Research Article

Path Optimization Model of Rural Red Tourist Attractions Based on Ant Colony Algorithm

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As an important historical and cultural heritage, rural red tourism sites have high historical, cultural, and social values. Moreover, rural red tourism sites are suitable for development and protection as tourism resources due to their unique landscape, architecture, culture, and art. In this paper, we propose a path generation model based on an ant colony algorithm to recommend the best path for tourists to visit rural red tourism sites. First, this paper investigates the modeling methods of path planning and multiobjective planning and their related solution algorithms to prepare for the establishment and solution of the tour path generation model for rural red tourism sites. By analyzing the problem description, this paper proposes the two model objectives of the shortest tour path and the highest total rating of the tourist attraction, and the model limitation of the total tour usage time, to model the model with a multiobjective planning approach. Then, by modifying the calculation of visibility and pheromone increments of the ant colony algorithm, the modified ant colony algorithm can take into account the two objectives of shortest path and highest total rating when constructing the path. Finally, this paper proposes to update the optimal path by using the number of ratings per unit path length as the update criterion of the optimal path.

1. Introduction

In the era of mass tourism, tourism has become an important way for people to enrich their experience and relax, tourists pay more attention to tourism quality and user experience, tourists’ tourism tends to be personalized and differentiated, and destinations, tourism demand, tourism consumption, and tourism products are becoming more and more diversified. Rural red tourism attractions are also listed as an important choice direction for travel by more and more tourists [1]. The red tourism industry continues to grow faster, the scale of the red tourism industry continues to expand, and the red market is becoming more prosperous, showing a healthy and orderly development momentum with rich levels and sustained growth. After the concept of “smart tourism and smart city” was put forward, the development of smart tourism was introduced to a new height. As a part of “smart tourism,” rural red tourism, along with the continuous development and improvement of rural infrastructure, has also begun to appear a spurt of development, becoming a new trend in tourism development [2]. The travel mode of tourism has tremendously changed, from the initial single-group sightseeing form of travel to the current self-drive tour, self-guided tour, and other forms of diversified structure expansion, and from these changes, it can be seen that tourists pay more attention to personalized experience in travel, but it is undeniable that these routes are simply a list of information, the lack of humanization, and rationalization of the need, no independent selectivity.

Smart tourism is a new concept proposed in the context of the development of artificial intelligence and big data technology. It is not enough to consider the humanized service for tourists but should also try to meet the individual needs of tourists. The proposed smart tourism is essential to improve the tourist experience of tourists, but how to analyze and research to establish a set of mathematical
optimization models that is closer to reality for the tourist law and how to get a better solution according to the model is the goal that has been pursued in this field [4]. In this paper, based on the geographic data and evaluation information collected by the cloud service platform for cultural protection and heritage of rural red tourism sites based on big data architecture, we combine an ant colony algorithm to build a tour path generation model for rural red tourism sites and generate a tour path for each rural red tourism site to guide tourists to visit rural red tourism sites. The recommended tour paths for rural red tourism sites can guide people who come to rural red tourism sites for the first time and do not have any knowledge of the rural red tourism sites to a recommended tour path for rural red tourism sites so that they can visit the rural red tourism sites for the first time and be more satisfied with the sites, to let tourists know more about the charm of the rural red tourism sites and improve their satisfaction with the tour. To promote the development of rural red tourist attraction tourism, we recommend the paths of rural red tourist attractions so that they can visit the attractions for the first time and be satisfied. To establish the rural red tourism attraction tour path generation model, this paper will investigate the path planning-related models. Since the model in this paper has to meet two objectives, first, the path taken during the rural red tourism attraction tour should be as short as possible; second, the evaluation of the rural red tourism attraction visited should be as high as possible to highlight the characteristics of the rural red tourism attraction, and it also needs to meet the time limit provided by the user, so it also needs to investigate multi-objective planning and some of its related solutions, and at the same time, to follow the evaluation of the rural red tourist attractions, the knowledge related to evaluation and weighting needs to be investigated. Subsequently, the ant colony algorithm for solving the traveler’s problem is improved to solve the multiobjective planning model of rural red tourist attraction path generation so that it can get a rural red tourist attraction tour path with the shortest tour path and the highest tour attraction rating while satisfying the tour time full limit.

2. Related Jobs

Because the complexity of the algorithm for solving the traveler problem using enumeration is too high, there are now many evolutionary algorithms such as genetic algorithms and some bionic algorithms such as particle swarm algorithms and ant colony algorithms, and many improvements have been made to the algorithm for solving the traveler problem to fit the traveler problem.

In the literature [5], the students proposed a new hybrid genetic algorithm by using connected subgraphs as the crossover operator of the genetic algorithm, which solves the defect that the old crossover operation of the genetic algorithm generates nonsense paths, and combines the small habitat operation, migration algorithm, and local search. Shao et al. [6] presents the traveler problem with node service time, and the node service time is a linear or quadratic function based on the start service time and proposes the method of additional subloops to eliminate the constraints. Lutero et al. [7] propose improvements to several evolutionary algorithms in the field of solving the generalized traveler problem. He added local search to the traditional genetic algorithm to improve the solution accuracy of the traditional genetic algorithm, set the threshold switch and searched list to enhance the solution efficiency of local search, and also simulated the behavior of ants to find the path from new when they deviate from the colony walking path, combined with methods such as local search and variation operator to further enhance the solution accuracy of the ant colony algorithm. In the literature [8], the maximum-minimum ant system algorithm was proposed to limit the pheromone concentration based on the ant colony system to prevent the algorithm from stagnation. To improve the ant colony algorithm, the researchers started with the pheromone update formula, state transfer probability, and the introduction of an adaptive system, so that the efficiency of the improved ant colony algorithm is greatly improved. In [9], a hybrid ACO is proposed to solve the vehicle path problem by combining the ACO and the decentralized search algorithm and adding a new domain search algorithm to the decentralized search framework to improve the solution of the algorithm. The literature [10] combines the ant colony algorithm with the preservation algorithm and the exchange mechanism to improve the convergence speed of the algorithm, introduces the disaster operator, and adjusts the pheromone update formula to avoid the algorithm from falling into local optimum in the search process. Mahajan et al. [11] studied the use of the ant colony algorithm to solve the vehicle path problem, adapt to the characteristics of the vehicle path problem, and made some changes to the ant colony algorithm; they introduced insertion and exchange operations after the ant colony algorithm finished a round of local pathfinding; and the customers served by each ant were subjected to random exchange and insertion operations according to the probability calculated by certain conditions so that the modified hybrid ant colony algorithm could get a better solution. Arzamendia et al. [12] investigated the use of an improved simulated annealing method for solving the vehicle path problem with pending time windows; he proposed to use the two-operation method for the neighborhood search of the solution by arbitrarily swapping the positions of two passengers in the arrangement of known optimal solutions to form a new solution; and their experiments showed that such a modification leads to better quality solutions. The literature [13] addresses the multiobjective tourist route planning problem in urban tourism using a multiobjective orientation algorithm. For each tourist who has different travel preferences, the Pareto ant colony optimization algorithm is applied to design a personalized travel route that satisfies the tourists. Issaoui et al. [14] solve the complex tourist route optimization problem by using the heuristic shortest path algorithm, and the route planning works well. Goel and Maini [15] used an improved ant colony algorithm to improve the quality of the global optimal solution, established a mathematical model with road factor, waiting for factor and interest factor as influencing factors in scenic
spots, and analyzed the application of the ant colony algorithm in route planning with tourist satisfaction as evaluation criteria; the results proved that the improved ant colony algorithm solves the road map based on tourist satisfaction; and the effect is significant compared with the previous tourist satisfaction. Ashkezari and Yazdi [16] used a recommendation algorithm to solve multiobjective path planning problems, and finally obtained path recommendation based on geographic location; and the recommended method was tested to have a better effect in terms of the accuracy rate of recommendation.

3. Ant Colony Recommendation Algorithm Based on Multiobjective Evolutionary Computation

3.1. Multifactor Interest Point Recommendation Problem for Path Optimization of Rural Red Tourism Attractions.

With the development of the internet, recommendation algorithms are commonly used in major internet platforms; people are more and more enthusiastic about the research of recommendation algorithms; and recommendation algorithms for various application scenarios of attractions are born, but recommendation algorithms designed for the field of tourism are not common.

There are a huge amount of recommendation algorithms, among which content-based and collaborative filtering algorithms are the most widely used. These two algorithms consider different factors. The content-based recommendation algorithm starts from the user’s point of view, discovering the user’s preferences by collecting the user’s history information, and then associating the preferences with the items to get a recommendation list according to the similarity [17]. The collaborative filtering algorithm, on the other hand, uncovers groups with similar behaviors to the user and gives recommendations to the user indirectly through the history of the group. As the requirements of personalized recommendations become higher and higher, it is often difficult to achieve accurate recommendations if only a single factor is considered when making recommendations in the field of travel, which requires a comprehensive consideration of multiple targets and then recommending the best solution to the user. The entropy weighting method is a method of weight calculation using information entropy. In information theory, information entropy is a concept used to measure the amount of information. When the information entropy of an index is smaller, the more information it provides, the greater its influence on the evaluation result, and the greater the weight. With the development of travel platforms, the data related to users’ personalized recommendations have become more and more rich and diversified. In addition to user history and collaborative characteristics, there are many factors such as network hotness, user tags, and environmental characteristics that are closely related to users’ next choice [18]. However, there are conflicts among the factors, and the recommendation solutions obtained by using a single feature factor often differ. Figure 1 shows the flowchart for exploring the two-location travel options.

The recommendation algorithm considers a variety of factors and needs to eliminate these conflicts so that the final recommendation solution meets the characteristics of each factor as much as possible. The multifactor point-of-interest recommendation problem in this paper is based on the results obtained by other traditional recommendation algorithms considering a single factor, and since there are differences in the recommendation results obtained by considering different factors, it is necessary to effectively unify the results of various types of recommendations, which are described as shown in the following equation:

$$S = \frac{1}{a^n A_i} \begin{pmatrix} n \\ \vdots \\ k \end{pmatrix} (-1)^k g(x - ak),$$

(1)

where $x$ represents a recommended solution, $a$ represents the number of factors considered, $A_i$ represents the value of the recommended solution $g(x)$ as a function of the $i$th objective, and there are $a^n$ objective functions when considering the $a^n$ factors. Each objective function is shown in the following equation:

$$Q_N(w) = \frac{1}{2} \sum_{i,j} P_{ij} (1 - P_{ij})^2 + \|w^T X_i\|^2_2,$$

(2)

where $\|w^T X_i\|$ denotes the recommendation value obtained by using the traditional recommendation algorithm considering the factor of category $i$ alone, and $Q_N(w)$ denotes the Euclidean distance between the recommendation solution obtained by considering all factors together and when only one category is considered.

A large number of objectives and their conflicting nature make them significantly more difficult to solve. Maps have become one of the most challenging problems in evolutionary optimization, and they pose a great challenge to traditional multiobjective evolutionary algorithms, especially those that rely on the dominance principle [19]. The first difficulty is that the selection strategy of Pareto domination fails on maps. The main reason is that when the optimization objectives reach more than three, the number of nondominated solutions exponentially explodes, making it difficult to effectively discriminate between the superiority and inferiority of the solutions, which greatly reduces the algorithm’s performance in finding the best. The second difficulty lies in the maintenance of diversity. In the objective space of MaOPs, the solutions are often sparse, and it is difficult to estimate the similarity of solutions using existing techniques such as crowding distance and k-nearest distance. Third, the variational operator may be useless on MaOPs because the offspring may be far away from both parents in the high-dimensional target space [20]. To address the above difficulties, current high-dimensional multi-objective evolutionary algorithms are divided into three
main categories. The first category is the modification of the traditional Pareto domination method. They achieve the purpose of increasing the selection pressure by improving the Pareto dominance relation. Due to the end condition of ant-constructed paths, which makes each path a path that passes through as many attractions as possible, it is no longer possible to increase the number of attractions visited on the path within the specified touring time. At this point, to judge the merit of each path, this paper decided to use the total rating score of attractions per unit path length as the criterion to update the optimal solution of the model generated by the tour path of rural red tourism attractions. For example, the $\varepsilon$-MOEA and Gr EA are based on the dominance relationship, and the $\theta$-DEA is based on the reference vector dominance relationship; the second type of algorithm is based on performance metrics. For example, the HypE algorithm uses the hypervolume metric as the selection criterion, and the MaOEA/IGD algorithm uses the reverse generation distance metric. Since the traditional Pareto dominance relation is not used to zone the quality of the decomposition, the decomposition-based evolutionary algorithm has a significant improvement in operational efficiency and convergence speed, and the uniformly distributed reference vectors in the target space also help to maintain good diversity of populations.

To address the above problems, this paper improves the existing decomposition method and proposes a weakly correlated adaptive evolutionary ant colony algorithm, which breaks the previous restriction that a solution can only be associated with one reference vector and proposes an association strategy based on the angle subspace to better maintain the ant colony population diversity; second, this paper proposes the concept of weak correlation and designs a bimodal scalar function based on this concept. Finally, the adaptive parameters are designed to dynamically adjust the size of the penalty parameters, which is conducive to enhancing the generalizability of the algorithm.

3.2. Improved Weakly Correlated Adaptive Evolutionary Ant Colony Algorithm for Multipath Optimization Problems. As the size of the problem increases, the problems of early convergence and poor local search ability of conventional ant colony algorithms in solving tourism path planning greatly restrict the accuracy of the results. In response to the shortcomings of the genetic algorithm, a new hybrid weakly associative ant colony algorithm, based on the ant colony algorithm, is proposed in this paper. This method is proposed to take advantage of the positive feedback mechanism of the association strategy based on the angle subcontrol and the fast convergence at initialization, and we apply it to the second step in the ant colony algorithm, initializing the population, which is used to improve the situation that the ant colony algorithm relies too much on the initialized population, the poor adaptation of the population individuals, and the premature maturity of the algorithm. The coding operation is a mapping of expressions to genotypes [21]. Combined with the characteristics of route planning, the path-encoding approach is used to identify the attractions with natural numbers of 1, 2, . . . , i, which are connected into a string in the order of route arrival to form the route chromosome individuals. This coding method is relatively simple and at the same time conforms to the characteristics of the trip planning model. For example, the first code of code string 136847952 indicates that the path from the last city 2 back to city 1 is in the problem solution space array, and the second code indicates that the path from city 1 to city 3 is in the problem solution space array. The choice of
the fitness function in the ant colony algorithm will have an impact on the convergence speed and the search for the optimal solution of the algorithm. The trip planning model is the problem of minimizing the objective function, the inverse of the objective function is directly taken as the fitness function, and the formula is as follows:

\[ L_{\text{local}} = \alpha_1 - \sum_i (a_2 + a_1)(E_n + \lambda_1) \left( \lambda_2 + \lambda_1 \right). \]  

The larger the fitness function represents the better the individual ant colony, that is, the shorter the total path length found.

As shown in Figure 2, after initializing the parameters, \( m \) ants are randomly placed on each node; the position is recorded in the corresponding forbidden table taboo; and the next visited node of ant \( k \) is selected according to the state transfer probability formula \( j \), putting the nodes that satisfy the constraints into tabu until the paths of all ants are constructed. The path constructed by each ant is locally optimized using the fireworks algorithm to obtain the locally optimal path constructed. The path constructed by each ant is locally optimized using the fireworks algorithm to obtain the locally optimal path, and the path is updated according to equation (3). By calculating the total shortest route, we obtain the global optimal solution \( L_{\text{global}} \), update the global pheromone according to equation (4), until the termination condition (number of iterations \( \geq \) maximum number of iterations) is satisfied, and then stop the loop and output the optimal solution.

\[ L_{\text{global}} = \sum_{i} Y_i. \]  

The ant colony algorithm is improved in two ways: the first is the introduction of the elite ant system, which means that additional pheromones are added to the optimal path [22]. Therefore, the currently found path is optimized using the fireworks algorithm to obtain the locally optimal path Local, and to increase the attractiveness of the optimal path to the ants in the next cycle; and the local pheromone update formula can be expressed as follows:

\[ L_{\text{local}} = \alpha_1 - \sum_{i=1}^{k} (a_2 + a_1)(E_n + \lambda_1) \left( \lambda_2 + \lambda_1 \right). \]  

The second aspect is the introduction of the max-min ant system, which means limiting the range of pheromone concentrations. Since the addition of the elite ant system to the local pheromone update formula may cause the pheromone on a path to grow too fast, the pheromone values are restricted to the interval \([\tau_{\min}, \tau_{\max}]\) to prevent the stagnation of the algorithm search, and the global pheromone update formula can be expressed as follows:

\[ L_{\text{global}} = \tau_{\min} \frac{\partial Y_i}{\partial \lambda} + \frac{1}{\tau_{\max}} \sum_{i=1}^{n} Y_i. \]  

In an evaluation system, the role played by each evaluation index overall is often different, and to judge the importance of each evaluation index in the evaluation system, weights are generally introduced to measure it. Weight is a relative concept, and the weight of a certain evaluation index refers to the relative importance of that index in the whole evaluation system. The evaluation system is used to convert the already quantified values of each evaluation index into a composite value through weights, which is used to evaluate something or make decisions about something [23]. Smart tourism is a new concept proposed in the context of the development of artificial intelligence and big data technology, and it is not enough to consider the humanized service for tourists, but should also try to meet the individual needs of tourists. The proposed smart tourism is essential to improve the tourist experience of tourists. The reasonableness of the weight setting is directly related to the scientific validity of the evaluation results, and the change in the weight of a certain indicator will affect the evaluation results of the whole evaluation system, so the weight setting must be scientific and objective. At present, there are many weight setting methods, and according to the original data source and the process of calculating the weight, it can be divided into two categories: subjective weighting method and objective weighting method. The entropy weighting method is a method of weight calculation using information entropy. In information theory, information entropy is a concept used to measure the amount of information. When the information entropy of an index is smaller, the more information it provides and the more influence it has on the evaluation result, and the greater the weight is. Using the entropy weighting method, it is necessary to first calculate the ratio between the value of each indicator in each sample and the sum of that indicator in all samples, then calculate the information entropy of the \( j \)th indicator, and finally use the information entropy to calculate the weight of the \( j \)th indicator \( \omega \) with the following formula.

\[ U \omega = \frac{1}{\sum_{i=1}^{n} U \omega_i}. \]  

In this paper, we set up a technician for algorithm iteration in the algorithm, i.e., starting from the first generation, the number of iterations of the search for the optimal solution is recorded, and if the optimal solution is not found during this iteration, the stagnation counter is added 1. When the optimal solution is found in this iteration, the iteration counter must have accumulated to a certain amount at this time, noted as \( Z \). Additional pheromone updates are performed for the section of the optimal solution.

\[ PF(x_i) = \frac{Z \phi F(x_i)}{\sum_{i=1}^{n} F(x_i)}. \]  

In the above equation, the effect of the stall counter on the additional pheromone is fully exploited, i.e., the larger the number of stall counters, the more generations the algorithm does not find the optimal solution in the process of finding the optimal solution; and then if by chance the optimal solution is found, the size of the value on the stall counter is used to change the size of the pheromone in the
algorithm, and the increased pheromone will be proportional to the value of the counter. The increased pheromone will be proportional to the size of the counter. The penalty function is also set, and the main idea of the penalty function is to transform the constrained problem into several unconstrained problems and then computationally solve one of the unconstrained problems to achieve the final solution of the constrained problem. This method is a critical and useful solution in solving constrained problems [24]. When constructing the penalty term, we have a certain principle that if infeasibility is encountered during the iteration, then a penalty should be added and the value will be positively correlated with the infeasibility point; the larger the infeasibility point is, the larger the value will be; and when the iteration reaches the feasible point, the penalty will disappear. The purpose of setting the penalty function is to make the iteration point closer and closer to the feasible domain and eventually to quickly find the feasible solution.

### 4. An Improved Ant Colony Algorithm-Based Tour Path Generation Model for Rural Red Tourism Attractions

The main purpose of the rural red tourist attraction tour path generation model is to solve a tour path so that when tourists visit a rural red tourist attraction, they can visit more attractions representing the characteristics of the rural red tourist attraction in a given time, and make the shortest path for tourists to visit so that tourists have more time to visit the attractions instead of wasting on the road between attractions. With the increasing demand for personalized recommendations, it is often difficult to achieve accurate recommendations if only a single factor is considered when making recommendations in the field of travel, which requires a comprehensive consideration of multiple objectives and then recommending the best solution to the user. The process of solving the ant colony algorithm for the tour path generation model of rural red tourism attractions can be divided into the following steps (Figure 3).

In the first step, the data required for the algorithm are initialized, including the maximum number of iterations, the number of ants, the information heuristic factor, the expectation heuristic factor, and the pheromone volatility factor, and the data such as the scores and the path length are normalized.

In the second step, the forbidden table for this iteration is initialized and the remaining time is set to the initial value.

In the third step, we choose an ant to start from the entrance of the rural red tourist attraction and start traversing the rural red tourist attraction.

In the fourth step, we calculate the selection probability of the attractions currently reachable by this ant, and use roulette to select an attraction for the ant to transfer and add

![Algorithm flowchart of improved ant colony algorithm.](image-url)
the selected attraction to the taboo table, and update the remaining time.

In the fifth step, we determine whether there are still spots that can be reached without exceeding the remaining time, and return to step 4 if there are, or continue to step 6 if there are not.

In the sixth step, in this loop, we see whether there are any ants in the ant queue that have not been traversed, and return to step 3 if there are, or continue to step 7 if there are not.

In the seventh step, we calculate the walking path of each ant and update the path pheromone according to the taboo table, select the optimal path from it to compare with the globally optimal path, and update the globally optimal path.

In the eighth step, we determine whether the number of iterations reaches the maximum; if yes, we continue to execute the ninth step; and if not, we return to the second step to start a new round of iterations.

When all ants in this iteration have explored their own countryside red tourist attraction tour paths according to the algorithm, it is necessary to do a pheromone update of the countryside red tourist attraction tour paths according to the taboo table of that iteration. In order not to let the algorithm converge too quickly and fall into a local optimum, in this paper, the ants update the pheromone considering all the paths taken by the ants instead of only updating the confidence of the optimal path for that iteration. Moreover, this paper uses a pheromone volatility factor $\rho$ to let the pheromone retained by the path before the update volatilizes partly to prevent the ants from being too influenced by the paths taken by the previous ants when choosing the paths in the next iteration. Then, according to the ant colony algorithm, the pheromone intensity contained in the path from attraction $i$ to attraction $j$ in the rural red tourist attraction after the completion of the teeth iteration can be composed of two parts: one is the pheromone intensity remaining after the pheromone of the path in the previous iteration that is volatilized, and the other is the sum of the pheromone increments brought by each ant to the path in that iteration.

Since the rural red tourism attraction tour path generation model is a multiobjective planning model, it needs to achieve both the goal of the shortest tour path length and the goal of the highest overall rating of the visited attractions. The larger the number of stagnation counters, the more generations the algorithm has not found the optimal solution in the process of finding the optimal solution; then if by chance the optimal solution is found, the size of the pheromone in the algorithm will be changed using the size of the value on the stagnation counter; and the increased pheromone will be proportional to the size of the value of the counter. We can easily see that

Figure 3: The flow of the ant colony algorithm for solving the tour path generation model of rural red tourism attractions.
these two objectives are contradictory, and one solution can make the tour path length the shortest, but its corresponding tour attraction may not have the highest total rating, while the other solution can make the tour attraction have the highest total rating, but its corresponding tour path length is not the shortest. This is the time to set a criterion for updating the optimal path. Because the end condition of the ant-constructed path makes each path a path that passes through as many sights as possible, it is no longer possible to add more sights to visit on the path within the specified touring time. At this point, to judge the merits of each path, this paper decided to use the total rating score of attractions per unit path length as a criterion to update the optimal solution of the model generated by the tour path of rural red tourism attractions. The total rating score per unit path length is the value obtained by dividing the total rating of the tourist attraction by the length of the path. If this value is larger, the better the corresponding solution is considered.

The module is designed using SpringMVC and MyBatis. The module is divided into four layers: the persistence layer, the service layer, an interface layer, and the presentation. The persistent operation layer is mainly implemented by the MyBatis persistence framework, which mainly provides common SQL operations, stored procedures, and object mapping for the service layer to operate on the database. This module is mainly in the form of interface services, using the MyBatis object mapping framework, according to the definition of the XML file, mapping the database data into the data model consisting of ordinary Java objects, and providing the database data to the service layer.

The service layer is in the form of a service that provides route planning services to the interface layer. The service layer is composed of three modules: attraction scoring, data initialization, and path construction. The attraction scoring module mainly uses the attraction scoring model to calculate the score of each attraction. The data normalization module is to normalize the factors that affect the path construction, such as attraction rating, the distance between attractions, and visiting time of attractions, so that all factors can be considered more fairly when constructing the path. The path-building module is the core module, which is used to calculate a recommended path with the shortest possible path and the highest possible total rating of the visited attractions using the modified ant colony algorithm in this paper. The interface layer is the controller layer in the MVC architecture, which is mainly responsible for receiving HTTP requests from the display layer and calling the path planning service of the service layer to complete the user’s path planning request and return the data to the display layer in JSON format. The display layer is mainly used to better interact with users and present the planned paths in a more visual form for users to see. The display layer is a web page, mainly using HTML to plan the content of the page, using CSS to define the style of the page, using jQuery to complete some user interaction, and using AJAX technology to allow the display layer and the interface layer to interact with JSON data. The whole architecture is built in an MVC way, the display layer only through the interface layer to call services, making the view logic and service logic decoupled, making the whole framework of coupling reduced.

5. Experimental Verification and Conclusion

5.1. Overall Evaluation of the Model. The rural red tourism site tour path generation model is a multiobjective planning model, so the solution is a Pareto optimal solution set; and to select the optimal solution, the solution with the highest total score of the unit path is used as the optimal solution. Figure 4 shows the highest total score of the unit path for each of the 100 iterations, and it can be seen that after 24 iterations, the total score of the unit path gradually converges to the maximum value of 315.3 points/meter, indicating that the modified ACOA can relatively quickly arrive at a near-optimal solution.

Figure 5 shows the results of the optimized algorithm compared with the basic algorithm. It can be found from the comparison results that under the limitation of the total tour time of 12,000 seconds, the path run by the modified ant colony algorithm in this paper visited more attractions than the unmodified one; the ratings of the visited attractions were higher, so the total ratings of the attractions of the path run by the algorithm in this paper were much higher than those of the unmodified one; and the goal of the total ratings of the attractions of the model was as high as possible. Although the path length becomes longer, the total rating of attractions per unit distance is higher, which indicates that the path run by the algorithm in this paper has a higher value.

The algorithm improves the initialization population and crossover probability mechanism to improve the average population fitness of the population. According to the idea of a genetic algorithm, the average population fitness is measured by whether the average population fitness is closer to the maximum population fitness, as shown in Figure 6. In this section, we take the dataset Oliver30 as an example and compare it before and after the improvement of the algorithm, and we can find that the improved algorithm can make the average population fitness closer to the maximum population fitness after fewer iterations, which means that the improved population fitness can be rapidly improved and has a higher ability to search for the optimal solution. In contrast, the population fitness ability of the traditional ant colony algorithm is poor at the beginning, and the fitness ability is improved only after several iterations at a later stage, but the solution speed is very slow. To illustrate the effectiveness of the algorithm, Oliver30, eil51, eil76, and kroA100 are tested in TSPLIB international data set, respectively. The results show that the algorithm has better performance than traditional ant colony algorithm. To illustrate the effectiveness of the algorithm, the solution space capability of the improved ant colony algorithm is significantly faster and the efficiency of finding the optimal solution is better.

The travel itinerary planning problem is a highly subjective research area that focuses on the desire to provide high-quality and enjoyable customized travel itineraries for
tourists. In this section, the multiobjective constraint problem is solved by a modified hybrid genetic algorithm using the above tourism resource data and the established itinerary planning model, and the optimal route result map satisfying the conditions is simulated and solved by MATLAB programming. The aim is to provide tourists with convenient tourism services.

5.2. Practical Testing of the Algorithm. Figure 7 plots the convergence speed curves of the modified ant colony algorithm and the comparison algorithm for cities A, B, C, and D. Since the two-stage algorithm and the trip-planner algorithm are based on a stage process search rather than a generation-by-generation search, these two algorithms are not involved in the plot here. The starting point for the one-day, three-day, and five-day curves is located at 2000, 6000, and 10000 adaptation evaluations, respectively. The performance of the algorithm at the initial point mainly demonstrates the optimization capability of the algorithm, which is less influenced by the initialization method. It can be observed from the figure that the adaptation value of the improved ACO always converges faster than that of the comparison algorithm and can reach a better adaptation value faster. The data normalization module is used to normalize the factors that affect the path construction, such as attraction ratings, distances between attractions, and attraction visit times so that all factors can be considered more fairly when constructing a path. The improved ant colony algorithm has higher population diversity and can locate a better solution faster. TS and VNS algorithms perform a local search based on the current solution; the algorithm performance is very sensitive to the quality of the initial solution; and the convergence speed is steeply enhanced when individuals jump out of the local optimum. The experimental results demonstrate the high search efficiency and fast convergence of the improved ant colony algorithm.

In the next experiments, we investigate the results of analyzing the target parameters and further analyze the relationship between the optimization objectives. In the experiments, the weight parameters of the three optimization objectives are noted as \( w_1, w_2, \) and \( w_3 \). Here, a representative combination of weights is chosen: \( w_1 + w_2 + w_3 = 1 \), where \( w_1, w_2, w_3 \in \{0.00, 0.25, 0.50, 0.75, \).
There are 15 sets of weight parameters to satisfy the above requirements. Figure 8 plots the overall target value $f$ and the normalized targets $f_1$–$f_3$ for the one-day and three-day trip scenarios for three weight values. The three axes in each subplot indicate the weight parameters $w_1$, $w_2$, and $w_3$, and the legend indicates the magnitude of the target values with color bands. It is shown that the overall target value $f$ obtains the best value in both extreme weight combinations (one weight is 1, and the remaining two weights are 0), and the compromise weight combination achieves excellent target values. Furthermore, it is known that the different objectives have a trade-off relationship, and a larger weight value corresponds to a better objective value.

As can be seen from the figure, the differences between the different itinerary solutions are significant and the adaptability of these solutions is very close. The algorithm customizes three optimization objectives from a practical
point of view, considering different preferences of travelers, which are minimizing travel road time consumption, maximizing attraction ratings, and maximizing attraction types.

6. Conclusions

Optimization problems are widely found in academic research and engineering applications, and researchers usually treat optimization problems as global single-solution optimization problems and use various methods to solve them. While solving optimization problems, researchers try to avoid the multisolution feature of the problem, because the multisolution feature makes the algorithm easily fall into the local optimal solution, resulting in the algorithm not being able to obtain the global optimal solution. In this paper, a decomposition evolutionary algorithm based on weak association is proposed to solve the problem that multiple different characteristic factors can be considered comprehensively when recommending rural red tourist attractions; an archival-based ant colony algorithm is proposed to solve the problem that journey planning includes transportation selection and the need to simultaneously optimize multiple objectives; and a multiobjective interval ant colony algorithm is proposed to solve the real-world traffic time uncertainty problem. When performing travel route recommendations, the final population obtained by solving the evolutionary algorithm used in this paper contains a batch of feasible solutions. How to take more into account the personalized characteristics of users further filters this batch of solutions, and selects only two or three sets of travel solutions that best match the user’s preference to recommend to the user, further reducing the user’s selection time. This is far-reaching in enhancing user experience and worthy of further research. We optimize the blending effect of virtual objects with the framing screen. We add more to the display function to display more and more complex 3D graphics and add interactive features to improve the usability of the application. [3].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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