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Deep Neural Network-based Dynamic Sensing and Emergency Response Technology for Environmental Protection Risks during the Construction Period of Transmission and Substation Projects

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Abstract Due to the lack of control and technology in the development and construction of new power systems, the current construction of transmission and substation projects in certain regions still have environmental risks that cannot be ignored. Based on the characteristics of the power grid, this paper proposes eight power environmental assessment indicators. On the basis of the definition of the indicators, the calculation method of the indicators and the scoring are designed. At the same time, BIM technology and BP neural network algorithm are integrated to design the processing method of transmission and substation engineering data. Based on the Bayesian network algorithm, the steps of environmental risk assessment during the construction period of transmission and substation projects are explained, so as to establish the environmental risk assessment model. The expert scoring method and principal component analysis are adopted as the practical application methods of the assessment model, so as to realize the dynamic perception of environmental protection risk during the construction period of transmission and substation projects. The environmental risk assessment model constructed has a good consistency in assessing the probability of occurrence of risks at different stages of the construction period as 85.7%, 79.9%, and 89.7%, respectively, and the model is able to perceive the environmental risks of transmission and substation projects during the construction period more accurately.

Index Terms environmental risk assessment, transmission and substation project, BP neural network algorithm, Bayesian network algorithm

I. Introduction

Accompanied by the continuous improvement of the scale requirements of power transmission and transformation, it is not difficult to find that in the past a long period of time, too much emphasis on the construction scale and economic benefits, while ignoring part of the transmission and transformation project in the construction process for the destruction of the ecological environment, but also the lack of environmental protection laws and regulations to strictly comply with [1]-[4]. From the perspective of the construction of power transmission and transformation projects, power transmission and transformation projects include line projects, substations, converter stations and so on [5]. Compared with municipal projects, most of the transmission and substation projects are located in remote locations and easily arranged in special terrain such as mountains, lakes, wetlands, etc., which on the one hand can easily lead to multiple types and levels of environmental hazards [6]-[8]. On the other hand, due to the remote location, the control and treatment conditions for accidents are more limited, once caused serious environmental damage often can not get the attention of managers and appropriate measures [9]-[11]. It can be seen that the construction of transmission and substation projects is characterized by the uncertainty of the occurrence of environmental risks, the persistence of environmental impacts, and the complexity of governance [12], [13]. Therefore, the environmental risk dynamic perception and emergency response technology during the construction of transmission and substation projects is of great significance to improve the level of environmental risk management, and the development of artificial intelligence can lay the foundation for realizing this goal [14]-[16].

Deep neural network is a multilayer perceptron, which consists of an input layer, multiple hidden layers and an output layer [17], [18]. The input layer of this network receives raw data, such as text, images, and audio, followed by nonlinear transformations and feature extraction through multiple hidden layers, and finally outputs the target result [19], [20]. It simulates the neural network structure of human brain with highly complex functionality and intelligence, and has been widely studied and applied in the past few years [21]-[23]. In the field of power engineering, the dynamic perception and emergency response technology based on deep neural network is gradually being used as an important means of environmental risk perception, prevention and control, and its technical architecture integrates data collection, intelligent analysis and dynamic decision-making to build a management system for environmental risks throughout the engineering cycle [24]-[27].

This paper first combines the characteristics of the power grid system and selects 8 power environmental assessment indicators during the construction period of transmission and substation projects. The meaning of the eight indicators and the calculation method are described in detail, and the scoring setting of the indicators is carried out. Next, the processing method of transmission and substation project data under the combination of BIM technology and BP neural network algorithm is described. The Bayesian network algorithm is introduced to design the process of environmental risk assessment during the construction period of transmission and substation projects, and the environmental risk assessment model is established. Meanwhile, based on the expert scoring method and principal component analysis method, the application steps and methods of the environmental risk assessment model are discussed. Subsequently, in order to strengthen the practical application effect of the environmental risk assessment model, the basic credibility assignments of the eight assessment indicators are constructed and their reliability and validity are analyzed. At the same time, the Bayesian probability distribution and the marginal probability of the eight assessment indicators are calculated, so as to obtain the weights of the risk sources and the total risk of each indicator. Finally, the validity of the designed model is examined, and the emergency response strategy for environmental risks during the construction period of transmission and substation projects is proposed based on the analysis.

II. Establishment and calculation of indicators for environmental risk assessment of electricity

II. A. Power environmental risk assessment indicators

Think of the entire grid as a complex system of inputs and outputs, where some of the inputs are non-renewable resources, such as coal, natural gas, and oil. Some of them are renewable, such as solar energy, wind energy, tidal energy and so on. Summarizing the above analysis, this paper identifies eight assessment indicators: (I1) resource consumption value, (I2) average line loss rate, (I3) greenhouse gas emission value, (I4) human toxicity value, (I5) ecosystem impact value, (I6) environmental impact value, (I7) new energy penetration rate, and (I8) risk of environmental violation.

Some of these 8 indicators are (I10) single-attribute indicators, such as (I7) new energy penetration rate, (I2) average line loss rate, some are (I20) mixed-attribute indicators, such as (I5) ecosystem impact value, (I6) environmental impact value, (I4) human toxicity value, (I8) risk of environmental violation, which need to be discounted comprehensively, and the remaining belong to the (I30) remaining attribute indicators, such as (I1) resource consumption value, (I3) greenhouse gas emission value.

II. B. Indicator-related definitions

II. B. 1) Meaning of indicators and how they are calculated

This paper considers the year as the time span, and all indicator values except energy efficiency and new energy penetration are normalized to the unit of electricity consumption of the grid.

The resource consumption value is the resource consumption of electricity generated from non-renewable energy sources, converted to standard coal, in the unit electricity consumption of the regional grid. It is calculated as in equation (1):

$$R = \sum_{r \in RE} R_r \tag{1}$$

where R is the amount of resources consumed per unit of electrical energy in the regional grid. R_r is the amount of non-renewable resource r consumed. RE is the set of non-renewable resources used to generate electricity in the regional grid.

The GHG emission value is the amount of GHG emissions per unit of electricity generated from non-renewable energy sources. It is calculated as in equation (2):

$$G = \sum_{g \in GA} G_g \tag{2}$$

where G is the total amount of greenhouse gases emitted per unit of electricity generated by the regional power grid. G_g is the emission of greenhouse gas g. GA is the set of greenhouse gases emitted by power plants in the regional power grid.

The human toxicity value is the sum of harmful substances to humans emitted from the grid, calculated as in equation (3):

$$H = \sum_{h \in HP} H_h \tag{3}$$

where H is the sum of hazardous substances to humans emitted from the power grid in the region. H_h is the degree of toxicity caused by h hazardous substances emitted from the power grid in the region. HP is the set of hazardous substances to humans discharged from power plants in the region's power grid.

The ecosystem impact value refers to the degree of impact on the ecosystem of the substances emitted from the power grid, which characterizes the degree of friendliness of the power grid to the ecosystem, and is calculated as in equation (4):

$$A = \sum_{a \in AP} A_a \tag{4}$$

where A is the degree of ecosystem impact of the regional grid discharge site. A_a is the result of the impact caused by the ecologically influential substance a, and AP is the set of ecosystem hazardous substances discharged from the power plants of the regional power grid.

The environmental impact value is the degree of impact on the environment caused by the substances emitted from the regional power grid, such as water bodies, air, soil, etc. It is calculated as equation (5):

$$F = \sum_{f \in FY} F_f \tag{5}$$

where F is the degree of environmental impact of substances discharged from the grid in the region. F_f is the environmental impact caused by the environmentally impactful substance F. FY is the set of environmentally influential substances discharged from power plants in the regional grid.

The risk of environmental violation refers to the losses in the regional power grid due to penalties for environmental non-compliance, as well as being ordered to rectify. This indicator is more difficult to quantify, and in this paper we use the product of economic losses and its probability of environmental non-compliance as the calculated value.

Average line loss rate refers to the ratio of network-wide active loss to network-wide electricity consumption of the regional power grid. New energy penetration rate: refers to the percentage of electricity generated by new energy in the regional power grid in relation to the total electricity consumption.

II. B. 2) Scoring of indicators

Some of the above indicators are positive, i.e., the larger the value the better, while others are negative, i.e., the smaller the value the better. Obviously, in order to have a unified judgment standard, it is necessary to convert each indicator to get the corresponding evaluation score. Indicators related to environmental protection regulations, such as greenhouse gas emission values, human toxicity values, ecosystem impact values, environmental impact values, etc., are calculated according to the prescribed emission limits, and those exceeding the emission standards receive lower scores. In addition, when calculating indicators with mixed attributes, the proportion of each component is also taken into account, such as the proportion of hazardous substances in the total amount of emissions, the proportion of greenhouse gases, and so on.

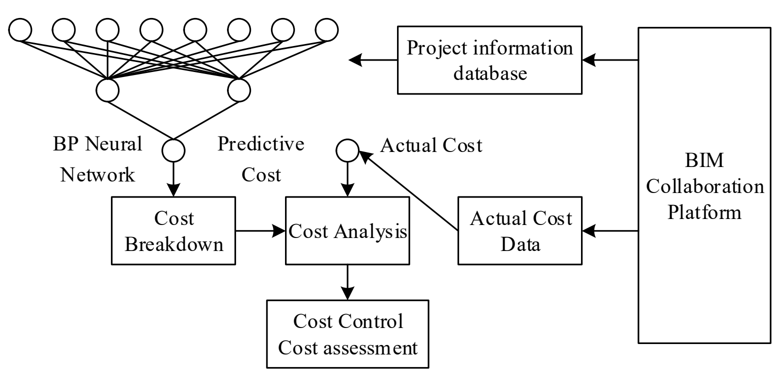

Figure 1: Data processing for power transmission and transformation projects

III. Environmental risk assessment model based on Bayesian algorithm

III. A. Data processing methods

BIM technology is combined with BP neural network algorithm and applied to the transmission and substation engineering data processing. The data processing algorithm of transmission and substation project based on BIM and BP is shown in Fig. 1.In the paper, firstly, the transmission and substation project is modeled based on BIM, and a grid engineering database and collaborative interface are constructed. Then the historical engineering data is used as sample data to train BP neural network for cost prediction of transmission and substation engineering. Finally, the predicted cost is decomposed and analyzed to determine the influencing factors and weights, so as to realize the control of environmental risks during the construction period.

III. B. Modeling

III. B. 1) Bayesian network risk assessment methodology

Based on Bayes' theorem, it refers to the process of finding the posterior probability through the prior probability as in equation (6):

$$P(H_i \mid E) = \frac{P(H_i)P(E \mid H_i)}{P(E)} = \frac{P(H_i)P(E \mid H_i)}{\sum P(H_i)P(E \mid H_i)} \tag{6}$$

The Bayesian method specifically deals with an event, if faced with a complex object that includes multiple events, the Bayesian network method is utilized to express and deal with it, the Bayesian network is composed of three parts: the directed acyclic graph, the node parameters, and the directed edges of the relationship between the node variables. In the composed directed acyclic graph, a single node represents a variable, and the arrows represent the causal links between two connected variables. In constructing the model and in-depth analysis, the target results are obtained by inference according to the causal links between the variables and the Bayesian definition.

III. B. 2) Presentation of an environmental risk assessment model

The Bayesian modeling process is illustrated in Figure 2, which defines environmental risk as a comprehensive assessment of the probability of a risk occurring and the impact of that risk if it occurs. As a result, the environmental risk assessment can be obtained, including two components, one is the likelihood of the occurrence of the risk P. The other is the impact E of the occurrence of the risk.

The environmental risk is expressed mathematically as equation (7):

$$R = f(E, P) \tag{7}$$

R is the risk. P is the probability of the risk occurring. E is the impact of the risk.

In this risk model, R is positively correlated with P and E, i.e., each risk R is composed of a "probability P" and an "impact E", and therefore the above two factors should be weighed comprehensively in the risk assessment process.

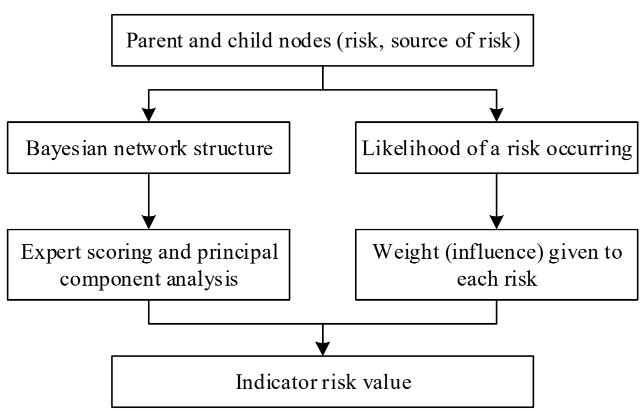

Figure 2: Model establishment

In this paper, the eight indicators proposed above prevail, combined with historical data, further using a questionnaire to obtain the relevant parameters, the survey targets are mainly the transmission and substation management, environmental experts and project team members, and statistical methods are used to process the questionnaire in order to obtain scientific and comprehensive information. The weight of each environmental risk is obtained by using a combination of expert scoring and principal component analysis. Finally, according to the probability of occurrence of environmental risks in the identification stage and the weight of the risk, the two are multiplied together to form a comprehensive risk assessment value.

III. B. 3) Implementation process of Bayesian network decision-making methods

Inferring the node variables (i.e., child and parent nodes) of the Bayesian network structure is the intent of the risk assessment, and the following section explains how to implement this process.

(1) Generation of a risk list

For each risk, identify the risk sources that influence its occurrence and generate an initial risk list. At the completion of the process, a final risk list is generated that includes both risks and risk sources, which serves as the basis for the next stage.

(2) Constructing a Bayesian Network Diagram

According to the risk list obtained earlier, the causal link between risks and risk sources is clarified, which is used as the construction standard of Bayesian network structure diagram, and the process of building the Bayesian network structure model is shown in Figure 3.

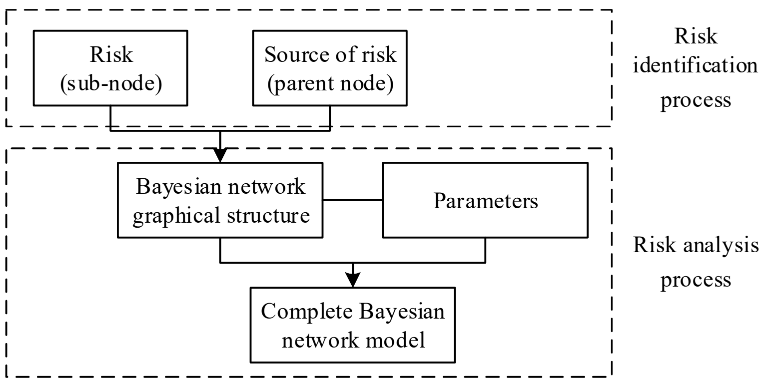

Figure 3: Bayesian modeling process

III. B. 4) Application of Combined Expert Ratings and Principal Component Analysis

(1) Expert Scoring Method

In this paper, the management of the transmission and substation enterprises, environmental experts and members of the audit project team should be assessed by the assessment team, using a Likert scale in the form of expert scoring method to assess the “importance of the impact on the environmental risk of the chemical enterprise” is divided into five levels. The basic steps are as follows:

1) Establish an expert assessment team and conduct the expert assessment anonymously to ensure independence.

2) Send the environmental data and questionnaires to the experts, put forward the purpose and requirements for solving the problems, and ask the experts to rate the problems.

3) Retrieve the questionnaires and collect and summarize the assessment results of the expert group members.

(2) Principal Component Analysis

1) Basic Principle

Using an orthogonal transformation, the original random vector associated with the components as in equation (8):

$$X=(x_1,x_2,\cdots,x_p)^T \tag{8}$$

transformed into a new component-agnostic variable as in equation (9):

$$U=(u_1,u_2,\cdots,u_p)^T \tag{9}$$

Let it refer to the p orthogonal directions with the most open degree of scattering of sample points, and subsequently implement the dimensionality reduction of the multidimensional variable system, so that it can change the higher precision into a low-dimensional variable system.

2) Calculation steps

Construct the sample array as equation (10):

$$X=\begin{bmatrix} x_1^T \\ \vdots \\ x_n^T \end{bmatrix}=\begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix} \tag{10}$$

x_{ij} is the value of the j th variable in the i th set of sample data.

Transforming the sample array X yields $Y=[y_{ij}]_{n\times p}$, which has equation (11):

$$y_{ij}=\begin{cases} x_{ij}, & \text{Positive indicators} \\ -x_{ij}, & \text{For negative indicators} \end{cases} \tag{11}$$

Doing the normalization transformation for Y yields the normalization matrix as in equation (12):

$$Z=\begin{bmatrix} z_1^T \\ \vdots \\ z_n^T \end{bmatrix}=\begin{bmatrix} z_{11} & \cdots & z_{1p} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{np} \end{bmatrix} \tag{12}$$

$Z_{ij}=\dfrac{y_{ij}-\overline{y}_j}{s_j}$, y_i, s_j are the mean and standard deviation of the j th column in the Y array.

The sample correlation coefficient array of the normalized matrix Z is calculated as in equation (13):

$$R=[r_{ij}]_{p\times p}=\frac{Z^TZ}{n-1} \tag{13}$$

The eigenvalues are obtained as in equation (14):

$$\left|R-\lambda J_p\right|=0 \tag{14}$$

Solve for p eigenvalues $\lambda_1\geq\lambda_2\geq\cdots\geq\lambda_p\geq 0$.

Determine the value of m so that the utilization of the information exceeds 80%. The criterion for determination is equation (15):

$$\sum_{j=1}^{m}\lambda_i\Big/\sum_{j=1}^{p}\lambda_i\geq 0.8 \tag{15}$$

For each λ_j, $j=1,2,\cdots,m$. Solve the equation to obtain $Rb=\lambda_j b$ and obtain the unit vector as in equation (16):

$$b_j^0=\frac{b_j}{\left\|b_j\right\|} \tag{16}$$

Find the m principal component components of $z_i=(z_{i1},z_{i2},\cdots,z_{ip})^T$ as in equation (17):

$$u_{ij}=z_i^Tb_j^0,\ j=1,2,\cdots,m \tag{17}$$

The decision matrix is obtained as in equation (18):

$$U=\begin{bmatrix} u_1^T \\ \vdots \\ u_p^T \end{bmatrix}=\begin{bmatrix} u_{11} & \cdots & u_{1m} \\ \vdots & \ddots & \vdots \\ u_{p1} & \cdots & u_{pm} \end{bmatrix} \tag{18}$$

where u_i is the principal component vector of the i th variable.

3) Re-modeling

Assume that there are h number of indicators that need explicit weights. Consult L experts in turn to get the rating values of h sets of weights, all of which include L elements in each set of rating values. Because the scientific fields of each expert are different, their ratings are also biased, which makes the weights come out with corresponding ambiguity. It has been shown that the greater the number of experts, the more scientific the weights, and at the same time, the more ambiguous the determination of the weights. Accordingly, the following hypothesis is proposed, that is, in the case of a certain number of experts, the number of experts actually scoring the number of experts with the help of the linear connection between the scores of the experts to simplify the same kind, so as to ensure the accuracy of the judgment of the weights. Through the analysis, the idea is similar to the basic principle of principal component analysis, so this paper tries to assess the weights with the help of principal component analysis.

The procedure for determining the weights is ultimately the process of principal component analysis to obtain a comprehensive evaluation function. In this process, the indicators in the original evaluation system become samples, and the existing indicators are experts.

The first primary weight model constructed is the principal component model as in equation (19):

$$\begin{cases} F_1 = u_{11}w_1 + u_{21}w_2 + \cdots + u_{L1}w_L \\ \vdots \\ F_m = u_{1m}w_1 + u_{2m}w_2 + \cdots + u_{Lm}w_L \end{cases} \tag{19}$$

where $F_1, F_2, \cdots, F_m$ are the m principal components obtained after analysis. u_{ij} is the coefficients in the decision matrix, which can be analyzed with stata software to obtain equation (20):

$$u_{ij} = \frac{f_{ij}}{\sqrt{\lambda_j}}, j = 1, 2, \cdots, m \tag{20}$$

On this basis, the comprehensive evaluation function is established as equation (21):

$$\begin{gathered} F_Z = \sum_{j=1}^{m} (\lambda_j / k) F_j = a_1 w_1 + a_2 w_2 + \cdots + a_L w_L \\ k = \lambda_1 + \lambda_2 + \cdots + \lambda_m \end{gathered} \tag{21}$$

$a_1, a_2, \cdots, a_L$ is the combined importance of the indicators $w_1, w_2, \cdots, w_L$ in the principal components. Under this premise, according to the actual scoring of experts, the original index score can be obtained as a synthesized value of the formula (22).

$$V_{Zi} = \sum_{j=1}^{L} a_j p_{ij}, i = 1, 2, \cdots, h \tag{22}$$

The secondary weight model is obtained as in equation (23):

$$\begin{cases} F_Z = \sum_{j=1}^{m} (\lambda_j / k) F_j = a_1 w_1 + a_2 w_2 + \cdots + a_L w_L \\ V_{Zi} = \sum_{j=1}^{L} a_j p_{ij} \\ \omega_i = V_{Zi} \Big/ \sum_{i=1}^{h} V_{Zi} \end{cases} \tag{23}$$

IV. Optimization and application testing of environmental risk assessment models

IV. A. Construction of the Basic Confidence Assignment

The identification framework θ is established as in equation (24), and the risk framework is set into five risk levels, where the elements are mutually exclusive, taking into account the specific conditions of the construction period of the transmission and substation project.

$$\theta = \{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5\} \tag{24}$$

where θ_1 = {low risk}, θ_2 = {low risk}, θ_3 = {medium risk}, θ_4 = {high risk}, and θ_5 = {high risk}. The elements of the risk framework are assigned corresponding quantitative values of risk, denoted as equation (25):

$$\theta = \{\{0.1\}, \{0.3\}, \{0.5\}, \{0.7\}, \{0.9\}\} \tag{25}$$

The construction period of the transmission and substation project is further subdivided into (P1) development phase, (P2) trial production phase, and (P3) production and operation phase. Processing summarizes the eight indicators proposed above, and obtains their basic credibility assignments as shown in Table 1. The probability that the indicators (I3) GHG emission value and (I5) ecosystem impact value are considered to be medium risk is 70.00% and 60.00%, respectively. From the reference of a large amount of information and the analysis of relevant data, it can be seen that although the current energy structure of power generation is gradually transforming to wind, light and other new energy sources, however, due to the huge demand of the electricity market and the limitations of new energy power generation, the traditional coal power and thermal power are still required as the main driving force during the peak period of electricity consumption. As a result, the construction of transmission and substation projects still needs to take into account the related setup, trial production and operation, which will lead to greenhouse gas emissions and ecosystem impacts that should not be underestimated.

Table 1: The basic credibility allocation of environmental assessment indicators

	Index	Evaluation				
		θ_1	θ_2	θ_3	θ_4	θ_5
P1	I1	0.3	0.3	0.2	0.2	0
	I2	0.5	0	0	0.4	0.1
	I3	0.2	0	0.7	0.1	0
	I4	0.4	0.1	0.2	0.3	0
	I5	0.2	0.2	0.6	0	0
	I6	0.1	0.1	0.5	0.2	0.1
	I7	0.5	0.2	0.3	0	0
	I8	0.4	0.1	0.5	0	0
P2	I1	0.2	0.2	0.3	0.3	0
	I2	0.3	0.2	0.1	0.4	0
	I3	0.1	0.3	0	0.6	0
	I4	0.4	0.1	0	0.5	0
	I5	0.3	0	0.3	0.4	0
	I6	0.2	0	0.2	0.3	0
	I7	0.3	0.2	0.1	0.4	0
	I8	0.1	0.1	0.4	0.3	0.1
P3	I1	0.5	0	0	0.4	0.1
	I2	0.4	0.3	0	0.2	0.1
	I3	0.3	0.1	0	0.4	0
	I4	0.3	0.2	0.2	0.3	0
	I5	0.4	0.4	0.2	0	0
	I6	0.2	0	0.4	0.3	0.1
	I7	0.2	0	0.5	0.3	0
	I8	0.1	0	0.3	0.3	0.1

Using the AHP method, the weights of the eight assessment indicators were obtained as shown in Figure 4.

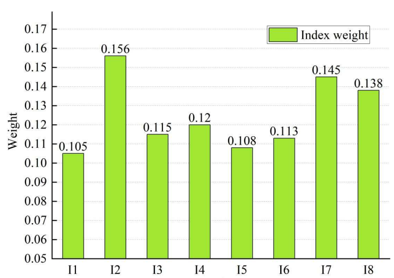

Figure 4: Weights of power environment assessment indicators

Table 2: Basic credibility allocation and weights

Index	$m(\theta_1)$	$m(\theta_2)$	$m(\theta_3)$	$m(\theta_4)$	$m(\theta_5)$	Weight
I1	0.3	0.3	0.2	0.2	0	0.105
I2	0.5	0	0	0.4	0.1	0.156
I3	0.2	0	0.7	0.1	0	0.115
I4	0.4	0.1	0.2	0.3	0	0.12
I5	0.2	0.2	0.6	0	0	0.108
I6	0.1	0.1	0.5	0.2	0.1	0.113
I7	0.5	0.2	0.3	0	0	0.145
I8	0.4	0.1	0.5	0	0	0.138

The basic credibility assignments and weights of the eight indicators during the development phase of the construction period are shown in Table 2.

IV. B. Reliability and validity analyses

Reliability coefficient is an important technical index to measure the goodness of the test, this paper adopts the internal consistency index to test the reliability of the scale, there are many ways to estimate the internal consistency, and it is often estimated by the Cronbach'α coefficient. The larger the Cronbach'α coefficient, the greater the correlation of each index of the variable, i.e., the higher the degree of internal consistency. Existing studies have concluded that if the Cronbach'α coefficient is above 0.7, the reliability of the scale is high and new, any reliability coefficient greater than 0.6 is acceptable, and 0.5 is the lowest acceptable level of reliability.

Through SPSS analysis, the reliability of the 8 indicators in the 3 stages as well as the overall reliability are shown in Table 3. Where each Cronbach'α value is greater than 0.5, it can be seen that the 8 assessment indicators proposed in this paper have a better internal structure basis, and the combination between the indicators is scientific and reasonable.

Table 3: The reliability of the 8 indicators in the 3 stages and the overall reliability

Index	P1	P2	P3
I1	0.609	0.757	0.831
I2	0.64	0.836	0.874
I3	0.598	0.796	0.813
I4	0.613	0.833	0.77
I5	0.601	0.816	0.803
I6	0.504	0.793	0.673
I7	0.703	0.643	0.768
I8	0.683	0.569	0.649
Total	0.795	0.805	0.752

Table 4: The Bayesian probability distribution result of the index

Probability distribution	IState0	IState1	IState2
I1State0	0.75	0.56	0.51
I1State1	0.11	0.26	0.16
I1State2	0.17	0.21	0.36
I2State0	0.4	0.32	0.28
I2State1	0.49	0.67	0.6
I2State2	0.14	0.04	0.15
I3State0	0.21	0.04	0.06
I3State1	0.38	0.73	0.46
I3State2	0.44	0.26	0.51
I4State0	0.51	0.64	0.46
I4State1	0.1	0.22	0.11
I4State2	0.42	0.17	0.46
I5State0	0.33	0.33	0.19
I5State1	0.55	0.57	0.51
I5State2	0.15	0.13	0.33
I6State0	0.47	0.35	0.51
I6State1	0.47	0.6	0.37
I6State2	0.09	0.08	0.15
I7State0	0.38	0.29	0.24
I7State1	0.12	0.14	0.14
I7State2	0.53	0.6	0.65
I8State0	0.23	0.11	0.15
I8State1	0.36	0.38	0.28
I8State2	0.44	0.54	0.6

IV. C. Probability distribution of environmental risk evaluation indicators

The eight indicators are regarded as the corresponding environmental protection risk sources, and the posterior probability of Bayesian formula is utilized for calculation, so as to derive the Bayesian probability distribution of each risk source during the construction period of transmission and substation projects, and the results of the specific Bayesian probability distribution are shown in Table 4. For ease of calculation, the probability of occurrence of the risk for each indicator was adjusted to the following three: State2 indicates a small probability of occurrence of the risk, State1 indicates a medium probability of occurrence of the risk, and State0 indicates a large probability of occurrence of the risk.

The results of the marginal probability distribution of different attribute indicators are shown in Table 5, which shows that each attribute indicator has a large probability of distribution on State2, all of which are at 0.40 and above, indicating that the probability of occurrence of risk is biased towards a smaller probability.

Table 5: The marginal probability distribution result of the indicator

Marginal probability distribution	State0	State1	State2
I10State0	0.3	0.4	0.5
I10State1	0.6	0.39	0.6
I10State2	0.13	0.24	0.5
I20State0	0.3	0.37	0.4
I20State1	0.51	0.47	0.5
I20State2	0.22	0.19	0.4
I30State0	0.36	0.55	0.5

IV. D. Analysis of the effectiveness of environmental risk assessment models

The standardization formula is used to standardize the degree of impact of the eight risk source indicators on the environment during the construction period of the project, and the results of the standardization of the eight risk source indicators are shown in Table 6.

Table 6: The standardized processing results of the indicators

Index	Probability of occurrence	Risk impact	Standardized processing value
I1	0.8249	0.3469	0.244048241
I2	0.4615	0.5391	0.347760738
I3	0.5113	0.3263	0.232932333
I4	0.4623	0.3491	0.245235377
I5	0.3619	0.302	0.219819879
I6	0.5539	0.2596	0.196940535
I7	0.4339	0.3329	0.236493741
I8	0.4623	0.3853	0.264769156

Through the collection of model data, the reasonableness as well as the accuracy of the constructed environmental risk assessment model for risk evaluation are concluded. The validation results of the environmental risk assessment model are shown in Table 7, where Istate0, Istatel, Istate2 denote the probability that the environmental risk during the construction period is large, medium and hourly, respectively.IiState0, IiState1, IiState2 denote the probability that the risk of each risk source of the environment during the construction period is large, medium and hourly, respectively.

Table 7: The verification results of the model

Predicted results	Istate0	Istate1	Istate2
IiState0	0.857	0.023	0.024
IiState1	0.049	0.799	0.041
IiState2	0.089	0.006	0.898

When the probability of occurrence of each risk source during the construction period is maximum, the overall risk of environmental risk during the construction period is 85.7%. When the probability of occurrence of each risk source during the construction period is medium, the overall risk of environmental protection risk during the construction period is 79.9%. When the probability of occurrence of each risk source during the construction period is small, the overall risk of environmental protection risk during the construction period is 89.8%. Through the validation analysis, the model's prediction results are consistent, while the prediction results are relatively accurate. Therefore, the effect of the model is relatively good.

IV. E. Emergency Response Strategies for Environmental Risks

Based on the above analysis, the following two emergency response strategies are proposed in this section for the environmental risks during the construction period of transmission and substation projects:

(1) Focus on the fine management of the transmission and substation project construction and production team, combined with the environmental risk assessment model based on Bayesian algorithm, monitoring and evaluating environmental risks from multiple construction and production links. By improving the level of fine management of all aspects of transmission and substation construction and production, constantly summarizing and optimizing the operation and regulation, and multi-directional monitoring of the environmental protection status of transmission and substation engineering construction. Thus guaranteeing the first warning of risk and providing effective support for emergency response.

(2) The introduction of wisdom construction system, the construction of perfect transmission and substation construction environmental risk response mechanism. Transmission and substation project construction management needs to keep pace with the times, by means of intelligent analysis, comprehensive interconnection, etc., to improve the level of construction and production of early warning response intelligence. Through the informationization of transmission and substation project construction process, strengthen the information management of construction, realize the environmental risk warning data correctly, timely collection, stable transmission, so as to strengthen the response linkage of each construction link to the environmental risk warning.

V. Conclusion

This paper establishes eight environmental risk assessment indicators, including resource consumption value, average line loss rate, greenhouse gas emission value, human toxicity value, ecosystem impact value, environmental impact value, new energy penetration rate, and risk of environmental protection violation, as the main assessment angles of environmental protection risk during the construction period of transmission and substation projects. At the same time, the BP neural network algorithm and Bayesian algorithm are integrated to construct the environmental risk assessment model as the dynamic perception method of environmental risk during the construction period.The Cronbach's α values of the eight assessment indicators at different stages of the construction period are all greater than 0.5, which has a better internal structure foundation. In the validity analysis of the designed environmental risk assessment model, the probability of risk occurrence in different stages of the construction period is 85.7%, 79.9% and 89.7% respectively, which is both consistent and accurate.

Synthesizing the content of the analysis, the following recommendations are made for the emergency response mechanism during the construction period of transmission and substation projects:

(1) It should focus on the fine management of the construction and production team, and monitor the probability of the occurrence of environmental risks in a multifaceted and all-round way with the assistance of the Bayesian algorithm-based environmental risk assessment model.

(2) Construct a smart environmental risk response mechanism to strengthen the response linkage of each construction and production linkage, so that an orderly and efficient response can be carried out at the first time of risk occurrence.

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