(i)} \tag{3.4}$$

where $Gini_l^{(i)}$ and $Gini_r^{(i)}$ are the Gini indices of the two new nodes after the branching of node q, respectively.

4) If the nodes in which the feature matrix X_j in the ith decision tree are set Q, then the importance of the feature matrix in the ith decision tree is calculated as $VIM_j^{(i)} = \sum_{q \in Q} VIM_{jq}^{(i)}$.
5) The total importance of the feature matrix in the I decision tree is calculated using $VIM_j = \sum_{i=1}^{I} VIM_{jq}^{(i)}$.
6) The importance of the feature indicator X_j is normalized and the weight $VIM_{j,1}$ of the feature indicator X_j is calculated.

3.3. Sharing method. We use the DEMATEL method and random forest and analyze the subjective and objective weights of each influencing factor. In order to calculate the combination weight of each factor, the objective function is established and derived the optimal combination weight based on the principle of minimum identification information [22], and then according to the indicator value of each city, the comprehensive score of each city is calculated, and the proportion of each city is obtained after normalization and then the cost-sharing on O&M is identified. The O&M cost is calculated as follows:

$$\xi_k = \frac{a_i^k \omega_i}{\sum_{k=1}^{r} a_i^k \omega_i} \tag{3.5}$$

Where ω_i^1 is subjective weight; ω_i^2 is object weight; ω_i is the optimal combination weight.

$$\omega_i = \frac{\left(\omega_i^1 \omega_i^2\right)^{1/2}}{\sum_{i=1}^{n} \left(\omega_i^1 \omega_i^2\right)^{1/2}} \tag{3.6}$$

4. Empirical analysis.

4.1. Influencing factor analysis results. An empirical analysis is carried out with the O&M data of 18 municipalities in a province, and the data are collected through the statistical yearbook as well as the actual situation of on-site O&M. The dataset includes data on population size, electricity consumption, urbanization rate, GRP, consumer price index, substation capacity, line length, average equipment running time, average annual outage time and number, equipment failure rate, comprehensive line loss rate, substation capacitance load ratio, power supply area, average temperature, topographic situation, and population density from 2016-2022. Using the influencing factor model, the correlation of each influencing factor is first analyzed.

The correlation analysis of each influencing factor is carried out by using Pearson correlation coefficient, and the analysis results show that there is a high correlation. If we use the ordinary least squares method to calculate the model parameters, it is certain that there is the problem of multiple covariance. Then ENR is used and three influencing factors are excluded, including urbanization rate, average equipment running time, and average temperature, and fourteen items are retained. The main reason is that the results of ENR show that the model coefficients of urbanization rate, average equipment running time and average temperature are 0, as shown in Table 4.1. From the model coefficients, the influencing factors that have a greater impact on the O&M cost include electricity consumption, population density, line length, power supply area, and population size. The less influential factors are equipment failure rate, comprehensive line loss rate, and so on.

4.2. Combination weight calculation. Firstly, based on the data of 14 indexes of population size, electricity consumption, GRP, consumer price index, substation capacity, line length, average annual outage time as well as the number of outages, equipment failure rate, comprehensive line loss rate, substation capacitance to load ratio, power supply area, topographic situation, population density, and so on, we use the five-level scale method, and invite 10 experts in O&M to determine the relationship between the influencing factors. After several rounds of discussion, we get the direct influence matrix. According to the steps of the DEMATEL method described above, the degree of influence, the degree of being influenced, and the degree of centrality of

Table 4.1: Elastic regression analysis results.

No	2nd level influencing factor	Symbol	Model coefficients
1	Population size	P1	0.1972
2	Electricity consumption	P2	0.6344
3	Urbanization rate	A1	0.0000
4	GRP	A2	0.0111
5	Consumer price index	A3	-0.0908
6	Substation capacity	T1	0.1441
7	Line length	T2	0.2125
8	Average equipment running time	T3	0.0000
9	Average annual outage time	T4	-0.0103
10	Average annual number of power outages	T5	0.0105
11	Equipment failure rate	T6	-0.0100
12	Comprehensive line loss rate	T7	-0.0050
13	Substation capacitance to load ratio	T8	-0.0314
14	Power supply area	E1	-0.2044
15	Average temperature	E2	0.0000
16	Topographic situation	E3	-0.0180
17	Population density	E4	-0.2149

Table 4.2: Centrality and weight of influencing factors.

No	2nd level influencing factor	Centrality	Weight
1	Population size	1.7356	0.1300
2	Electricity consumption	1.387	0.1039
3	GRP	0.8937	0.0669
4	Consumer price index	0.4579	0.0343
5	Substation capacity	1.7102	0.1281
6	Line length	1.7525	0.1313
7	Average annual outage time	0.6362	0.0476
8	Average annual outages number	0.7892	0.0591
9	Equipment failure rate	0.7253	0.0543
10	Comprehensive line loss rate	0.3561	0.0267
11	Substation capacitance to load ratio	0.5156	0.0386
12	Power supply area	0.9717	0.0728
13	Topographic situation	0.5285	0.0396
14	Population density	0.8925	0.0668

each influencing factor can be calculated. The weight of each influencing factor of O&M cost can be calculated by normalizing the centrality degree as shown in Table 4.2.

The centrality of the influencing factor can reflect the status and importance of the factor in all the influencing factors. Generally, the greater the centrality, the more important the factor. From the analysis of the centrality and weights, it can be seen that the main factors affecting the O&M cost are population size, electricity consumption, substation capacity, line length and power supply area. Then the data of 14 factors such as population size, electricity consumption, GRP is used to construct the random forest regression model and calculate the importance degree. Since the parameter of the number of decision trees in the random forest has the greatest influence on the effect of the model, the optimal number of decision trees is obtained using the grid search method. The regression analysis is carried out under the optimal parameters, and the results of the importance analysis of the influencing factors are obtained. From the results of the importance analysis, it can be seen that electricity consumption, GRP, substation capacity, line length is more important influencing

Table 4.3: Subjective, objective weight and of combination weight.

No	2nd level influencing factor	Subjective weight	Objective weight	Combination weight
1	Population size	0.13	0.0310	0.078
2	Electricity consumption	0.1039	0.2295	0.189
3	GRP	0.0669	0.1438	0.12
4	Consumer price index	0.0343	0.0008	0.007
5	Substation capacity	0.1281	0.3229	0.249
6	Line length	0.1313	0.2087	0.203
7	Average annual outage time	0.0476	0.0005	0.006
8	Average annual outages number	0.0591	0.0001	0.003
9	Equipment failure rate	0.0543	0.0131	0.033
10	Comprehensive line loss rate	0.0267	0.0065	0.016
11	Substation capacitance to load ratio	0.0386	0.0039	0.015
12	Power supply area	0.0728	0.0010	0.011
13	Topographic situation	0.0396	0.0014	0.009
14	Population density	0.0668	0.0367	0.061

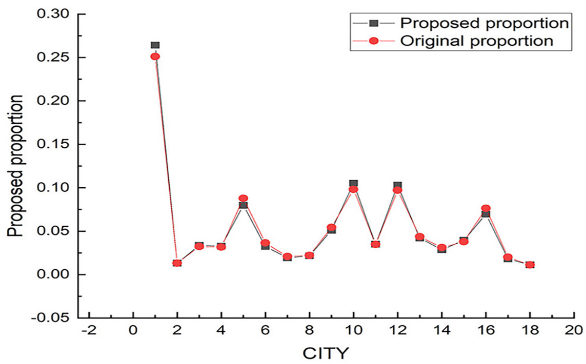

Fig. 4.1: Cost-sharing result

factors, and the consumer price index, the average annual power outage time and number are less important influencing factors.

4.3. Cost-sharing results. According to the subjective and objective weights, the combination weights of each O&M cost influencing factors are calculated as shown in Table 4.3. Based on the indicator values of each municipality, the combined score of each municipality is calculated, and the proportion of each municipality is derived after normalization. Finally the O&M cost is apportioned. The original proportion of cost-sharing and the proportion of this study are shown in Fig 4.1, the costs of city 1, city 10, city 12 should be increased, and the costs of city 5, city 6, city 9, city 14, city 16 and so on should be decreased. Through the further adjustment on O&M cost, it is possible to effectively improve the efficiency of O&M, and make the cost distribution more balanced and reasonable.

5. Conclusion. This paper analyzes the O&M cost influencing factors from three aspects: social factors, technical factors, and environmental factors. And the key factors are identified by constructing the STIRPAT influencing factor model. The key factors affecting O&M cost were determined by elastic regression analysis. By using the DEMATEL method and Random Forest, we put forward the O&M cost-sharing method for local and municipal companies. Finally using empirical analysis, we prove the feasibility of the method. The main results of this study include:

(1) With reference to the STIRPAT model, a model is constructed for analyzing the grid O&M influencing factors, and the problem of multiple covariance between the influencing factors is eliminated using elastic regression method. Through the analysis, the key factors are identified, of which the more influential influencing factors include electricity consumption, population density, line length, power supply area, population size, and substation capacity.

(2) Subjective weights are calculated using DEMATEL method, and objective weights are calculated using random forest, and the combination weights of the final O&M cost influencing factors are calculated, which shows that the factors that have a greater impact on the O&M cost include electricity consumption, GRP, substation capacity, and line length, and the factors that have a lesser impact include the annual consumer price index, topographic situation, the average annual power outage time and number.

(3) Combining the index value of each influencing factor of each city with the combination weights, the comprehensive score of each city can be derived. And after normalization, the proportion of O&M cost shared by each city can be derived, which provides a reference and basis for sharing and controlling the O&M cost of local municipal companies.

Due to the limitation of sample data, the analysis of this study is only limited to local municipal companies, and no comparative analysis of multiple provinces has been carried out. Further research is needed on whether the method is suitable for the cost management of provincial power grid companies.

The results of this study can guide the management of O&M cost of local municipal companies, and help to improve the economic benefits and technical level of operation and maintenance. Through further research and improvement, it can also be applied to the cost management of provincial power grid companies.

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