

Research Article

Transmission Line Planning Based on Artificial Intelligence in Smart Cities

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With the development of smart cities, it is particularly important to realize scientific and reasonable planning of transmission lines as the backbone of the power transmission system. Through the geographic information system (GIS) platform, this paper obtains the geographic information of the planning area. Then, through the typical design cost of the 110 kV transmission line subvolume of the typical cost of the power transmission and transformation project of the State Grid Corporation and the local documents of the smart city planning area, this paper obtains the estimated cost of each grid after gridding in the smart city area. After that, the research uses the ant colony algorithm to search for the optimal transmission line route in the smart city. Finally, the achievements of primary economic and technical indexes are evaluated in transmission line planning of smart city.

1. Introduction

Judging from the development trend of modern society, the scale of future cities will become larger and larger, and the urban population will increase accordingly. At present, the rapid development of cities in my country has led to the increasingly prominent problem of “urban disease” in some areas. The construction of smart cities can effectively solve the development problems of modern cities. A smart city is to analyze, detect, and integrate various key data of the city's core system through communication means and communication technologies so as to quickly and intelligently respond to the problems and needs in the city. Its essence is to realize the intelligent management and operation of the city, use the new generation of information technology to integrate analysis, make the city more suitable for human life and living, and realize the harmonious coexistence of the city and the people.

Geographical information system (GIS) is a computer system used to collect, store, manage, analyze, and display geographic spatial data [1]. Nowadays, GIS is ubiquitous and deeply integrated with other industries. It is widely used in various aspects of social life such as land, cities, resources and environment, public security, emergency response,

logistics, electricity, and pipeline networks. In recent years, with the surging wave of new generation technologies such as big data, smart cities, cloud computing, Internet of Things, and artificial intelligence (AI), the development of GIS has ushered in new opportunities and challenges. Among them, AI has developed rapidly and has been widely used in many fields such as face recognition, machine learning, language and image understanding, intelligent control, intelligent search, and automatic planning.

AI was first proposed by American scholars in related fields in a conference held at Dartmouth University in 1956. It has never given a strict definition. This article is more in favor of the AI concept defined by Tsinghua University professor Shi Chunyi and others. AI is summarized as the study of how to make computers imitate the thinking activities such as reasoning, learning, thinking, and planning that the human brain can perform to solve complex problems that can only be handled by human experts [2]. The general algorithms implemented by AI include artificial neural network, genetic algorithm, immune algorithm, ant colony algorithm, and particle swarm optimization algorithm [3].

Ozsari et al. [4] proposed to integrate traditional GIS software with intelligent statistical methods and

mathematical models to achieve location decision-making and strategic planning in the 1990s. The intelligence of their GIS was only reflected in statistical methods and mathematical models. "Intelligence" is still more limited and narrow. Korus et al. [5] had proposed in the book "Artificial Intelligence in Geography" that the heuristic search, neural network, and evolutionary algorithm included in AI methods had their importance and application potential for geography. Li Xia, a Chinese scholar, summed up the concept of intelligent GIS by summarizing the application of AI in GIS combined with previous research. This concept brought AI methods to the spatial data constructed by GIS. In order to solve data extraction, simulation, optimization, and decision-making assistance in complex spatial problems, Li Xia built an automated and intelligent spatial analysis method with self-learning. This concept made up for the goals that could not be achieved by modeling based on traditional mathematical methods [6]. In the past three decades, with the deepening of AI research, the application of AI in the field of GIS had been triggered. Liwei et al. [7] designed a multidimensional unified computing engine based on genetic algorithm to process different types of geographic data and data of different dimensions; Wang et al. [8] used artificial neural network and GIS to simulate soil erosion rate and spatial change; Donoho et al. [9] solved the multiobjective urban land space optimization allocation by constructing a model based on spatial genetic algorithm and obtained urban optimal allocation of space for construction-like land; Fyhn et al. [10] combined ant colony algorithm and GIS for the location selection of logistics distribution center; Yu et al. [11] applied simulated annealing algorithm, genetic algorithm, and particle swarm optimization algorithm, respectively, to the spatial optimization problem of multiobjective land allocation. By introducing AI into the field of spatial information processing, the ability of GIS spatial analysis has been improved, and a model for intelligent processing of spatial data has been built, which has increased the practicability, intelligence, and scientificity of spatial data analysis and processing, and has brought research in various fields of science. There are new ideas, but the combination of AI and GIS in thematic fields is not yet mature, and a mature method system has not yet been formed, and in-depth research is needed.

Path optimization is also an important research content in the application fields involved in AI algorithms. The purpose of path optimization is to find the optimal path. The "optimal" here is not simply the shortest path distance, but it can be a measure of economic consumption, cost, time consumption, efficiency, etc. Ant colony optimization (ACO) is a kind of swarm intelligence algorithm. It was proposed by Italian scholar Dorigo and others in the early 1990s by simulating the behavior of ant colony path optimization in nature [12]. The ACO algorithm is widely used to solve similar traveling salesman (TSP) problems. This algorithm uses a distributed, positive feedback, and parallel computer system. It is easy to combine with other methods and has strong robustness. The optimization problem has great potential [13]. Jiao et al. [14] proposed a robot path planning method in two-dimensional space based on ACO and added

artificial ants to improve the flexibility of optimization by considering user requirements and environmental conditions when making decisions. Liu et al. [15] proposed a pheromone distribution and pheromone update strategy based on ACO. It used time-varying characteristics such as inflection point optimization and local optimal expansion path to design inflection point parameters and an overall evaluation method. This method was used for path planning of mobile robots in complex environments, and it was verified that the ant colony expansion path optimization algorithm was better than the traditional ACO and the improved algorithm. The algorithm had better search performance, stronger search ability, and shorter path, avoided falling into local optimum, and realized the search of the optimal path of mobile robot. Obayashi and Masuyama [16] used cellular automata to build a robot's path planning environment model. On this basis, ACO was used to optimize path planning. Experiments proved the feasibility of the method. ACO has the advantages of distributed, positive feedback, and parallel computing in path optimization, but it also has shortcomings such as too long search time and falling into local optimum.

In addition to the overall planning of power grid, the optimization of transmission cable path also affects whether the operation can continue to be stable. Power transmission cables are an important part of the power grid due to their power transmission tasks [17]. Transmission cable design and planning is a huge project with high construction cost, long period, and strict conditions. It includes electrical design, basic design, path selection, insulation coordination design, grounding design, and various types of tower designs. In all tasks, the focus is to select the cable path, because the subsequent design work is directly affected by the path selection, which in turn has an important impact on the input cost and overall effectiveness [18]. The route of the transmission cable is selected to find the best route that meets the requirements of cost-effectiveness, convenient construction, stable operation, and compliance with national policies [19]. At present, a large number of scholars have conducted in-depth research on the optimization of cable selection. With the advancement of geographic information technology, intelligent route selection has become a hot topic in discussion [20]. In this paper, the AI route selection is used to study the route optimization of transmission cable, the main economic and technical indexes are established to evaluate the optimization results, and traditional manual route selection [21] and the Dijkstra algorithm are used for comparison.

2. Principles of AI Path Optimization Methods in Smart Cities

2.1. Process of Path Optimization Method. For route selection design of AI circuit, besides quantifying geographical elements that can influence route selection, comprehensive action index of each element should also be calculated [14, 22–23]. Therefore, the following optimization of AI transmission cable path can only be performed by discovering

the appropriate method to get the geographical information model of the smart city.

The following are detailed steps to use AI to optimize the transmission cable path in a smart city.

- (1) Obtain the final cost value matrix through the BP neural network algorithm and turn the geographical elements that affect the transmission cable into a measurable value, and then calculate the overall effect value of all the elements, which is used to perform the AI transmission cable path. Planning calculations
- (2) Mark the main cells that constitute the map route of the smart city planning area as the marker points and connect the marker points in sequence from the starting point to the end point to obtain the route plan
- (3) The ant colony pheromone updating mechanism is used to solve the path problem and bypass the obstacles in an appropriate way to obtain the best solution for cable transmission path in smart city

2.2. Geographic Information Model of Smart City Planning Area

2.2.1. Classification of Map Cells. In the smart city planning path, both natural and social factors will have an impact on the selection of the transmission cable path. Some of these factors are very restrictive, making it impossible to set up line towers in this area, nor to cross over in this area; but there are also areas that are not too restrictive, and paths can be designed for this area. According to the restrictive strengths of the geographic information factors in the above-mentioned planning area, the cells within the path research range can be divided into three categories: A, B, and C. Category A means that the line can pass through and can erect towers. Category B means that lines can pass through but the erection of towers is prohibited. Category C means that lines can neither pass through nor erect towers. Described from geographic information factors, category A is mainly high-altitude ice-covered areas of Xuefeng Mountain and Nanling Mountain, densely vegetated areas, densely housed areas, Yunma Forest Farm, Nandong Forestry Farm, etc. Category B is mainly rivers, lakes, geological hazards, etc., including 110KV Nanru Line, 110KV Yangbei Line, 35KV Chang'an Line, S219 Provincial Trunk Road, X088 County Trunk Road, X091 County Trunk Road and Township Highway. Category C is mainly for county planning areas, microwave communication towers, etc.

2.2.2. Estimation of Cell Cost Value. There are many factors that affect the selection of transmission cables, such as geology, landforms, hydrology, meteorology, pollution, vegetation coverage, power facilities, military facilities, and transportation facilities. It is difficult to comprehensively consider all factors. The traditional evaluation method is to construct a comparison matrix of the degree of influence between different factors through the analytic hierarchy pro-

TABLE 1: Comprehensive cost of unit length for different terrain conditions.

| Terrain | Wire model | Maximum wind speed (m·s ⁻¹), maximum icing (mm) | Comprehensive cost (ten thousand yuan) |
|-------------------|---------------|---|--|
| The ground | 2 × LGJ240/30 | 25, 5 | 49.49 |
| | | 30, 10 | 51.04 |
| River net bathing | 2 × LGJ240/30 | 25, 5 | 72.59 |
| | | 30, 10 | 74.54 |
| Hills | 2 × LGJ240/30 | 25, 5 | 51.83 |
| | | 30, 10 | 53.19 |

cess and then process the cost of the grid evaluated by the experts through the analytic hierarchy matrix to obtain the final cost value matrix [24]. The disadvantage is that the comparison of the degree of influence of the experts on the pairwise influences on the path selection of the transmission line is obtained through experience, which is highly subjective, and the result may not be accurate; when the amount of data is large, the number of grids is very large, and the evaluation will take a lot of time and energy.

In this paper, the BP neural network is used to simulate the actual cost of lines under different geographical conditions in the typical design of smart city planning area, and the BP neural network after fitting is used to predict the cost value of the cells across the transmission line under different geographical conditions, which is used as the reference value of the cell generation value. The planning area of this paper is a 110kV power transmission line somewhere in China, which belongs to the third meteorological region in China. The maximum wind speed is 25 m/s and the maximum ice cover is 5 mm. Refer to the typical cost of power transmission and transformation project of State Grid Corporation of China: the comprehensive cost of line unit length under different terrain conditions in the volume of 110kV transmission lines in 2006 [25] is shown in Table 1.

Considering that the influence of various factors on the cost value is nonlinear, a three-layer BP neural network function is used to complete the approximation task.

Taking into account that the influence of various factors on the cost value is nonlinear, the three-layer BP neural network function shown in Figure 1 is used to complete the approximation task.

Since the output layer of the network has multiple output nodes, the difference squares of each output node of the output layer need to be summed, so the loss function of each training example is obtained as

$$E(\vec{w}) = \frac{1}{2} \sum_{k \in \text{outputs}} (s_k - o_k)^2. \quad (1)$$

Among them, s_k is the expected output of the k neuron, o_k is the actual output of the k neuron, and w is the weight. Adjust the input weight vector in the output node according to the loss function, and then adjust the weight layer by layer

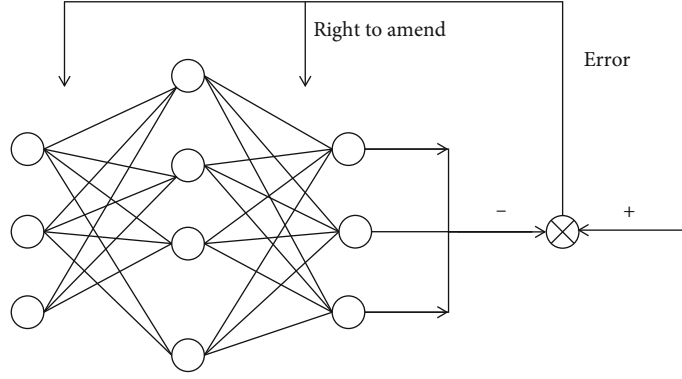


FIGURE 1: Schematic diagram of 3-layer BP neural network algorithm.

from back to front. Perform the following operations for each training of the metacell cost:

- According to the input of the example, calculate from front to back to get the output of each unit of the output layer. Then, the error term of each unit of each layer is calculated backward from the output layer
- For each neuron k of the output layer, calculate its error term:

$$\delta_k = o_k(1 - o_k)(s_k - o_k) \quad (2)$$

- For each hidden unit h in the network, calculate its error term:

$$\delta_h = o_h(1 - o_h) \sum_{k \in \text{outputs}} w_{kh} \delta_k \quad (3)$$

- Update each weight:

$$w_{ji} = w_{ji} + \eta \delta_j u_{ji}, \quad (4)$$

$w_{ji} = \eta \delta_j u_{ji}$ is called the weight update rule, u_{ji} is the input from node i to node j , w_{ji} represents the corresponding weight, and outputs represents the set of cell nodes in the output layer

Enter the samples in Table 1 to obtain the middle layer neural network. After processing the cells of the smart city planning area, the geographic conditions of each cell are obtained, and the cell cost value matrix is acquired by fitting the BP neural network to the geographic conditions of the cells. Additional special crossing and land acquisition costs are given to buffer cells located in areas such as roads, transmission facilities, and residential houses, as shown in Table 2, which ultimately forms a cost substitution value matrix for all cells in the smart city planning area.

TABLE 2: Special cost obtained by local file of planning region.

| Expense item | Standard fee (ten thousand yuan·km ⁻¹) |
|--|---|
| Requisition and clean-up fees for construction sites | 5.0 |
| Over 110 kV | 1.5 |
| Across 35 kV | 0.9 |
| Across 10 kV | 0.4 |
| Cross the grade highway | 2.5 |
| Highway | 5.0 |
| Charges for live-over housing measures | 0.5 |

2.2.3. Use GIS to Integrate Map Data of Smart City Planning Areas. Vector data and raster data models are two types of GIS data models [26]. Most of the geographic information in maps used at present are vector data. The grid size can be set according to the environmental parameters of GIS, and the corresponding grid data can be obtained from the original vector geographic information after transformation. Then, we merge and rank relevant geographic information and use BP neural network model to get cell cost value, so as to record coordinates of different grids.

The attribute information of the cell includes the position coordinate field $R(x, y)$, the cell type (A, B, C) , and the cell cost value c . The coordinate position of a cell represents the spatial position of the unit on a smart city planning map. Cell type indicates that smart city planning maps can form uncrossed line cells. The cell cost value is the cost value of the line passing over a cell.

2.3. ACO Transmission Cable Path Search Model. Cellular automata (CA) is used as the route selection model for transmission cables, and the search model is acquired by linking points in a straight line [27]. Mark main cells of the path on the map as marking points, connect one after the other from the starting point, and at the end of the search get a transmission cable path. The cells in smart city planning areas have three states: the initial state “0”, which indicates that the cell is not threaded through; if a cell is clearly marked as a cell at a time, the state must be changed to “1”; if a cell is on the route, then the status changes to “2,”

and finally the planned route is clarified according to “1” and “2” cells.

The pheromone mechanism of ant colony algorithm is usually used to settle the path searching issue, which helps to avoid obstacles and search for the path to obtain the optimal result. The rules of ACO search path are composed of avoidance rules, movement rules, and pheromone rules. According to these three rules, each ant finds the next moment position from the neighbor cells by roulette.

- (a) Search cell area analysis: set at a certain moment, where the ants are located e
- (b) Ant colony movement rule: set the neighbor grid to be selected, and then, the probability of moving from to is normalized as

$$p(x, y) = a_{xy}^\alpha b_{xy}^\beta m_{xy}^\gamma, \quad (5)$$

$$p_t(x, y) = \frac{p(x, y)}{\sum_{t=1}^N p(x, y)}. \quad (6)$$

Among them, $p(x, y)$ is the transformation probability of the cell, and a , b , and c are the information, cost, and direction control coefficients, respectively. Its control force is α , β , and γ , respectively. N is the number of optional neighbor cells.

When the transformation probability $p_t(x, y)$ is specified for all the neighbor cells, the roulette wheel is applied, and the next transformation cell is randomly chosen from a neighbor cell in a certain degree. The determination process is as follows: generate a random number r in the interval $[0, 1]$; if r satisfies formula (7), then t is the next grid position.

$$\begin{cases} 0 \leq r \leq \sum_{v=1}^t P_{e \rightarrow v}(x, y), & t = 1, \\ \sum_{v=1}^{t-1} P_{e \rightarrow v}(x, y) \leq r \leq \sum_{v=1}^t P_{e \rightarrow v}(x, y), & t \geq 2 \end{cases} \quad (7)$$

- (c) Pheromone update: pheromone concentration is one of the key heuristic factors for ACO path search. After each search obtains a feasible path, the pheromone concentration of the path cell needs to be updated. To avoid the excessive concentration of pheromone accumulated in multiple search results resulting in premature path maturity, the pheromone volatilization coefficient needs to be introduced. The final update formula of cellular pheromone concentration is as follows:

$$m'_{xy} = (1 - \sigma)(m_{xy} + \Delta m), \quad (8)$$

where m is the control coefficient of pheromone in cell transformation probability, m_{xy} is the pheromone concentration before cellular renewal, Δm is the increase in cellular pheromone concentration, $\Delta m = \lambda/z$, z is the total cost of the path, and λ is the correction coefficient

3. Optimization Process of Transmission Cable Path Based on AI

The high-voltage power transmission cable passes over many places. To obtain high accuracy in searching, the partitioned method is used in the process of processing the covered places. The important points that the line must pass through can be correctly marked on the map between the beginning and end points. The integrated final path results are obtained by automatic searching of each regional path.

- (1) Regional geographic information planned for smart city is divided according to grid form, each of which is a cell. The cells can be divided into three types according to the geographic information constraints of grids. The first kind can be connected to tower cell constructing. The second kind can be passed through the line, which cannot construct the tower cell. The third kind cannot pass the line and cannot establish the tower cell. Among them, the network area is county planning area, high altitude repeated ice area, densely populated housing area, rivers and lakes, etc., and the linear shape is power line
- (2) Obtain the final value matrix through the BP neural network algorithm, and then, perform the initial setting of the pheromone value of each cell
- (3) The cell positions of the start and end points as well as the distance from which the tower and pole are determined
- (4) Neighbor cells need to meet some requirements, and the cell of the line traversing is not the cell of the line that has been erected
- (5) The transformation cells perform the rules by selecting any of the adjacent cells according to the transformation rate. A cell with a low cost value, a high pheromone concentration, and a small line turning angle has a high conversion probability and low converse conversion probability
- (6) Steps (4) and (5) are repeated until the search reaches the end of the cell. Link all the converted cells to produce a transfer path and then calculate the cell cost value
- (7) There is only one case where the cost value is lower than the accumulated cell cost value from the previous search. Repeat step (4) to step (7) until the number of calculations is made

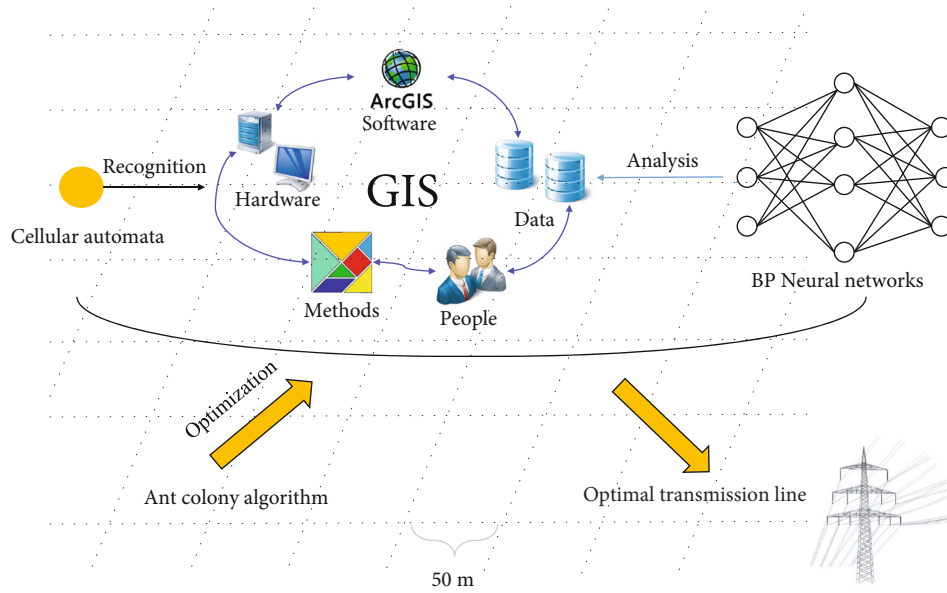


FIGURE 2: Scenario for transmission line planning.

- (8) Update cell pheromone values on scheduled routing, and repeat step (4) to step (8) until a specified number of calculations is made. Record the final solution cell and path

4. Results

4.1. Experimental Data. To verify the feasibility of the model and method, this study used drone aerial photography technology, combined with the transmission line routing requirements, and produced a GIS map (a vector diagram with a resolution of 5 m) of a smart city planning area. The following applies the path search model of the transmission line established in this article to conduct a specific path search test analysis for this area. Considering the accuracy requirements of path selection and the data volume (the smaller the grid size, the larger the data volume), the grid size is set to 50 m × 50 m, and the ArcGIS tool is used to generate a grid format GIS map. At the same time, the elevation data of the original vector GIS map is converted into slope data. Combine terrain information and geographic images to set noncrossable areas (such as airports and protected areas; the cost value of the grid is marked as -9999) and cross-over areas and their buffers (such as highways, rivers, and transmission lines) are 50 m.

4.2. Comparative Analysis. The scenario for transmission line planning is shown in Figure 2. In smart city transmission cable route selection, AI route optimization is used simultaneously with Dijkstra algorithm's route search and manual route selection. Through manual route selection, combined with detailed fund collection and field investigation, the recommended route scheme is finally determined. The comparison between the AI path of this research and the path search and manual routing results of Dijkstra algorithm is shown in Table 3. As indicated in Table 3, the general trend of AI path is basically the same as that of manual

TABLE 3: Comparison of different search results.

| Parameter | This research | Dijkstra algorithm | Manual route selection |
|----------------------------|---------------|--------------------|------------------------|
| Path length (km) | 14.19 | 14.96 | 14.56 |
| Number of corners | 15 | 18 | 20 |
| Number of poles and towers | 58 | 60 | 63 |
| Cost (yuan) | 1580.08 | 1755.46 | 1900.56 |

route selection, but there is little difference. The evaluation indicators obtained by using this article based on the AI transmission line path search processing mechanism are better than the results obtained by the Dijkstra algorithm. In particular, the number of corners and the number of poles of the line path are significantly reduced, which has a lower cost value.

After analysis, the difference between this algorithm and manual line selection is mainly due to the following reasons.

- (1) GIS information lacks elevation information of crossline, so it can be crossed at any point of default crossline in intelligent algorithm. Since the intersection point is actually selected in manual route selection, there are some differences in the selection of intersection point, leading the differences in the path
- (2) There is a difference between the route selection process of GIS with that of AI system, which leads to the lack of timely update time of the new route information, such as the lack of AI in the process of construction optimization
- (3) Owing to insufficient depth of AI research, the requirements for the mechanical construction of

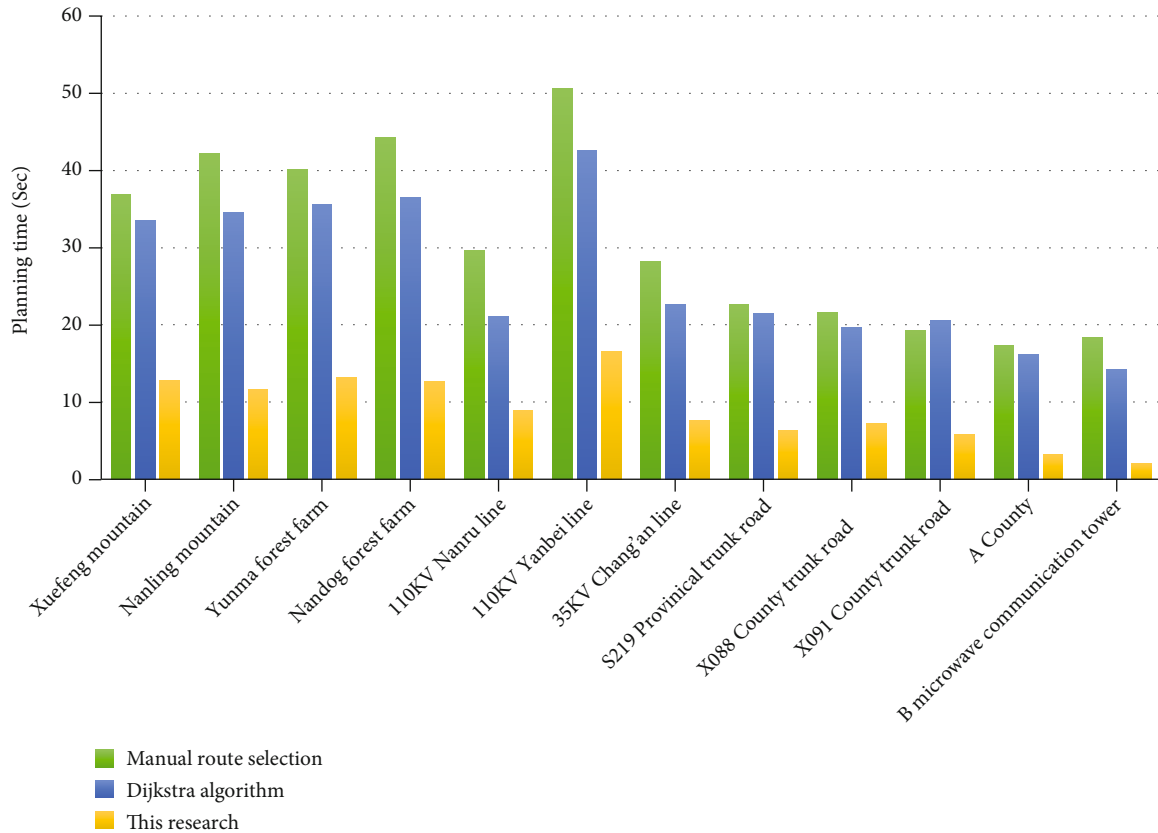


FIGURE 3: Line planning time in each simulation scenario.

the project cannot list the corresponding constraints. However, where routes are manually selected to guarantee an optimal route, the requirements for mechanistic construction are adjusted accordingly, so there are some differences in route directions

In addition, by simulating the scenarios of the three types of areas mentioned in Section 2.2.1, as indicated in Figure 3, the line planning time of the algorithm studied in this paper is always the lowest. Overall, line planning time is highest for area A due to the complexity of the geographical environment, while the planning time for areas B and C is shorter. However, the 110kV Yangbei line is a special one, mainly because geological disasters often occur there. In conclusion, the algorithm proposed in this paper has a good performance in line planning time, indicating its effectiveness and pertinence.

5. Conclusions

In this paper, ArcGIS is used as the geographic information collection and analysis platform for the selection of transmission cable routes in the construction of smart cities, and an automatic search model for transmission cable routes based on AI is established. The CA model can accurately recognize geographical information; then, we use BP neural network to analyze the cost that can avoid and selectively traverse the limitations. After rigorous comparison, it can be found that some special factors cannot be considered by

AI; the artificial route selection scheme has a small amount of difference between the result of the route and the AI route. Thus, it can be concluded that, without considering some special factors, AI path optimization can obtain the mathematical optimal path of transmission line. The path planning is instructive for the artificial selection of transmission cable routes in smart cities. It can be used to verify that the path plans achieve better benchmark values. In the future, this research direction can further optimize the ACO and introduce a path search direction control mechanism, which overcomes the problems of poor search direction and easy path detours of the traditional ACO and improves the search efficiency.

Data Availability

All data used to support the findings of the study is included within this paper.

Conflicts of Interest

The authors declare no conflicts of interest in this paper.

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