Digital Engineering and Digital Twin

Tech Science Press

DOI: 10.32604/dedt.2024.048142

ARTICLE

Research on Substation Siting Based on a 3D GIS Platform and an Improved BP Neural Network

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Received: 28 November 2023 Accepted: 07 March 2024 Published: 31 December 2024

ABSTRACT

Substation siting is an important foundation and a key task in power system planning. The article is based on a three-dimensional GIS platform combined with an improved BP neural network algorithm and proposes a substation siting method that is more efficient, accurate and provides a better user experience. Firstly, the BP algorithm is enhanced to improve its convergence speed and computational efficiency for a more accurate and reasonable calculation of optimal site selection. Then, a 24-item selection index system with 7 categories is proposed, which provides quantifiable data support and an evaluation basis for substation site selection. Finally, based on the 3G GIS platform, combined with the improved BP algorithm, site selection evaluation indicators, and multi-source data automatically extracted by the platform, the application research of substation site selection was carried out. The experimental simulation results show that the method proposed in the paper has better robustness and accuracy compared with traditional methods such as PCA and AHP. Compared to traditional manual site selection, site selection based on a 3D GIS platform has a better intuitive experience and convenience, which improves the efficiency of site selection and the user experience level.

KEYWORDS

Substation siting; digital twin; 3D GIS platform; back propagation (BP); principal component analysis (PCA); analytic hierarchy process (AHP)

1 Introduction

The power industry is a crucial aspect of the national economy, and the provision of electricity is vital for promoting its rapid development. Substations, as a critical component of power grid infrastructure, facilitate power transmission and voltage conversion and constitute the core and key of power grid planning and layout [1]. Substation engineering projects have the characteristics of high technical requirements, a complex on-site environment, and high project investment. Hence, a thorough and equitable assessment of the project site selection is imperative prior to commencing substation engineering [2]. The appropriate pick of substation site plays a pivotal role in the overall cost-effectiveness and safety of construction investment, construction velocity, and subsequent operation and maintenance. During the conventional process of selecting a site for a substation, multiple system sites that satisfy the criteria are initially identified through an analysis of the substation's location, capacity, power load, and the comprehensive picture of the power grid architecture. Following this, professionals carry out inspections and comparisons at pertinent system sites, subsequently selecting a few alternative locations. Finally, the best-recommended site is selected through a comprehensive comparison of these alternative sites. Therefore, the traditional substation site selection process often requires enormous manpower, material resources, and time [3].

In light of advancements in digital technology, new approaches to substation project site selection have emerged. Chen et al. [4] proposed a substation location selection method founded on geographic information systems (GIS), and gray correlation can aid in the amalgamation of GIS geographical information. However, indicator data needs to be manually collected, organized, and calculated. Yan et al. [5] suggest a method for optimizing the location of substations using a genetic algorithm improved with particle swarm optimization. This method can accurately select the substation location, but its convergence speed is slow. Vahedi et al. [6] proposed an innovative approach based on analyzing a raster map in a geographic information system to perform substation expansion planning for a very large-scale real network. Han et al. [7] proposed deep learning-aided joint DG-substation siting and sizing in distribution network stochastic expansion planning. In this method, a Long Short-Term Memory (LSTM) deep neural network is used to forecast DG output and load, where the electricity growth rate, bidding capacity of the electric expansion, and industrial difference are all considered. Bosisio et al. [8] proposed a GIS-Based approach for primary substation siting based on Voronoi diagrams and the particle swarm optimization (PSO) method. This method uses PSO to locate the new main substation and combines Voronoi diagram algorithms to find the main substation's service area and load, ensuring that the distribution transmission distance is as short as possible, reducing feeder costs, power outage costs, and service interruption risks. Feng et al. [9] proposed a deep learning algorithm for preliminary substation location selection in distribution network planning. This method extracts features related to substation location principles and uses multichannel data representation. These features are then fed into one of the deep learning algorithms, the Convolutional Neural Network (CNN), for inference to obtain optional preliminary substation addresses. Other methods such as fuzzy comprehensive evaluation, AHP evaluation, operations research, multivariate statistical analysis, and gray system theory, due to their lack of self-learning ability, are often influenced by human factors when determining evaluation weights, which affects the objectivity of evaluations [10].

To enhance the precision and promptness of methods for selecting substation locations, this article posits a substation location selection method reliant on a three-dimensional GIS platform and a boosted BP neural network. Firstly, in response to the problem of BP networks being prone to local minima, we improved the BP neural network by adding momentum terms and adjusting SSE to change the learning rate, achieving the goal of reducing network training time. Secondly, we combine the BP neural network algorithm with the 3D GIS platform, fully leveraging the ability of the 3D GIS platform to organize, store, and apply multidimensional data, as well as the spatial computing and digital twin display capabilities, to achieve visual and data-driven system landing point selection and candidate site selection, improving site selection efficiency and user experience. Thirdly, through the improved BP neural network model described in the article, the indicator data of the initially selected alternative site is automatically extracted and calculated on the 3D GIS platform, accurately obtaining the evaluation indicators of each alternative site. The highest-rated site is the recommended site.

2 Materials and Methods

2.1 Improved BP Neural Network Algorithm

The BP algorithm is a widely recognized learning algorithm for multi-layer perceptrons. To summarize, it offers the benefit of being capable of approximating any nonlinear mapping relationship and displaying good generalization ability. However, there are also drawbacks, such as slow convergence speeds and local extremism [11].

One major issue with BP neural networks is that they can encounter local minima, static points, or oscillations during the learning process. The article adopts the method of introducing momentum terms to modify the adjustment formulas for the weight coefficients and thresholds of the BP network [12]:

$$\Delta_{w_{ij}}(n) = \alpha \Delta_{w_{ij}}(n-1) + (1-\alpha)\,\eta\delta_i(n)\,Pj(n) \tag{1}$$

$$\Delta b_i(n) = \alpha \Delta b_i(n-1) + (1-\alpha)\,\delta_i p_j(n) \tag{2}$$

Note: (1) n refers to the number of training iterations. (2) Δ_w denotes the change in weight value. (3) η refers to the learning rate. (4) δ_i is the error calculation of the output node i. (5) p_j is the calculated input of the input node. (6) α denotes the momentum factor which is typically set at around 0.95.

The principle of adding momentum terms is to consider not only the effect of errors on gradients but also the influence of changing trends on the error surface when correcting network weights. Its function is like a low-pass filter, allowing for negligible, small changes on the network [13]. The specific explanation is as follows: when the momentum factor value is zero, the weight change only occurs according to the gradient descent method. When the momentum factor is set to 1, the new weight change is set as the last weight change, while the changes generated by the gradient method are ignored, causing the adjustment of the weight to change towards the average direction at the bottom of the error surface. When the network weight enters the flat area at the bottom of the error surface, δ_i will become very small, so $\Delta_{w_{ij}}(k+1) \approx \Delta_{ij}(k)$, which prevents the occurrence of $\Delta_{w_{ij}} = 0$ and helps the network jump out of the local minimum of the error surface.

To address the issue of gradual convergence pace in BP neural networks, the proposed solution in this article utilizes the annealing algorithm outlined in reference [14] to enhance the learning rate, which is pivotal in determining the amount of weight adjustment produced in every round-robin training. A high learning rate could cause system instability, whereas a low learning rate can lead to extended training time and gradual convergence. As a general rule, it is recommended to opt for a smaller learning rate to guarantee system stability. The range of learning rate selection lies between 0.01 and 0.8. The notion of the learning rate employed in this article can be articulated as follows:

$$\eta(n+1) = \left\{1 + \frac{\operatorname{sgn}[SSE(n) - SSE(n+1)]}{\left[1 + e^{\frac{SSE(n+1)}{SSE(n)}}\right]\tau}\right\}\eta(n) \tag{3}$$

Specifically, the learning rate is adjusted through changes in SSE. When $SSE(n+1) > SSE(n)$, it indicates that the weight coefficient adjustment is too large. The above equation can reduce the learning rate for correction. At the same time, the larger $SSE(n+1)$ is compared to $SSE(n)$, the smaller the learning rate is adjusted. When $SSE(n+1) < SSE(n)$, it indicates that the correction value of the weight truly reduces the error function, that is, the selected learning rate value is small, which can be increased by the above equation. When $SSE(n+1) = SSE(n)$, it indicates that the learning rate remains unchanged. In the above equation, τ refers to the adjustment coefficient which is typically set at 10, η (0) is set at 0.6.

2.2 Design of Site Selection Indicators for Substation

The planning of substations is a vital aspect of power system construction and necessitates careful consideration of project costs and construction rationality [15]. When selecting new substation sites, the critical factors to consider include:

(1) When adding a new substation, it is essential to determine the capacity based on the annual load forecast of the planned area and select the site of the substation according to the saturated load. Therefore, when selecting a new substation site, it is necessary to consider the area between the station site and the load center, as well as the newly added power supply area, to maximize the service capacity of the new substation.

(2) Considering the distance from the load center, whether it is close to the load center will directly determine the amount of electrical energy loss and whether the distribution of the substation is reasonable. Generally speaking, when selecting the location of the substation at the load center, the investment funds for substation construction and line electrical energy loss will also be relatively small, and the power supply radius will also be relatively small.

(3) When choosing a substation location, geographical location is a crucial factor to take into account. Typically, the city has already planned or requisitioned areas such as buildings, rivers, and roads, making it impossible to place the substation in these locations. When choosing a substation location, it is crucial to maintain communication with urban planning, transportation, and other departments. This is to guarantee that the substation location does not clash with the plans of other departments [16].

(4) When deciding on the location of a substation, it is crucial to obtain the urban planning department's approval and adhere to the city's unified layout. Scenic spots, historical sites, and cultural relic protection areas should be actively avoided. To enhance the city's aesthetics, the construction of a substation should coordinate with the urban landscape, save land, and safeguard the surrounding environs.

(5) The substation's location ought to be far from public communication facilities. Grounding faults within the power system could cause potential rises, which can damage the normal functions of radio stations, military radar stations, and airports. Hence, the location of the substation should be kept as far away from communication facilities as possible.

(6) When choosing a site for the substation, it is vital to take into account the environmental and meteorological factors in the area. It is important to steer clear of regions with frequent lightning occurrences, strong winds, and fog, as well as areas with regular activities by protected bird species and other animals.

(7) It is essential to consider relevant factors, including flood and earthquake prevention, in their entirety [17].

Based on the above considerations, following the principles of comprehensiveness, scientifically, systematically, feasibility, operability, quantitative analysis, and qualitative analysis, as shown in Fig. 1 below, the article has designed a total of 7 categories and 24 substation site selection index systems, including service capacity, economic benefits, traffic conditions, construction conditions, meteorological conditions, natural environment, social environment, etc. [18].

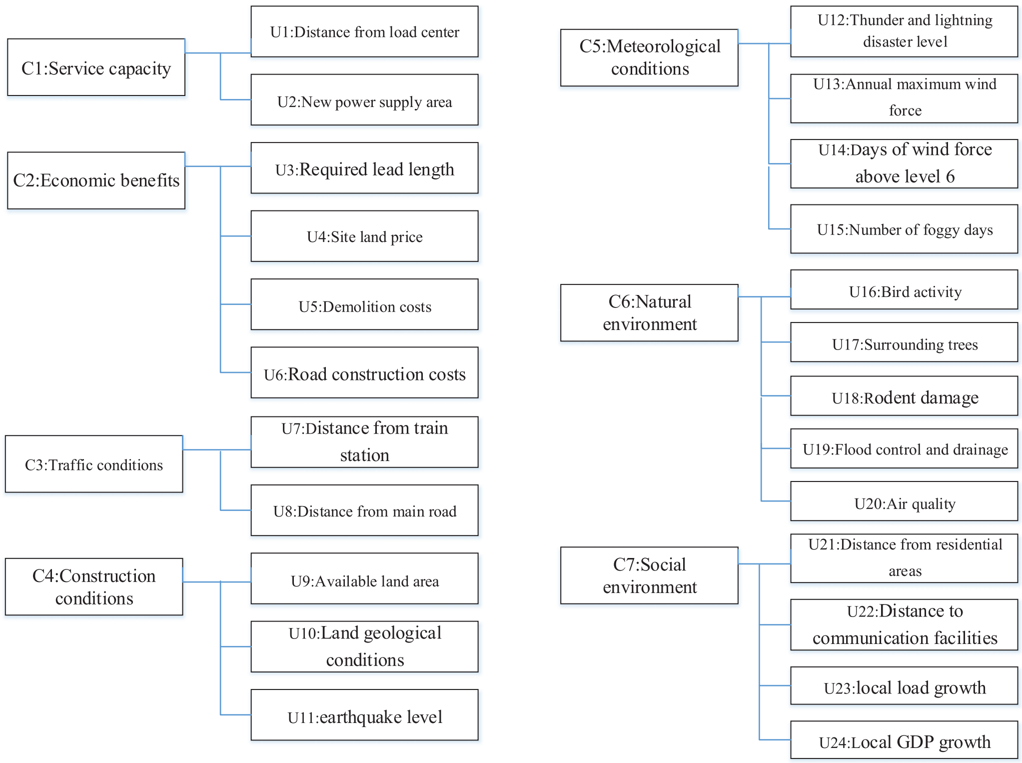

Figure 1: Substation site selection index system

Due to the varying dimensions and types of indicators, it is necessary that the evaluation indicator values be dimensionless. Assuming $\max\limits_{1\leqslant i\leqslant m} x_{ij} = a_j$, $\min\limits_{1\leqslant i\leqslant m} x_{ij} = b_j$, then:

1. For benefit indicators, $y_{ij} = \dfrac{x_{ij} - b_j}{a_j - b_j}$.
2. For cost-based indicators, $y_{ij} = \dfrac{a_j - x_{ij}}{a_j - b_j}$.
3. For moderate indicators, $y_{ij} = \dfrac{1}{1 + |q - x_{ij}|}$.
4. For interval-type indicators, $y_{ij} \begin{cases} 1 - \dfrac{q_1 - x_{ij}}{\max(q_1 - b_j, a_j - q_2)}, & x_{ij} < q_1 \\ 1 - \dfrac{x_{ij} - q_2}{\max(q_1 - b_j, a_j - q_2)}, & x_{ij} < q_2 \\ 1, & q_1 \leqslant x_{ij} \leqslant q_2 \end{cases}$.

In the formula, [q1, q2] are the optimal intervals for this indicator.

For qualitative indicators, the Delphi method can be used for quantification [19]. Through the above calculation, a dimensionless data matrix can be obtained: $Y = (y_{ij})_{m\times n}, y_{ij} \in [0, 1]$.

2.3 Substation Site Selection Using a 3D Platform and BP Algorithm

With the progress of 3D visualization technology and spatial geographic data and building upon traditional substation location technology, it is feasible to integrate the enhanced BP neural network algorithm, outlined in this article, with high-precision 3D geographic information models for substation site selection. Constructing a lifelike three-dimensional environment on-site and transferring the complex site selection process onto the computer screen can considerably enhance resource utilization and data efficiency. As a result, the precision and efficiency of substation site selection would be enhanced [20].

Firstly, the article utilizes the three-dimensional GIS-integrated platform for power grid planning and design, referred to as the three-dimensional platform, with the selection of three-dimensional locations for substations as the service process. The platform integrates and manages data from diverse sources, including geographic, image, power grid resource, power grid thematic (such as pollution area maps, bird harm maps, etc.), traffic network, various surpasses, geological, model, and engineering data. This integration provides extensive data support for the selection of substation sites [21].

Secondly, the 3D platform is founded on 3D refined models, utilizing aerial survey technology, 3D visualization technology, virtual reality technology, and information integration technology, combined with engineering and geographic information, which are integrated through data-driven models in the form of 3D digitization. This enables the integration of terrain and geomorphic details in power grid engineering and construction process data. The BP neural network model is utilized for calculating alternative address scores and selecting the optimal address [22].

Finally, the 3D platform provides services for 3D substation siting by creating a real 3D environment on site. Combined with the data processing tools provided by the platform, high-precision aerial image data, and digital elevation model data are segmented and encoded step by step and published according to OGC (Open Geospatial Consortium) specifications. The 3D platform invokes the published image and elevation data services to construct a refined 3D scene of the engineering area. By using naked-eye 3D to realistically restore the three-dimensional situation of the engineering corridor and by using efficient 3D rendering technology based on the level of detail model, the construction of large-scale 3D visualization scenes based on massive data and high-speed browsing of large-scale scenes are achieved, providing a smooth, seamless user experience and supporting the substation site selection work [23].

Specifically, unlike traditional site selection methods, the method proposed in the article combines the needs of power system planning, transmission, and transformation specialties and can intuitively and visually select system locations and candidate station locations on a three-dimensional platform; secondly, after the initial selection of alternative sites is completed, the improved BP neural network model described in the article can be combined to extract the indicator data of each alternative site through various multi-source data integrated into the three-dimensional platform and perform relevant calculations, finally achieving quantitative scoring selection [24]. The site selection process is illustrated; see Fig. 2 below.

The key steps in the substation siting process are as follows:

(1) Systematically selecting landing points.

Substation siting refers to the process of constructing substations in suitable areas based on the geographical environment, load demand, urban planning, and other factors. The purpose of site selection is to make the construction of substations more in line with actual needs and to improve the operational efficiency and reliability of the power grid. See Fig. 3 below, the article proposes a map scene based on a three-dimensional platform that marks the location of the system landing point to determine the scope of site selection [25].

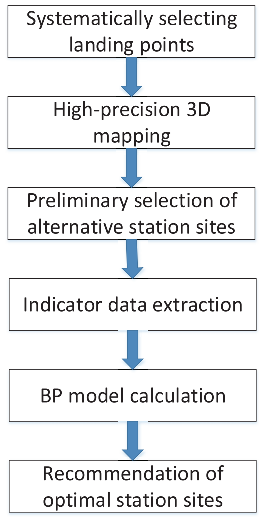

Figure 2: Substation site selection flow chart

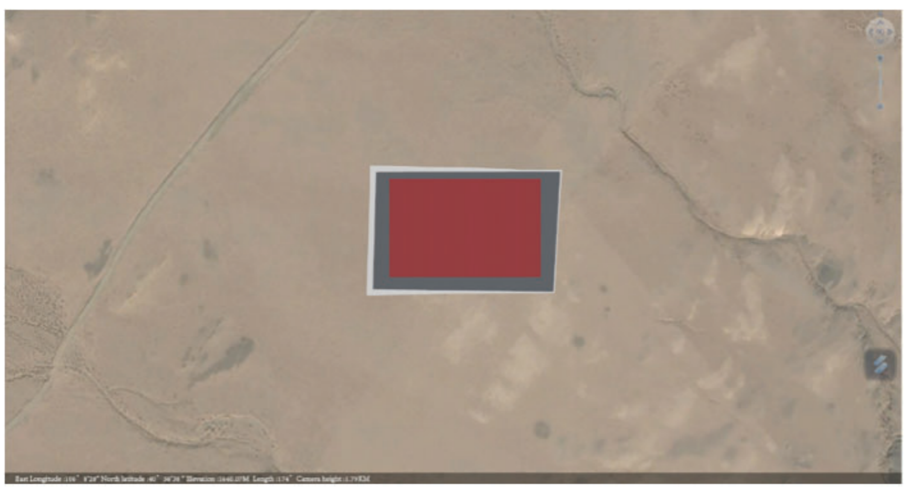

Figure 3: Schematic diagram of the site selection system for substations

(2) Preliminary selection of alternative station sites.

Based on the load distribution area provided by the system profession, the final scale of the system, and the system access plan, the proposed range of station sites and the area of station site walls are preliminarily determined, and alternative station sites are preliminarily selected on a three-dimensional platform, as shown in Fig. 4 below. During the initial selection, sensitive points such as the overall planning map, land use overall planning map, and ecological red line map need to be imported into the 3D design platform so that the terrain map data in the platform can be overlaid with the information of each sensitive point to avoid sensitive points involved in functional departments such as minerals, environmental protection, forestry, culture, tourism, water conservancy, and military [26].

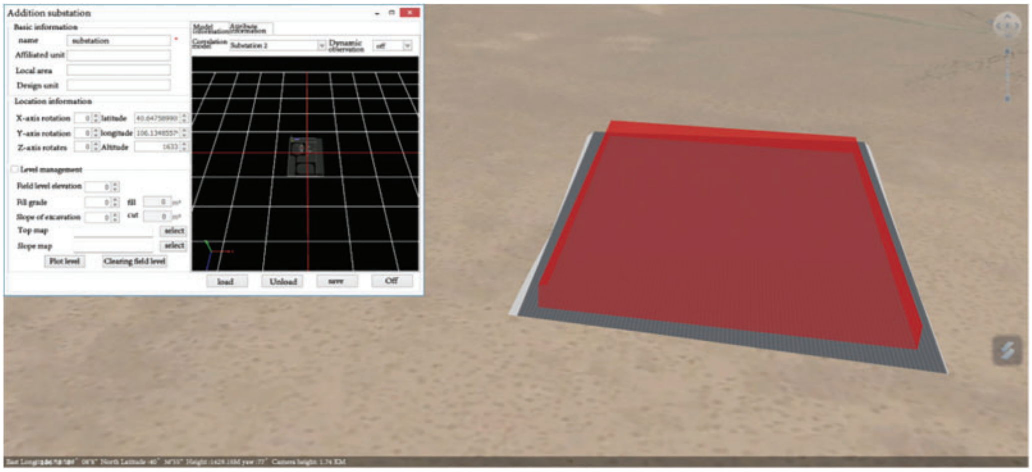

Figure 4: Schematic diagram for the preliminary selection of alternative substation sites

The preliminary selection of alternative station sites should be considered in conjunction with the substation and transmission characteristics. In the case of a substation, the terrain and topography will determine the approximate elevation and excavation and backfill conditions of the station site. The traffic conditions around the station site will determine the direction and length of the access road. The nature of the land has a direct impact on the feasibility of the station site. The location of water sources and external drainage is directly related to the water supply and drainage of the station site. Based on the three-dimensional geographical data and the elevation platform of the station site, the earthwork volume of the station site can be calculated, which provides powerful data for the selection of the station site. For the power transmission industry, it is crucial to ensure that the feeder corridor is open. Narrow outlet corridors require other complex technical solutions to solve the problem, which has a direct impact on the shape of the outlet and the tower of the substation, often resulting in huge investments. Therefore, outlet corridors are an important link that influences the choice of station locations [27].

The preliminary selection of alternative station sites can be carried out by a three-dimensional platform, which can provide data and spatial calculation support for the preliminary selection of alternative station sites based on the platform's functions such as terrain mapping, GIM (Grid Information Model) cross-object extraction and recognition, vector data import, three-dimensional oblique photography, and multi-source data such as geographic information data, power thematic data and survey data [28].

(3) BP model calculation and Recommendation of optimal station sites.

After obtaining the alternative site, the geographical coordinates of the alternative site can be used to automatically extract primary and secondary indicator data such as traffic conditions, construction conditions, meteorological conditions, and the natural environment from the massive multidimensional data collected on the 3D platform. After dimensionless processing, the data can be fed into the improved BP model described in the article for calculation, and the indicators and evaluation results of each alternative site can be obtained, the optimal result being the recommended site, as shown in Fig. 5 below.

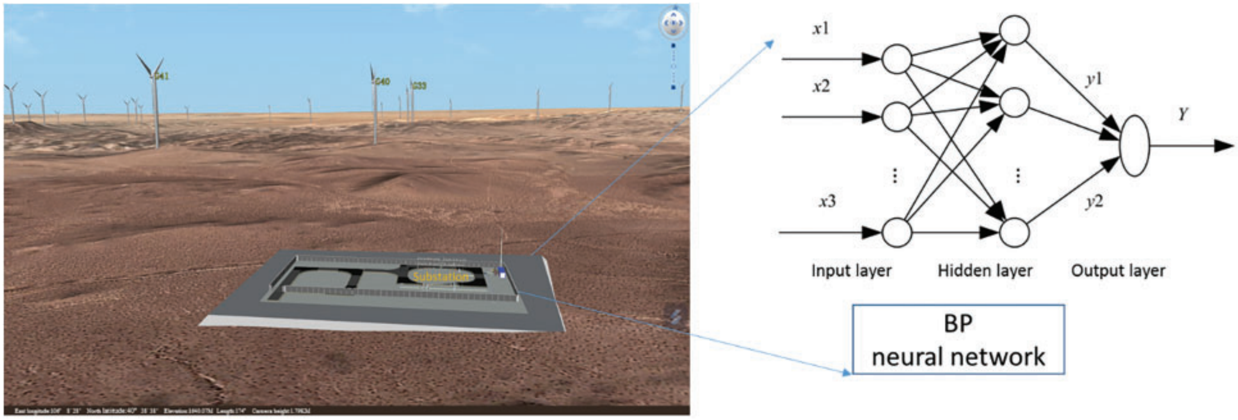

Figure 5: Schematic of BP model selection for substation location

3 Result and Discussion

3.1 Data Preparation

To validate the method described in the article, an effective experiment was conducted in conjunction with the 110 kV substation project in Cangnan County, Wenzhou City. The regional economy in Cangnan County is developing, and the highest load in the area is approaching full capacity. To improve the reliability of regional power supply and alleviate the tense situation of power supply, a new substation project is planned for construction. With this background, taking into account constraints such as power grid flow and structure, the method described in references [29,30] can be used to obtain 10 sample station sites for training purposes and 3 alternative substation sites for testing purposes. Then, the method used in this article is used for indicator calculation and evaluation. The indicators and evaluation results are shown in Tables 1–3. In the table, U1∼U24 are the evaluation indicators for substation site selection, SS1∼SS10 are the sample sites, ASS1∼ASS3 are the candidate sites, PCA represents the Principal Component Analysis, AHP represents the Analytic Hierarchy Process, and PCA @ AHP represents the arithmetic mean of the evaluation results obtained by PCA and AHP evaluation methods and normalized. Then, by integrating data on power grid planning, geographic environment, planned land use, natural environment, social environment, economic benefits, etc., into the multi-source database of the 3D GIS platform, we were able to extract and normalize indicator data for each station site. The results are presented in Tables 1 and 2. In these tables, U1∼U24 represent the evaluation indicators for substation site selection, while SS1∼SS10 are the sample sites and ASS1∼ASS3 are the candidate sites.

Table 1: Example of substation site indicator data

Parameters	SS1	SS2	SS3	SS4	SS5	SS6	SS7	SS8	SS9	SS10
U1	1.00	0.96	0.84	0.76	0.71	0.84	0.93	0.94	0.95	0.61
U2	1.00	0.35	0.64	0.98	1.00	0.97	0.66	0.67	0.64	0.36
U3	1.00	0.93	0.94	0.97	0.94	0.93	0.92	0.97	0.94	0.91
U4	1.00	0.95	0.97	0.96	0.95	0.96	0.92	0.93	0.93	0.91
U5	1.00	0.95	0.98	0.96	0.97	0.97	0.98	0.96	0.96	0.84

(Continued)

Table 1 (continued)

Parameters	SS1	SS2	SS3	SS4	SS5	SS6	SS7	SS8	SS9	SS10
U6	1.00	0.88	0.92	0.81	0.92	0.73	0.71	0.81	0.59	0.48
U7	1.00	0.88	0.23	0.88	1.00	0.87	0.68	0.77	0.53	0.46
U8	1.00	0.94	0.91	0.95	0.99	0.96	0.94	0.91	0.92	0.89
U9	1.00	0.96	0.97	0.95	0.93	0.92	0.91	0.93	0.92	0.72
U10	1.00	0.83	0.76	0.93	1.00	0.81	0.65	0.76	0.56	0.43
U11	1.00	0.98	0.91	0.98	0.94	0.93	0.92	0.91	0.92	0.84
U12	1.00	0.96	0.93	0.96	0.81	0.95	0.81	0.93	0.84	0.86
U13	1.00	0.94	0.86	0.95	0.74	0.81	0.74	0.85	0.93	0.71
U14	1.00	0.81	0.79	0.81	1.00	0.78	0.61	0.80	0.61	0.42
U15	1.00	0.86	0.94	0.95	0.96	0.85	0.93	0.79	0.95	0.83
U16	1.00	0.95	0.96	0.97	0.96	0.95	0.94	0.92	0.91	0.88
U17	1.00	0.79	1.00	0.88	0.95	0.86	0.65	0.79	0.57	0.45
U18	1.00	0.76	0.48	1.00	0.95	0.76	0.48	0.76	0.48	0.49
U19	1.00	0.81	0.66	0.93	0.85	0.81	0.68	0.73	0.61	0.48
U20	1.00	0.96	0.99	0.94	0.99	0.96	0.95	0.96	0.94	0.93
U21	1.00	0.97	0.96	0.97	0.96	0.93	0.94	0.95	0.91	0.92
U22	1.00	0.94	0.97	0.96	0.94	0.97	0.97	0.98	0.96	0.96
U23	1.00	0.97	0.96	0.96	0.97	0.94	0.93	0.91	0.97	0.96
U24	1.00	0.96	0.97	0.98	0.97	0.94	0.90	0.91	0.92	0.86

Table 2: Alternative substation site indicator data

Parameters	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12
ASS1	1.00	0.99	0.98	0.96	0.93	0.94	9.96	1.00	0.94	1.00	0.95	9.99
ASS2	0.97	1.00	0.93	0.97	0.96	0.90	0.95	0.93	0.96	0.96	1.00	0.95
ASS3	0.95	0.98	0.95	0.93	1.00	0.93	0.95	0.94	0.96	0.97	0.99	0.96
Parameters	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	**U21**	**U22**	**U23**	**U24**
ASS1	0.96	0.98	0.96	0.96	0.98	1.00	0.95	0.98	0.96	0.96	0.95	1.00
ASS2	0.95	0.92	0.96	1.00	0.99	0.95	1.00	0.98	1.00	1.00	0.98	0.95
ASS3	1.00	0.96	0.95	0.97	0.98	0.96	0.98	0.96	0.94	0.96	1.00	0.94

3.2 Experimental Result

The method proposed in this article is used for the calculation and evaluation of substation optimization siting. The evaluation results are shown in Table 3. In the table, PCA represents the Principal Component Analysis, AHP represents the analytical Hierarchy Process, and PCA @ AHP represents the arithmetic mean of the evaluation results obtained by PCA and AHP evaluation methods and normalized.

Table 3: Training and evaluation results

Parameters			BP algorithm sample training results		Evaluation results of alternative station locations		
PCA	AHP	PCA@AHP	Training results	Sample site	Result sorting	Calculation results	Alternative site
3.22	3.16	1.00	1.00	SS1	1	0.9923	ASS1
2.86	2.94	0.91	0.91	SS2	3	0.9858	ASS2
2.76	2.82	0.87	0.87	SS3	2	0.9884	ASS3
2.98	3.03	0.95	0.93	SS4			
2.96	2.96	0.94	0.94	SS5			
2.86	2.88	0.92	0.92	SS6			
2.676	2.73	0.86	0.86	SS7			
2.82	2.78	0.88	0.88	SS8			
2.62	2.85	0.85	0.85	SS9			
2.28	2.66	0.77	0.77	SS10			

From the example results, it can be seen that the calculation results of the three alternative sites are generally higher than those of the ten sample sites, in the order of ASS1 = 0.992 > ASS3 = 0.988 > ASS2 = 0.986. The example results show that the BP algorithm proposed in the article has good robustness. According to the method described in the article, the optimal recommended site is evaluated as ASS1, with a score of 0.992, which is close to 1, indicating that the improved BP algorithm described in the article has good accuracy.

The project team enlisted experts to evaluate the optimal site, ASS1, derived from the experiment, and manually verify the indicators. The evaluation results confirmed that ASS1 is indeed the optimal site. After the ASS1 substation project was put into operation, the post-project evaluation feedback indicated that the project had successfully met the design plan and project expectations.

4 Conclusion

The scientific and accurate location selection of substations has important value and significance for power grid construction and power security. Based on a three-dimensional GIS platform combined with an improved BP neural network algorithm, this paper proposes a substation site selection method with higher timeliness, higher accuracy, and a better user experience. Firstly, the ability to integrate multi-source data based on the 3D GIS platform provides rich data support and the basis for site selection. Secondly, by combining the powerful aerial survey technology, 3D visualization technology, virtual reality technology, and other technologies in the 3D GIS platform, more intuitive and efficient tools are provided for the initial selection of substation system landing points and alternative website addresses. Thirdly, combined with the improved BP algorithm, the convergence speed and learning and training efficiency of the network have been greatly improved. The experimental results indicate that the BP algorithm described in the article has better robustness and accuracy in calculating substation siting compared to other similar algorithms. The site selection process for alternative websites is based on the 3D GIS platform. This allows for intuitive visual operations and automatic calculations by combining multi-source data, greatly improving selection efficiency and the user experience. The research methods described in the article have practical value and promotional significance.

Acknowledgement: The present study was supported by the State Grid Corp of China Science and Technology Project (Research and Application of the Three-Dimensional Geographic Information GIS System of State Grid Shandong Economic Research Institute in the Design Review of Transmission and Transformation Projects in Shandong Province). The authors would like to thank the other members of the project team for their work, providing technical advice, information, and data.

Funding Statement: The present study was supported by the State Grid Corp of China Science and Technology Project (Grant Number Z520625200003).

Author Contributions: The authors confirmed contribution to the paper as follows: Yao Jin: Conceptualization, Funding acquisition, Methodology, Writing—original draft. Jie Zhao: Conceptualization, Methodology, Writing—original draft. Xiaozhe Tan: Data curation, Methodology, Writing—original draft. Linghou Miao: Visualization, Formal analysis, Writing—review & editing. Wenxing Yu: Software, Visualization, Writing—review & editing. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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