Construction risk evaluation of power mass entrepreneurship and innovation demonstration park under collaborative innovation

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Abstract—The power mass entrepreneurship and innovation demonstration park (PMEIDP) provides an incubation and transformation platform and the environment by converging resources such as technology, capital, and demand to promote regional economic development. This paper evaluates the effectiveness of further promoting systematic innovation and efficient use of resources from the perspective of collaborative innovation. Firstly, we build a risk indicators system for the construction risk evaluation of the PMEIDP. Secondly, we adopt the mutual information coefficient (MIC) to simplify the construction risk indicators. Thirdly, we train the fuzzy neural network (FNN) for the risk evaluation of the PMEIDP. Finally, we conduct a case analysis of 5 PMEIDP and provide support for the management of the future development and construction of the PMEIDP.

1. Introduction

To promote “mass innovation and entrepreneurship”, the State Grid Corporation of China (SGCC) has made a strategic plan to build mass entrepreneurship and innovation demonstration park. So, the power mass entrepreneurship and innovation demonstration park (PMEIDP) was officially inaugurated on Oct. 23rd, 2019 [1]. The PMEIDP focuses on conquering key technologies of electric power by pooling and coordinating the innovative elements of politics, industry, and academia [2].

The research on the construction risks of industrial parks mainly focuses on the following two points.

Firstly, traditional industrial park construction risk research focuses on clustering methods since computing capabilities and has not yet resorted to machine learning (ML). Zhang Jing [3] and Shi Jianying et al. [4] researched the construction of the park from the perspectives of the functional structure, spatial organization, and construction elements of PMEIDP. And, they explored the layout mode and environment construction strategy of the PMEIDP.

Secondly, with the development of the ML field, more and more deep learning algorithms are used in the construction risk evaluation of industrial parks. References [5,6] provide a strategy to evaluate and mitigate power system cascading interruptions that will affect the risk of power outages.

The construction of PMEIDP is facing many risks since PMEIDP is a new and innovative park. China and its government need to figure out which risks are PMEIDP facing and how to control the risks. We proposed a MIC-FNN model to evaluate the risk level of PMEIDP and ensure the smooth construction of PMEIDP.
Following is the structure of this paper. Section 2 is the construction risk of PMEIDP. Section 3 is the detailed describe of MIC-FNN model. Section 4 is the evaluation result. Section 5 is the conclusion.

2. Construction risk evaluation indicators system of PMEIDP

The influencing factors of PMEIDP are mainly the following five aspects, as shown in Fig. 1.

1. External environmental risks
   - Natural environment: The collaborative innovation park exists in a certain environment. And the park’s development and the natural environment are complementary to each other.
   - Economic environment: The development of the economy plays a vital role in the development direction of PMEIDP.
   - Legal and policy environment: The legal and policy environment is a crucial risk indicator to the PMEIDP’s development.

2. Market risk
   - Market demand: Market demand will directly affect the later development of PMEIDP. So, it should be predicted accurately through scientific models.
   - Market competition: Market competition is not only product competition, but also competition in areas such as the park’s innovation capabilities, achievement transformation capabilities, and resource allocation capabilities.

3. Technical risk
   - Technical risk refers to the risks caused by the uncertainty of the various technologies applied in the PMEIDP, such as compatibility, adaptability, and difficulty.

4. Management risk
   - The management model is a manifestation of soft power. It is mainly reflected in the top-level design, organizational structure, and functional division of PMEIDP. Therefore, management risks are mainly schedule, organization, and management ability.

5. Operational risk
   - Operational scheme: It describes how the enterprise realizes its survival and development.
   - Operational ability: Specific operation solutions must be formulated due to the particularity of PMEIDP products.
3. MIC-FNN theory

3.1. Maximum Mutual Information
Maximum Mutual Information (MIC) is developed based on Mutual Information (MI), which has strong fairness and extensiveness [7].

For a binary data set of two attributes like $X, Y$, MIC divides it into a grid of $X \times Y$, calculates the probability of each cell in the grid, and obtains the $D_G$ which is the probability distribution of the grid. Then MIC calculates the maximum MI value $\max (I[D(x,y)])$ and saves it as $I^*[D(x,y)]$, as shown in the equation (1):

$$I^*[D(x,y)] = \max (I[D(x,y)]) \tag{1}$$

Equations (1) and (2) standardize this MI and calculate the MIC.

$$M(D)_{x,y} = \frac{I^*[D(x,y)]}{\ln \min(x,y)} \tag{2}$$

$$F(D)_{MIC} = \max_{xy < B(n)} \{M(D)_{x,y}\} \tag{3}$$

Where, and $B(n)$ is a function of sample size, which identifies the constraint of the total number of $xy$ divided by grid $G$, generally $B(n) = n^{0.6}$. MIC is the normalized mutual information data. The value interval is $[0,1]$. The big MIC value shows a strong correlation between the two variables.

3.2. Fuzzy Set
The fuzzy set is a kind of imprecise set expression by setting the membership function to express the evaluation degree of the object under investigation. The fuzzy set uses the fuzzy transformation and calculation function of mathematics to analyze the research content.

Let $X$ be a set, $\mu_A$ is a mapping from $X$ on $[0,1]$, $\mu_A : X \rightarrow [0,1]$. $x \rightarrow \mu_A(x)$ is called a fuzzy set off $X$ on $\mu_A$. We call $\mu_A$ as the membership degree of $x$ to fuzzy set $A$.

When $X$ is a finite set, the fuzzy set can be expressed as $A = A_1/x_1 + A_2/x_2 + ... + A_n/x_n$. When $x$ is a finite and continuous field, the fuzzy set can be expressed as $A = \int \mu_A(x)/x$.

3.3. BP Neural Network
BP neural network is a multi-level feedforward neural network system (Back Propagation) of signal forward transmission and error response transmission [8,9]. The topological structure diagram of the BP neural network is shown in Fig. 2.

In Fig. 2, the input value is $X_1, X_2, ..., X_s$. The output value is $Y_1, Y_2, ..., Y_m$. The network weight matrix is $U_W, V_K$. $\theta_j$ is the threshold of the $j$-the neuron in the hidden layer. $\theta_l$ is the threshold of the $l$-the neuron in the output layer. When the number of neurons in the hidden layer meets the requirements, the neural network can be approximately regarded as a nonlinear function with the dependent input and output. The number of input nodes is $n$. And the number of output nodes is $m$. BP neural network has two workflows in fault diagnosis:

1. Forward pass. After setting the input mode, the input sequence is processed by the hidden layer and passed to the output layer. The output sequence is generated from the output layer. In the forward pass, neurons pass and update layer by layer.
2. Reverse transmission. This transmission calculates the difference between the real output sequence and the expected output sequence. And this process will reversely correct the weight of the neuron and generate a new training mode to minimize the error through the difference.

3.4. Fuzzy neural network
A fuzzy neural network (FNN) is an intelligent data processing system that combines the subjective fuzziness of human evaluation language with the intelligent classification system of a neural network.
\[ E(W) = \frac{1}{2} \sum_{j=1}^{3} (d_j - y_j)^2 \]  

Where, \( d_j \) is the expected output value, and \( y_j \) is the actual output value. We can calculate the gradient \( \frac{\partial E}{\partial w_{ij}} \) and the adjustment amount \( w_{ij} \) of \( \delta_j \) using error backpropagation and step optimization algorithm. Equations (5) and (6) are the calculation method.

\[ \delta_j = \frac{\partial E}{\partial \text{net}_j^{k+1}} = \frac{\partial E}{\partial O_j^{k+1}} \cdot \frac{\partial O_j^{k+1}}{\partial \text{net}_j^{k+1}} = [O_i - d_i]f'(\text{net}_j^{k+1}) \]  

\[ \frac{\partial E}{\partial w_{ji}^k} = \frac{\partial E}{\partial \text{net}_j^{k+1}} \cdot \frac{\partial \text{net}_j^{k+1}}{\partial w_{ji}^k} = \frac{\partial E}{\partial \text{net}_j^{k+1}} O_i^k \]  

Where, \( \text{net}_j^{k+1} \) is the input of the fourth layer, and \( \partial O_j^{k+1} \) is the input of the activation function.

Equations (7) and (8) show the calculation equations for the gradient \( \frac{\partial E}{\partial y_j} \) and the adjustment amount \( \delta_j^{(4)} \) of the fourth layer.

\[ \delta_j^{(4)} = -\frac{\partial E}{\partial y_j} = d_j - y_j \]  

\[ \frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial w_{kj}} = \delta_j^{(4)} z_k^{(3)} = -(d_j - y_j)z_k \]  

Where, \( z_k^{(3)} \) is the output of the third layer.

Equations (9) and (10) show the calculation equations of the gradient adjustment amount in the third layer.

\[ \delta_j^{(3)} = -\frac{\partial E}{\partial z_k} = -\sum_{j=1}^{3} \frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial z} = -\sum_{j=1}^{3} \delta_j^{(4)} W_{kj} \]  

\[ \frac{\partial E}{\partial w_{ik}} = \frac{\partial E}{\partial z_k} \cdot \frac{\partial z_k}{\partial w_{ik}} = -\delta_j^{(3)} x_k^{(2)} = -\left(\sum_{j=1}^{3} \delta_j^{(4)} W_{ik}\right) \bar{x}_i \]  

Where, \( z_k^{(3)} \) is the output of the second layer. Besides, in backpropagation, \( W_{ik}(0) \) and \( W_{kl}(0) \) are random values.
4. Case study

4.1. Basic data processing

This paper uses MIC to reduce the risk indicators of Section 2, reducing 13 risk indicators to 7. First, we expand the number of samples. Because a large number of samples make the accuracy of MIC high. And we can only collect three innovation and entrepreneurship parks. In this paper, three parks are randomly combined and normalized to generalize 4 categories such as Park AB, AC, BC, and ABC in Table 2.

| Indicators ID | Source     | Park A | Park B | Park C | Park AB | Park AC | Park BC | Park ABC |
|---------------|------------|--------|--------|--------|---------|---------|---------|----------|
| B1            | Yearbook   | 11.20  | 0.88   | 2.17   | 6.04    | 6.69    | 1.53    | 4.75     |
| B2            | Delphi     | 5      | 4      | 3      | 4.50    | 4.50    | 4.00    | 4.00     |
| B3            | Yearbook   | 1.01   | 0.78   | 1.08   | 0.90    | 1.05    | 0.93    | 0.96     |
| B4            | Delphi     | 5      | 5      | 4      | 5.00    | 4.50    | 4.50    | 4.67     |
| B5            | Delphi     | 5      | 4      | 4      | 4.50    | 4.50    | 4.50    | 4.33     |
| B6            | Delphi     | 5      | 4      | 4      | 4.50    | 4.50    | 4.00    | 4.33     |
| B7            | Delphi     | 3      | 3      | 4      | 3.00    | 3.50    | 3.50    | 3.33     |
| B8            | Delphi     | 3      | 3      | 2      | 3.00    | 2.50    | 2.50    | 2.67     |
| B9            | Delphi     | 5      | 5      | 3      | 5.00    | 4.00    | 4.00    | 4.33     |
| B10           | Delphi     | 4      | 3      | 2      | 3.50    | 3.00    | 2.50    | 3.00     |
| B11           | Delphi     | 5      | 4      | 3      | 4.50    | 4.00    | 3.50    | 4.00     |
| B12           | Delphi     | 3      | 4      | 3      | 3.50    | 3.00    | 3.50    | 3.33     |
| B13           | Delphi     | 5      | 4      | 3      | 4.50    | 4.00    | 3.50    | 4.00     |
| B14           | Delphi     | 4      | 5      | 2      | 4.50    | 3.00    | 3.50    | 3.67     |
| B15           | Delphi     | 4      | 4      | 3      | 4.00    | 3.50    | 3.50    | 3.67     |
| B16           | Delphi     | 5      | 4      | 2      | 4.50    | 3.50    | 3.00    | 3.67     |
| B17           | Delphi     | 4      | 3      | 3      | 3.50    | 3.50    | 3.00    | 3.33     |

Risk level  -  Low  Middle  High  Middle  Middle  High  Middle

4.2. Indicators selection

In this paper, we choose 3 of them to calculate the MIC of each indicator and risk level based on the original data. After repeating it 10 times, we form the MIC heat matrix as shown in Fig. 3. We will select the indicator if the MIC>0.5. After this process, we select {B2, B8, B9, B12, B13, B14} as the input matrix of FNN.

4.3. Case analysis

The learning process of the neural network is a training process. Firstly, this paper uses the data in Table 2 as the risk sample to train a BP neural network for evaluating the risks of the PMEIDP. After that, this paper collects the relevant data of the five parks shown in Table 3. And this paper evaluates the construction risk levels of these five innovation parks. The evaluation results are shown in Table 3.

The output of MIC-FNN is the probability of risk level. From the above evaluation results, it can be seen that there are Evaluations C, D, and E with lower risks and Evaluations A and B with medium risks.
Therefore, Evaluations A and B should pay more attention to the operation of the park, and there is no need to take measures.

Table 3 Source and risk level of evaluation park

| Park ID | B2 | B8 | B9 | B12 | B13 | B14 | Low Risk level | Middle Risk level | High Risk level |
|--------|----|----|----|-----|-----|-----|----------------|------------------|------------------|
| Evaluation A | 4  | 3  | 4  | 3   | 4   | 3   | 0.41           | 99.83            | 0.49             |
| Evaluation B | 4  | 3  | 5  | 4   | 4   | 4   | 0.29           | 99.63            | 0.58             |
| Evaluation C | 4  | 3  | 5  | 4   | 4   | 4   | 99.52          | 0.78             | 0.00             |
| Evaluation D | 3  | 2  | 3  | 2   | 3   | 3   | 91.13          | 0.32             | 0.16             |
| Evaluation E | 2  | 2  | 2  | 2   | 2   | 2   | 95.17          | 2.19             | 0.00             |

5. Conclusion

In this paper, the MIC-FNN method is adopted to evaluate the construction risk of PMEIDP. The main conclusions can be summarized as follows: (1) MIC-FNN can accurately evaluate the risk level of PMEIDP. (2) Evaluation C, D, and E are at lower risks. (3) Evaluation A and B are at high risks, which we need to pay high attention to. In terms of future work, we need to design several risk control measures to reduce the economic losses of PMEIDP.

Acknowledgments

This study is supported by the project of State Grid Zhilian E-commerce Co., LTD. “State Grid Zhilian E-commerce Co., LTD. 2021 Incubation capital project investment evaluation index and risk control system consulting project” (SGDSZL00SCWT2122167). The authors are grateful to the participants who help to improve the paper with many pertinent comments and suggestions.

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