

Research Article

Simulation of Sports Venue Based on Ant Colony Algorithm and Artificial Intelligence

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In order to improve the congestion of the evacuation plan and further improve the evacuation efficiency, this paper proposes the priority Pareto partial order relation and the vector pheromone routing method based on the priority Pareto partial order relation. Numerical experiments show that compared with the hierarchical multiobjective evacuation path optimization algorithm based on the hierarchical network, the fragmented multiobjective evacuation path optimization algorithm proposed in this paper effectively improves the evacuation efficiency of the evacuation plan and the convergence of the noninferior plan set. However, the congestion condition of the noninferior evacuation plan obtained by the fragmented multiobjective evacuation route optimization algorithm is worse than the congestion condition of the noninferior evacuation plan obtained by the hierarchical multiobjective evacuation route optimization algorithm. The multiple factors that affect the routing process considered in the probability transfer function used in the traditional ant colony algorithm routing method must be independent of each other. However, in actual route selection, multiple factors that affect route selection are not necessarily independent of each other. In order to fully consider the various factors that affect the routing, this paper adopts the vector pheromone routing method based on the traditional Pareto partial order relationship instead of the traditional ant colony algorithm. The model mainly improves the original pheromone distribution and volatilization coefficient of the ant colony, speeds up the convergence speed and accuracy of the algorithm, and obtains ideal candidate solutions. The method is applied to the location of sports facilities and has achieved good results. The experimental results show that the improved ant colony algorithm model designed in this paper is suitable for solving the problem of urban sports facilities location in large-scale space.

1. Introduction

When sudden disasters occur, the high-density people in the disaster area can be safely evacuated in the shortest possible time, and scientific and effective personnel evacuation strategies can be implemented to effectively reduce the serious consequences of the disaster [1]. The planning of the evacuation route is a key and important part of the evacuation. In order to be able to evacuate people in a specific area in a timely and effective manner, it is necessary to formulate an evacuation route plan [2]. If an efficient evacuation route plan can be implemented smoothly, it will be able to effectively reduce the evacuation time and shorten the length of the evacuation route. They reduce the degree of congestion and reduce casu-

alties and property losses [3]. Different evacuation scenes have different evacuation characteristics, and the exit position and internal structure of the evacuation scene have an important influence on the evacuation process [4]. Evacuation modeling based on the corresponding characteristics of the evacuation scene is beneficial to the improvement of the performance of the evacuation route plan. The open-air stadium has an approximate ring structure. The stand area is distributed around the inner ring, and multiple exits are distributed around the outer ring. There is a corresponding relationship between the stands and the VI. This structure determines that the evacuation of stadium personnel has the unique feature of evacuation from the inner ring stand area to the outer ring exit [5].

The current research on stadium personnel evacuation planning can be divided into path planning based on evacuation simulation and evacuation path planning from the perspective of optimization [6]. Most of the researches conducted from the perspective of optimization are single-objective evacuation route optimization or the conversion of multiobjective evacuation route optimization into single-objective evacuation route optimization. However, there are relatively few studies on multiobjective evacuation route optimization based on multiobjective optimization theory. Multiobjective evacuation path optimization often uses general multiobjective optimization algorithms, and there are fewer dedicated multiobjective optimization algorithms based on the evacuation characteristics of stadium personnel [7]. The general multiobjective optimization algorithm uses the pseudorandom ratio process to search the evacuation route, lacking the guidance of domain knowledge, and it is easy to fall into a blind search. A dedicated multiobjective optimization algorithm based on the evacuation characteristics of stadium personnel, with the help of domain knowledge, enhances the purpose of the search, reduces the scope of the search space, and easily obtains an evacuation route plan with higher evacuation efficiency and better evacuation performance [8].

In order to improve the evacuation efficiency of the evacuation plan and improve the evacuation performance, this paper presents the corresponding topological structure characteristics of the fragmentation for the stadium stand area and exit, abstracts the entire stadium into a fragmented network, establishes a fragmented network personnel evacuation model based on the characteristics of the stadium, and proposes a fragmented multiobjective evacuation path optimization algorithm based on this model. Using this structural feature, the stadium is abstracted into a fragmented network to guide the evacuation process of evacuated persons. In this paper, the problem of slow convergence of a traditional ant colony algorithm is improved. With reference to the idea of an artificial potential field method, a gravitational probability function with adjustable weights is constructed and added as a heuristic factor, so that the new algorithm can still converge at a faster speed. Under the guidance of the network, the evacuated persons can only evacuate to the exits located in their own shards, which prevents a long cross-shard path during the evacuation process, which is beneficial to shorten the length of the evacuation path and improve the evacuation efficiency.

2. Related Work

Ma and Tsai [9] put forward the problem of how to coordinate the contradiction of multiple goals, which is the embryonic form of the problem of a multiple 1:1 standard optimization. French economist Alatas (see [10]), from the perspective of political economy, summarized many incomparable goals into multiobjective optimization problems and gave the definition of multiobjective optimization problems for the first time. Gao et al. [11] gave the point of view of a game theory; it puts forward a multiobjective decision-making problem with multiple decisions that contradict each

other. Through the analysis of production and distribution activities, the multiobjective optimization problem is proposed, and the concept of the Pareto optimal solution is proposed for the first time. Tsai and Ma [12] gave the concept of the Pareto optimal solution to solve the vector extremum problem from the perspective of mathematical programming and analyzed the sufficient and necessary conditions for understanding. Since then, the problem of multiobjective planning has gradually attracted people's attention. After the 1990s, the multiobjective optimization problem formally became a branch of mathematics, attracting more and more scholars and experts in different fields to conduct systematic research, and it became a research hotspot. At present, the optimization of multistandard standards has formed a relatively complete theory and has obtained many important research results. Its theories and results have been widely used in various fields, showing its strong vitality more and more.

In terms of evacuation of people in buildings, a lot of research work tries to capture the evacuation behavior of people through the computer simulation of evacuation models and then uses experimental data to refine the proposed evacuation model. Researchers at home and abroad have proposed a number of evacuation models [13], such as Simulex, EXODUS, BGRAF, and EXITT, and formed pedestrian evacuation software: ACNET, SIMULEX, SGEM, HAZARD, EGRESSPRO, EXIT, STEPS, etc. In recent years, Ai et al. [14] have analyzed and summarized these models, including seven models and implementation methods: cellular automata models, lattice gas models, social dynamics models, fluid dynamic models, agent models, and game theory models and animals based on experiments. In analyzing the process of pedestrian evacuation, the cellular automaton model describes the environmental impact (such as friction and congestion) and pedestrian capabilities (such as path selection ability, coordination ability, action ability, and emergency experience). Objectively, they reflect the environment and pedestrian interaction process, as well as analyze the influence of obstacles, and realize the description and analysis of competitive exit behavior and two-way movement caused by human interference in emergency situations. The lattice gas model is a discrete-time system model. In each time unit, all pedestrians in the model are distinguished by random sequence rules. Kendall et al. [15] use a random selection function to complete the selection process of a random moving queue. Statistics and probability are commonly used to describe the characteristics of the flow of people. The lattice gas model can reflect the nature of the dynamic evacuation process and analyze the time and space distribution of the evacuation time of the flow of people. The mobile lattice gas model proposed by Fister et al. [16] reduces the computational intensity and supports the evaluation of the average evacuation time. However, since the collection of test data is more difficult, the pedestrian characteristic analysis in this model lacks an effective verification method.

In terms of vehicle evacuation on the road network, the evacuation can be divided into static network-based vehicle evacuation and dynamic network-based vehicle evacuation according to the nature of the road network [17]. The

problem of vehicle evacuation in static networks can be attributed to the shortest evacuation path, fastest evacuation flow, and maximum evacuation flow [18], for example, based on the traffic capacity of the road network, the evacuation path is studied based on the maximum flow method; Huang [19] studies the influence of pedestrians, vehicles, intersection travel time, and path selection changes on the evacuation time of the road network; based on the shortest path algorithm in graph theory, some scholars have proposed an optimal independent evacuation path method based on the K shortest path. The basis for determining the optimal evacuation path includes the maximum capacity and travel time on the road section; some scholars use the minimum cost flow problem for evacuation traffic allocation, the shortest evacuation plan method is proposed, and the shortest evacuation plan is obtained; there is also a dual-objective comprehensive optimization model for emergency evacuation, which strives to achieve the maximum passing capacity, realize the maximization of all the beneficial results during the evacuation period, and realize the optimization of the public evacuation time in stages; some scholars use the shortest route and different route algorithms to correct the basic information of the road network in complex situations such as public emergencies. The improvement of dissimilarity calculation makes the optimal path and dissimilarity path more in line with that of the traveler's [20]. Vehicle evacuation based on a static network can complete the optimal allocation of evacuation vehicles from a macro perspective, but the dynamic and unpredictable characteristics of the evacuation process make it impossible to implement this evacuation plan accurately, and the effect of the evacuation model is not ideal [21, 22].

3. Construction of Sports Venue Model Based on Ant Colony Algorithm and Artificial Intelligence

3.1. Spatial Distribution of Sports Venues. In single-objective optimization problems, the optimal solution is usually uniquely determined, while for multiobjective optimization problems, because the various objective functions conflict and cannot be compromised, the optimal solution set of multiobjective optimization problems is usually a set, which is the essential difference between a multiobjective optimization problem and a single-objective optimization problem. Figure 1 shows the spatial distribution of sports venues (see Figure 1).

In the multiobjective optimization problem, the Pareto dominate (dominate) is a very important concept; it is a partial order relationship of the solution, defined as follows: for any two decision vectors a and b in the decision space X , a governs b if and only if the target value of vector a is not greater than the target value of vector b . The corresponding target value of the vector is strictly smaller than the target value corresponding to vector b .

$$x(t+1) = (1-t) \times x(t) + \Delta t. \quad (1)$$

The so-called optimal solution of the multiobjective optimization problem refers to the Pareto optimal solution, so all the Pareto optimal solutions constitute a set of reasonable solutions for the multiobjective optimization problem.

$$y(x) = \begin{cases} x(t)^\alpha * \eta(t)^\beta, & x < t, \\ 0, & x > t. \end{cases} \quad (2)$$

In most cases, there is no definite optimal solution in multiobjective optimization problems, only Pareto optimal solutions exist, and multiobjective optimization problems usually have multiple Pareto optimal solutions. The Pareto optimal solution of the multiobjective optimization problem can be regarded as an acceptable noninferior solution.

$$D(i, j) = \sqrt{(x(i) - X)^2 + (y(i) - Y)^2}. \quad (3)$$

Pareto optimal solution: for any vector a in the decision space X , a is Pareto optimal, if and only if there is a decision vector of the Pareto dominance vector a in the decision space X .

$$u(i, j) = \frac{\sum |\Delta D(m, n)|}{\sum |\Delta D(m, n)| - D(i+1, j)}. \quad (4)$$

Pareto optimal solution set: it is composed of all Pareto optimal solutions in decision space x and defines the target vector set corresponding to this set as a Pareto Optimal Front.

$$v(i, j) = \frac{x(i+1, j)}{\sum x(m, n)} + \frac{k * D(i+1, j)}{1+k}. \quad (5)$$

Based on the above description of the characteristics of deep learning theory, a deep learning optimization ant colony algorithm suitable for project technical and tactical decision-making is established to solve the actual technical and tactical decision-making optimization problem.

$$w(i, j) = \begin{bmatrix} x_{11} & 0 & 0 \\ 0 & \cdots & 0 \\ 0 & 0 & x_{(i,j)} \end{bmatrix}. \quad (6)$$

The optimization process is as follows: (1) Set the number of iterations and the initialization of pheromone data. (2) Record the information of each confrontation process, including time and combination of skills and tactics to construct a taboo table for both sides' technical and tactical decision-making, use deep learning to conduct self-organized deep learning on the taboo table data, and use the output result decision-making combination taboo table to judge optimal technical and tactical decision-making route. (3) Construct the optimal solution: complete the technical and tactical changes and construct the technical and tactical decision-making route. The task of each ant is to find the optimal technical and tactical decision-making route. (4)

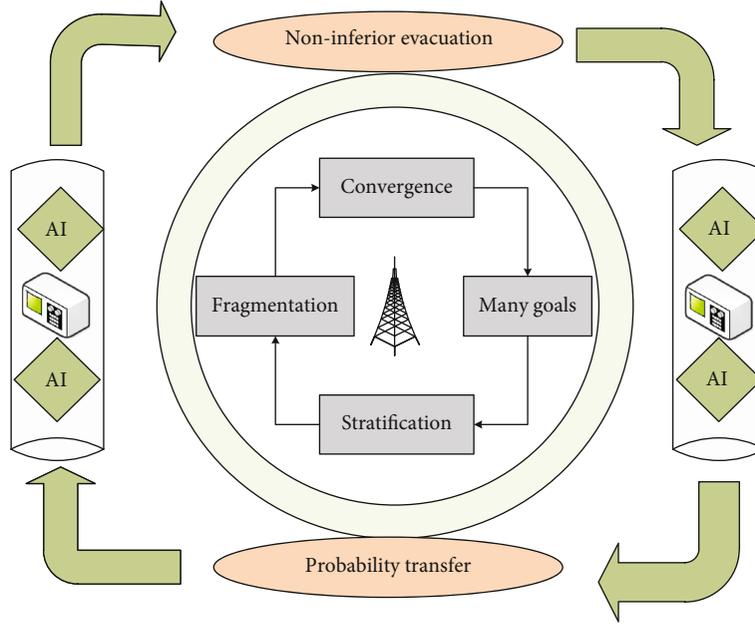


FIGURE 1: The spatial distribution of sports venues.

Update the data in the taboo table to determine whether the optimal victory has been achieved.

3.2. Information Iteration of Ant Colony Algorithm. The traditional basic idea of solving multiobjective problems is to convert multiobjective optimization problems into single-standard optimization problems, that is, to aggregate multiple subobjectives into a single-objective function with positive coefficients (weights) in the form of weighted summation and then use single-objective optimization. In the basic ant colony algorithm, the ants select the next node according to the transition probability, and this depends on the heuristic information of the candidate node and the information decay concentration, but the heuristic information has locality and cannot connect the current position with the evacuation exit. The pheromone concentration of the basic ant colony algorithm may cause the pheromone concentration to be too high as the ants gather on a certain path. The algorithm is solved, and the coefficients are determined by the algorithm designer or adaptively adjusted by the optimization method.

$$\begin{cases} \sum x(i, j) = 1, & i \in N, \\ \sum x(j, j) = p, & j \in N, \end{cases} \quad (7)$$

$$\frac{\partial u(x)}{\partial x} * \frac{\partial v(x)}{\partial x} = \frac{\partial z(x)}{\partial x}.$$

The solution method based on the Pareto dominance relationship can be divided into two stages according to the development process. The first-generation evolutionary multiobjective optimization algorithm combines Pareto ranking, fitness sharing, and niche strategies. The corresponding

algorithm has a multiobjective genetic algorithm (MOGA), which is not inferior.

$$[f1, f2, \dots, f(n)] * \begin{bmatrix} x1 \\ x2 \\ \dots \\ x(n) \end{bmatrix} = \sum \sum \min(\text{dis}(u(x)) * \text{road}(p)). \quad (8)$$

This kind of agent makes real-time decision-making at runtime, usually based on limited information and simple situation-action rules, which can establish a direct mapping between sensory information and action sets and has strong adaptability. Compared with the deliberate structure, the reaction structure can better meet the real-time requirements (see Figure 2).

Figure 2 shows the iterative process of ant colony algorithm information. We use a global high-level decision-making module to determine the team's current tactics, formation, and agent-to-role mapping and notify each player agent of the results of high-level decision-making, and then, the player agent will react according to its own knowledge and instructions from the high-level decision-making module. Agents on the field are divided into two states: strategic running state and active state. Agents in the strategic running state perform strategic moves according to the current team formation and their own roles; agents in the active state will perform reactive actions based on their surrounding environment. The sending module in the vision system puts the information and uses the TCP protocol to send it to the data forwarding server, and the data forwarding server sends the data to the decision-making system. The advantage of 4 partitions is that there are not many areas, the coding work is not

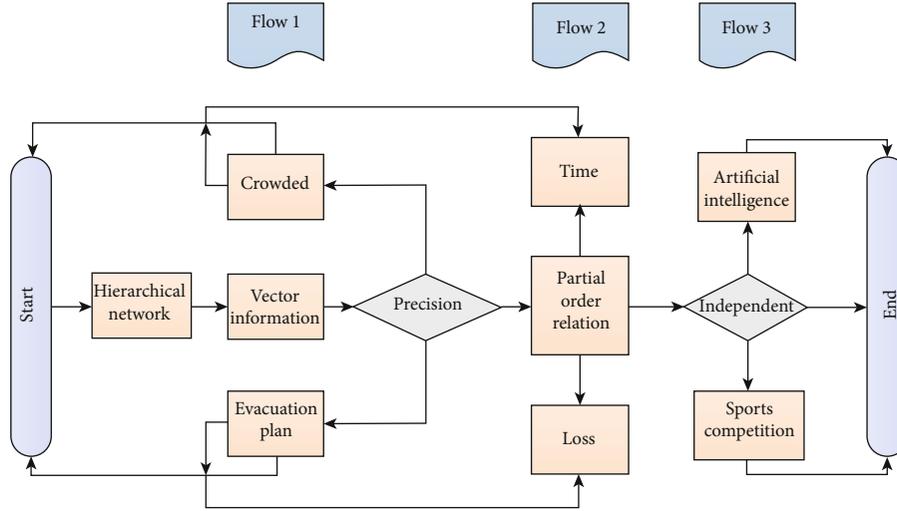


FIGURE 2: The iterative process of ant colony algorithm information.

heavy, and the jumping of the area is refined, which effectively prevents the sudden jump of the target. Zoning also reflects the obvious division of offensive and defensive areas, basically accommodating all specific situations. According to the division of these areas, and then considering the current distribution of robots, the ball-holding side, and the scores of both sides, the decision-making system can formulate the overall strategy of the team.

3.3. Artificial Intelligence Level Optimization. The evolutionary multiobjective optimization algorithm is an optimization algorithm characterized by the heuristic search of the population and the partial order relationship of the solution (such as the Pareto dominance relationship). Its appearance brings a new way to solve the multiobjective optimization problem [23–25]. The algorithm can not only solve the single-objective optimization problem well but can also obtain a set of compromise feasible solutions through one operation by using the Pareto dominance relationship. The decision maker can choose a suitable solution among the feasible solutions according to the corresponding domain knowledge and preference requirements. Since the perception range of the crowd is limited, new paths may be blocked by obstacles again. The walking stage of the entire crowd is a process of constantly updating the electronic map and planning new paths. The method is very suitable for solving multiobjective optimization problems. The essence of deep learning optimization is to learn more useful features in the data by constructing a machine learning model with a high-level hidden layer and massive training data and ultimately improve the accuracy of classification and prediction, including the depth of multiple hidden layers [26–28]. Figure 3 shows the comparison of histograms of site space units under different algorithms. In deep learning, it is different from traditional artificial neural network learning, which is reflected in the deep model structure and feature learning: (1) the depth of the model structure increases from the shallow three-layer hidden layer to 5, 6, and even 10 layers; (2) clear feature learning, through layer-by-layer feature training, the

learning samples are transformed from original features into new feature learning, making classification and prediction easier (see Figure 3).

With a hybrid structure, the entire decision-making process is divided into two layers. Figure 4 shows the framework of the sports venue model based on ant colony algorithm and artificial intelligence. The first layer is the team coordination layer based on reasoning. The decision-making information comes from the visual information sent by the vision server and the referee information sent by the referee box. It formulates the overall strategy of the team and determines the current team's formation and the role of each player. The role of the player is to coordinate the actions between the players; the second layer is the player action layer based on the reactive structure, according to the team's decision-making layer's formation and assigned roles; we select the player's actions and actions to be used in the next cycle (see Figure 4).

In the early stage of path planning, the pheromone concentration is insufficient. At this time, the potential field force is mainly used to inspire information. The role of the potential field force ensures the accuracy of the path planning direction, reduces the randomness of the search, and produces poor quality solutions. With the deepening of the search, the role of pheromone concentration and distance enlightenment is exerted, and the effect of the potential field force is gradually reduced to prevent the path from being excessively concentrated in the direction of the potential field gradient. The improved distance heuristic information function enables the search to advance to the target point with a high probability, which improves the efficiency.

4. Application and Analysis of Sports Venue Model Based on Ant Colony Algorithm and Artificial Intelligence

4.1. Ant Colony Algorithm Data Collection. The study area is dominated by the entire area, covering an area of 304.9 km². The entire area is divided into 512 × 512 spatial units. The

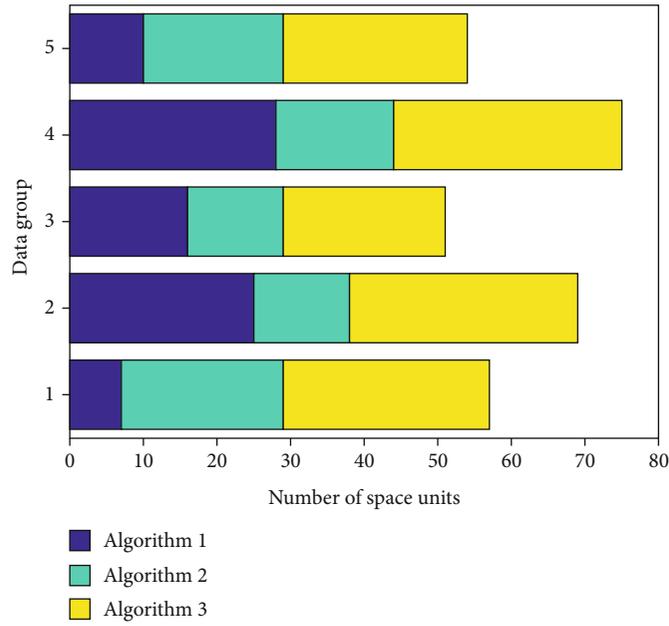


FIGURE 3: Comparison of site space unit histograms under different algorithms.

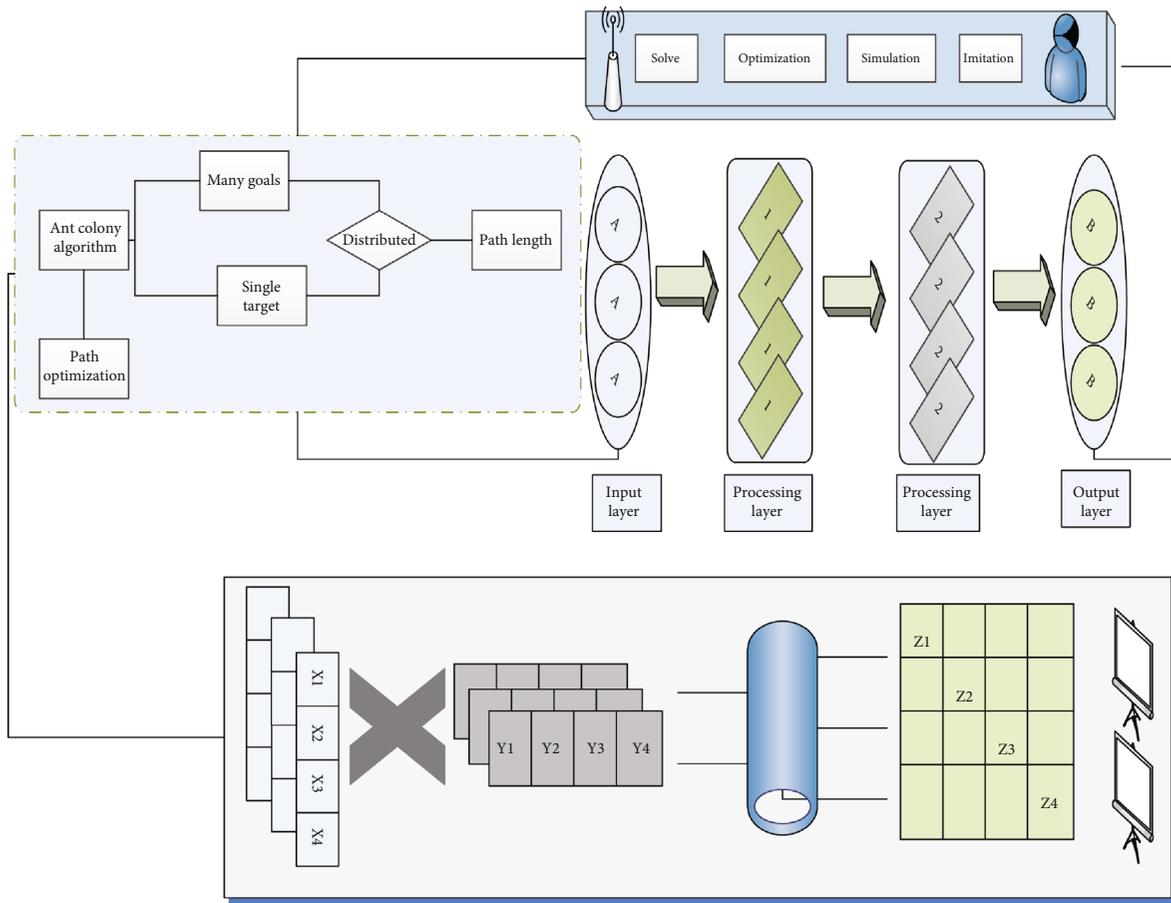


FIGURE 4: Sports venue model framework based on ant colony algorithm and artificial intelligence.

area of the unit grid is $12 \times 12 m^2$. In ant colony algorithm path planning, the number of ants m affects the algorithm's global search capability and convergence speed. Increasing

m can increase the randomness of the search, but the convergence speed will slow down. If m is too small, the search will stop prematurely. In a grid environment of 20×20 , $m = 20$ is

used in this paper. The pheromone factor Q is related to the positive feedback effect of the algorithm search. Increasing Q can increase the convergence speed, but too large Q can easily fall into the local optimal solution. Pheromone concentration volatilization coefficient ρ , pheromone concentration factor α , and heuristic information factor β reflect the strength and convergence speed of the randomness of the algorithm search process. The best value range of the three parameters is $0.1 \leq \rho \leq 0.99$, $0 \leq \alpha \leq 5$, and $0 \leq \beta \leq 8$. In this paper, $\alpha = 1$, $\beta = 7$, and $\rho = 0.3$ (see Figure 5).

The selected spatial data information mainly contains the vector data information of 12 streets. At the same time, ARC-GIS software is used to edit the geographic data information. Through editing, 512×512 spatial raster data information can be obtained, which is further processed into data information in text format. Figure 5 shows the site selection curve for different data points. When the grid map is initialized, each node is given equal pheromones, which can expand the initial search range of the electronic ant as much as possible. Then, use the site selection model of this article for simulation calculation and visually display the calculated data results. Java language is used to implement the sports facility location model in this article. Before the model runs, the parameters in the system need to be set. The current setting of the ant colony algorithm initialization parameters is determined by empirical methods or a large amount of experimental data. According to the empirical value method, we set the pheromone intensity in this article as $Q = 10000$, the pheromone volatilization coefficient is $\rho = 0.01$, the number of ants in the ant colony is initialized to $\text{ant_nums} = 30$, pheromone heuristic factor is $\alpha = 1$, and the pheromone expectation heuristic factor is $\beta = 0.3$. In this paper, the maximum number of repetitions of the ant colony algorithm M and the number of iterations P are used as the conditions for the termination of the algorithm, which can reduce the execution time of the algorithm. Through continuous experiments and tests, we can obtain sports facilities with different numbers of locations.

4.2. Path Simulation of Sports Competition Venue. In order to verify the effectiveness and superiority of the algorithm in this paper, using the Matlab 7.6 simulation platform, a large number of path optimization experiments were performed on the classic ant colony algorithm and the hybrid artificial potential field-ant colony algorithm in a 20×20 grid environment. Taking into account the actual performance and environmental conditions, the optimal path is not the shortest path. Because the robot takes time and energy to turn, the smoothness of the path is also very important. The fewer inflection points and the smaller the corners are, the better the smoothness is. Based on the above description of the characteristics of the ant colony optimization algorithm, we establish an ant colony algorithm suitable for the technical and tactical decision-making of resistance projects to solve the problem of optimization of actual skills and tactics. The process of ant colony algorithm for technical and tactical decision optimization is as follows: (1) Let the number of iterations be I . The pheromone T on various technical and tactical decision-making routes is initialized. (2) Randomly

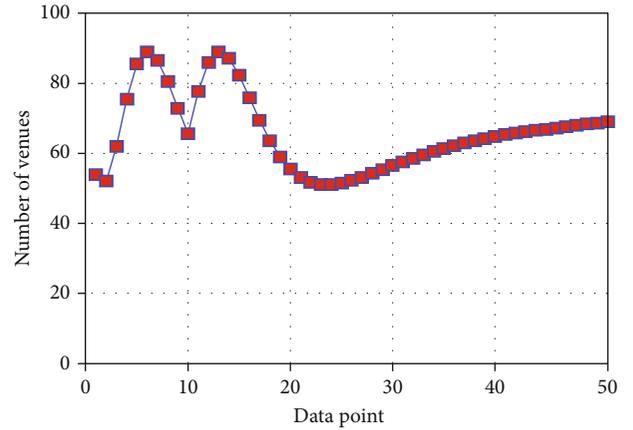


FIGURE 5: Curve of site selection for different data points.

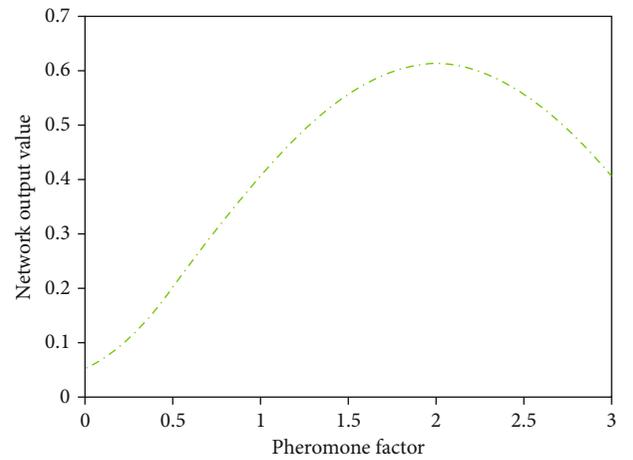


FIGURE 6: Pheromone output value curve of ant colony algorithm.

place m ants at the end of the technical and tactical decision-making route; establish our technical decision-making taboo table and the opponent's technical decision-making taboo table. (3) Adopt a combination of technical and tactical decision-making and taboo tables to determine the best technical and tactical decision-making route. (4) Construct a solution. Each ant constructs a solution step by step according to the state change rule, that is, a technical and tactical decision route is generated. The task of the ant is to find the best technical decision-making route. Figure 6 shows the pheromone output curve of the ant colony algorithm (see Figure 6).

According to the different mixing ratios of people and vehicles, the ant colony scale is 1000 and running for 200 generations. The two objective function values under different mixing ratios are obtained. It can be seen that the total time of all evacuated objects has decreased first. After the rising trend, it reaches the minimum when the ratio of pedestrians to vehicles is 1:1, and the trend of the total idleness of the road network is still decreasing first and then increasing. The difference is that when the ratio of pedestrians is 80%, the mixed utilization of the road network during the evacuation process is the highest. When pedestrians and

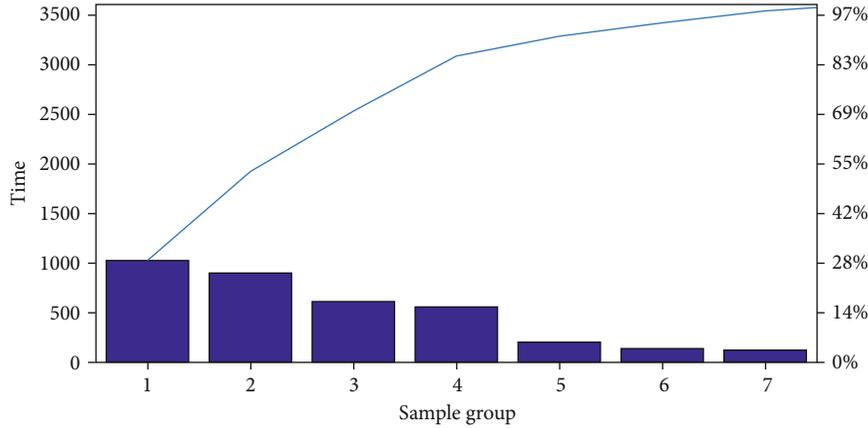


FIGURE 7: Algorithm iteration optimization of different sample groups.

vehicles are mixed in different proportions, the simulation results are shown in paper. According to the above experimental data and analysis, it can be concluded that a single traffic mode cannot get the best evacuation results. When the proportion of pedestrians is 50% to 80%, the effect of mixed evacuation of pedestrians and vehicles is between two values (see Figure 7).

In order to facilitate the comparison of the performance of the two algorithms in path planning, the two algorithms were run 30 times and related indicators were calculated. Considering the optimization results of the aforementioned different mixing ratios in terms of the total evacuation time and the degree of mixed utilization, as well as the evacuation efficiency multiple factors, once again, in mixed evacuation, a high ratio cannot get the best evacuation result. Figure 7 shows the iterative optimization of the algorithm for different sample groups. (1) The obstacle environment coverage rate is 30%, the optimal path is obtained, and the relevant performance indicators of the two algorithms are shown. Experiments show that in a general obstacle environment, both algorithms can converge to the optimal path, but the algorithm in this paper has a faster convergence speed and better optimization effect, and a higher quality of the path is obtained. (2) The barrier environment coverage rate is 35%, and both the optimal path obtained and the related performance indicators of the two algorithms are shown.

4.3. Example Application and Analysis. Path planning based on the hybrid artificial potential field-ant colony algorithm is combined with the dual heuristic information of the potential situation and the target distance, the path search is more efficient, the algorithm's global search ability is stronger, and it can effectively avoid falling into the local optimum; at the same time, it adopts the pheromone update mechanism and improves the quality of the path. They are simulations of the evacuation effect of pedestrians and vehicles according to a 1 : 1 ratio of pedestrians and vehicles (500 for pedestrians and vehicles). The evacuation of all objects takes 4660 seconds. With the passage of time, the pheromone left by the previous generation of electronic ants gradually disappears. The parameter is used to indicate the degree of pheromone disappearance. After time, the electronic ant completes a

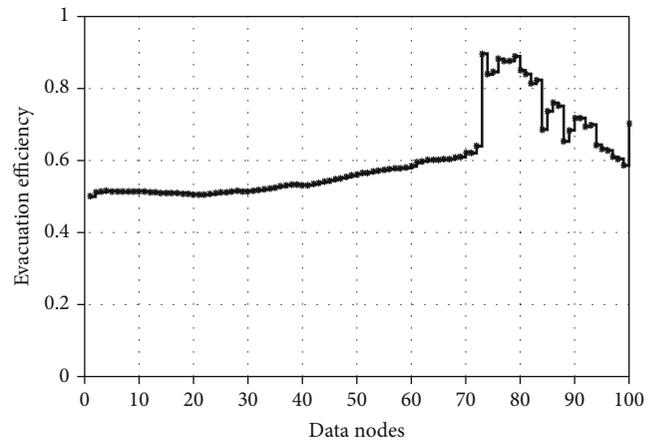


FIGURE 8: The dependence curve of model evacuation efficiency with data points.

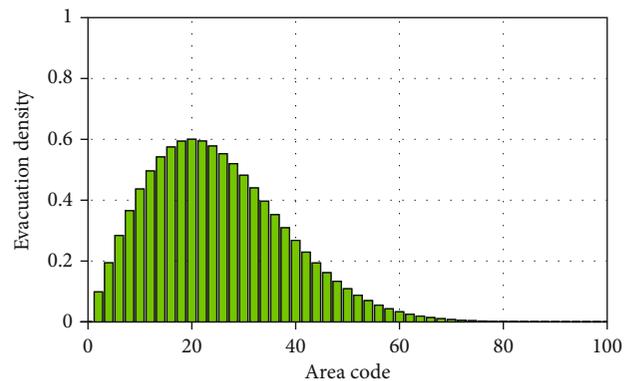


FIGURE 9: Evacuation density distribution map of different subzone codes.

search, and the amount of information on each node is adjusted. It is the distribution of people and vehicles on the road network at the beginning of the evacuation. It can be seen from the figure that as the node goes by, the number of remaining evacuees gradually decreases, and as the evacuation process progresses to 1000 seconds (21% of the total evacuation process), 73.6% of pedestrians have been

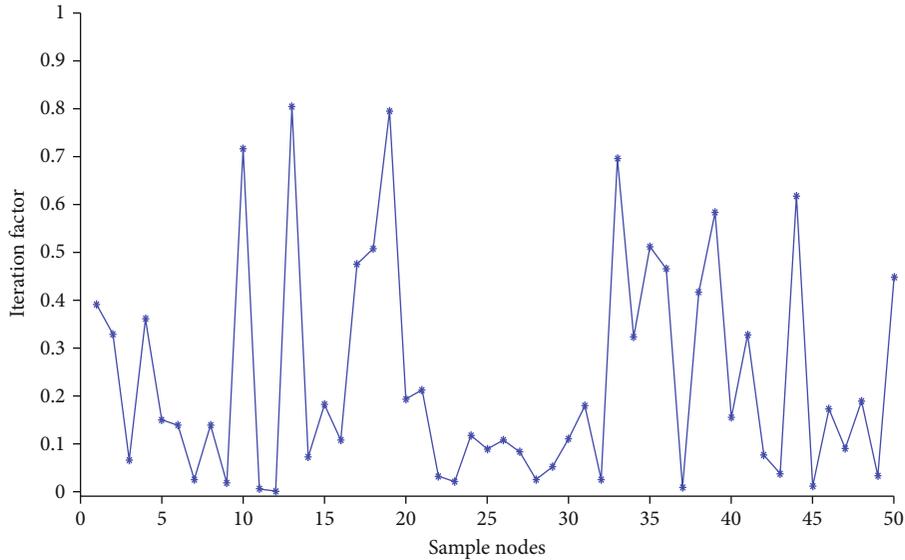


FIGURE 10: Algorithm iteration factor line chart of different nodes.

successfully evacuated and 77.8% of vehicles were evacuated, and at 2000 seconds (43% of the total evacuation process), such as shown in the paper, 95.6% of pedestrians were successfully evacuated and 97% of vehicles evacuated. It can be seen that this model can transfer more than 50% of the evacuees to a safe area within about 20% of the evacuation time. Figure 8 shows the dependence curve of model evacuation efficiency with data points (see Figure 8).

The figure shows the relationship between the percentages of people who have been evacuated over time when the pedestrian mixing ratio (R_p) is 10%, 50%, and 90%. It can be seen from the figure that the efficiency of different pedestrian ratios is not different in the later stage of the evacuation process. The main difference lies in the initial stage of the evacuation. The smaller the proportion of pedestrians is, the faster the evacuation is. This is mainly caused by the difference in the movement speed of people and vehicles. A high proportion of vehicles will inevitably speed up the evacuation process. The number of people is gradually mixed with vehicles in the road network. The higher vehicle mixing ratio does not bring the advantage of evacuation efficiency, but reduces it. Figure 9 shows the evacuation density distribution map of different subzone codes. Therefore, we consider the optimization results of the aforementioned different mixing ratios in terms of the total evacuation time and the degree of mixed use of roads, as well as multiple factors of evacuation efficiency; once again, in the mixed evacuation of people and vehicles, a high proportion of pedestrians or vehicles cannot be used. The best evacuation results are obtained; combined with the above analysis, it is concluded that when the pedestrian ratio is minus 80%, the mixed evacuation of pedestrians and vehicles is better in terms of total time, road utilization, and efficiency (see Figure 9).

Experiments show that in a complex environment, the ant colony algorithm has low optimization efficiency, and it is easy to fall into a local optimum. The algorithm in this paper has a stronger optimizing ability, faster convergence speed, and better environmental adaptability. According to

the simulation results, the basic multiobjective ant colony algorithm and the improved multiobjective ant colony algorithm are used to conduct experiments according to the ratio of people to vehicle of 1:1. Obviously, the improvement Pareto frontier obtained by the multiobjective ant colony algorithm is better than the basic ant colony multiobjective optimization algorithm. As time goes by, the evacuated objects are gradually distributed on various road sections. Figure 10 shows the line graph of the algorithm iteration factor for different nodes (see Figure 10).

Comparing the results of the two algorithms, it can be found that there are basically no people stranded in the stadium. In it, there are still people in the stadium that have not been evacuated outside within 600-1000 seconds. The number of individuals in the marked area is significantly lower than that in the corresponding area. The above analysis shows that the improved multiobjective ant colony algorithm is better than the basic multiobjective ant colony algorithm in terms of evacuation efficiency and safety.

5. Conclusion

The vector pheromone routing method based on the priority Pareto partial order relationship can give priority to factors closely related to evacuation performance such as evacuation efficiency and congestion conditions (such as the distance to the center of the stadium and the distance to the exit), and effectively filter out secondary factors. The interference of factors can more effectively improve the evacuation efficiency, congestion, and other evacuation performance. In order to improve the congestion of the evacuation plan obtained by the fragmented multiobjective evacuation route optimization algorithm, the vector pheromone routing method based on the priority Pareto partial order relation is used to replace the vector based on the traditional Pareto partial order relation in the algorithm. In this paper, a priority-based Pareto partial order relationship is proposed, and based on this, a vector pheromone routing method based

on the priority Pareto partial order relationship is proposed. Compared with the vector pheromone routing method based on the traditional Pareto partial order relationship, the vector pheromone routing method based on the priority Pareto partial order relationship can give priority to factors closely related to evacuation performance such as evacuation efficiency and congestion, and filter interference of secondary factors can more effectively improve the evacuation efficiency, congestion, and other evacuation performance. Aiming at the mixed evacuation of people and vehicles in the integrated environment of large buildings and road networks, heuristic information, taboo rules, and information update strategies suitable for this problem are proposed. The simulation results show the effectiveness and feasibility of the model and algorithm. Through the analysis of the evacuation performance under different mixture ratios of people and vehicles, the effect of the mixed evacuation of people and vehicles is better. This paper compares the pros and cons of the solution obtained by the basic ant colony algorithm and the improved method, as well as the differences in the temporal and spatial distribution of the evacuated objects. It shows that the improved multiobjective ant colony optimization algorithm can solve the large-scale mixed evacuation problem more quickly and safely. The advantages and disadvantages of the Pareto solution obtained by the basic ant colony algorithm and the improved method are compared, as well as the differences in the temporal and spatial distribution of evacuated objects, which shows that the improved multiobjective ant colony optimization algorithm can solve the large-scale mixed evacuation problem of people and vehicles more quickly and safely.

Data Availability

All information is within the paper.

Conflicts of Interest

No competing interests exist concerning this study.

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