Application of Improved Multi-Objective Evolutionary Algorithm in Intelligent Tourism Interest Point Recommendation and Itinerary Planning

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In the context of a boost in tourism and transportation, people's needs for the quality of tourism services are also increasing. Traditional scenic spot recommendations and itinerary planning methods cannot meet the personalized needs of tourists. Therefore, to achieve personalized services for tourist attractions and itineraries, this study introduces weakly correlated adaptive evolutionary algorithms and archival strategy algorithms to improve multi-objective optimization algorithms. It proposes an adaptive multi-objective evolutionary algorithm model for interest point recommendation and a multi-objective archival ant colony algorithm model for itinerary planning. The experimental results demonstrated that the proposed algorithm exhibited a 10% superiority over the enhanced algorithm in the recommended value of tourist attraction heat features and a 22.2% superiority in the recommended value of tourist attraction social network features. In trip planning, the convergence speed of the proposed algorithm model was faster, and the optimal solution could be found in 100 iterations, while the traditional algorithm needed 140 iterations. In addition, the DTLZ and WFG function test sets were used to evaluate the algorithm's performance. When the target number was 8, the HV value of the proposed algorithm was 0.42 and 0.16 higher than that of the improved algorithm and MOEADD algorithm, respectively. In the trip planning experiment, the total trip length was shortened from 213.4 km to 170.2 km by optimizing the path, effectively reducing unnecessary travel distance. The introduction of a weak correlation adaptive evolutionary algorithm and archiving strategy has led to a notable enhancement in the precision and efficacy of travel interest point recommendation and trip planning. Furthermore, this study has delineated a novel technical avenue for the advancement of personalized tourism services.

Povzetek: Predlagan je izboljšan večciljni evolucijski algoritem za priporočanje turističnih točk in načrtovanje poti, ki skrajšuje potovalno razdaljo, povečuje priporočila in izboljšuje program glede na individualne preference turistov.

1 Introduction

With the development of the tourism industry and the continuous progress of information technology, people's demand for tourism is also constantly increasing [1]. In the context of smart tourism, itinerary planning, and interest point recommendation are two core application scenarios. Journey planning needs to consider multiple factors, such as travel time, cost, attraction preferences, etc., while point of interest recommendation needs to be personalized on the ground of user preferences and behavior patterns. As a commonly used optimization technique, a multi-objective evolutionary algorithm (MOEA) can be used to solve these problems [2]. However, there are still some problems in the application of current MOEA, such as single recommendation results, lack of real-time performance, and inability to handle large-scale data [3]. Traditional travel planning methods typically use greedy or heuristic algorithms to find the optimal solution [4-5]. These methods often only consider a single objective function, such as the shortest travel time or the lowest cost, while ignoring other factors, such as attraction preferences. Therefore, this study proposes a multi-objective (MO) ant colony algorithm (ACA) with a fusion of archiving strategies for path planning and an adaptive evolutionary algorithm based on weak correlation to address the demerits of traditional methods. The innovation of the research lies in the proposal of two algorithmic models for scenic spot recommendation and itinerary planning. These models are designed to consider multiple objective functions simultaneously and to use archiving strategies to filter and retain solutions, thereby improving search efficiency. The first part of the study will provide a review of relevant research, introducing the current application status and existing problems of MOEA. The second part will offer a detailed introduction to the research methods and implementation steps of adaptive evolution and archiving strategies that integrate weak correlations. The third part will conduct case studies to verify the feasibility of the algorithm model through experiments. Finally, the fourth part will summarize the research results and propose future research prospects. Through in-depth research and practice of this technology, it is expected to promote the intelligence of tourism services while meeting the tourism needs of different groups.

2 Background

MO algorithms are often applied to problems that require considering multiple conflicting objectives. To optimize the uneven distribution of individuals in the target space, Qiao et al. presented an adaptive hybrid evolutionary immune algorithm on the ground of MO algorithms. After experimental verification, the results showed that the algorithm could effectively avoid local optima and possessed a high convergence speed [6]. To investigate the impact of energy replenishment and data collection on network performance, Wang's team proposed a MO path planning model for joint energy replenishment and data collection. After verification, the target values of the model in data collection increased by 1.87%, 1.22%, 4.49%, and 2.10% [7]. To achieve MO optimization structural design of upper structure composite sandwich panels, Gholami et al. proposed a new MO niche Memetic particle swarm optimization algorithm. After experimental verification, the model proposed by the research has better performance [8]. Moghdani et al. proposed a MO volleyball super league algorithm to solve global optimization problems with MO functions and used it to solve 10 complex MO benchmark problems. The outcomes showed that this algorithm was superior to two state-of-the-art algorithms in MO benchmark problems [9]. To analyze the preferences of different decision-makers, Liu's team proposed a new decomposition MO evolutionary algorithm based on multi-layer interaction preferences. After testing, the results showed that the algorithm could effectively utilize preference information to search for the optimal solution and successfully handle many objective optimization problems [10].

The preferences of different groups towards tourist attractions and itineraries drive the development of tourism services. To achieve urban planning and tourism policy goals, Gil et al. used GIS search engines to analyze frequency and determine the most popular points of interest (POIs), and conducted correlation and regression analysis. The results indicated that this method provided effective information on scenic spots and tourist preferences for urban planners and tourism policies [11]. Liu et al. presented a new negative sampling method for increasing the accuracy of recommending interest points to users, considering both geographic distance and POI classification distance. Experiments have shown that the research method was at least 19.7% higher in F1 scores than the most advanced models, and at least 24.4% higher in NCG scores [12]. Chen et al. fused different categories of interest point data and multi-source remote sensing data to construct a three-dimensional model. This was to explore the nonlinear relationship between different geographical prediction factors and different heat source AHEs. After research, the results indicated that POI data had great potential in improving the accuracy of AHF mapping [13]. Uclea et al. conducted a sample survey of Romanian social media users and conducted multiple regression analysis, aiming to determine the role of social media in estimating the attractiveness of tourism destinations. The results indicated that social media possessed an essential influence on the tourism planning process [14]. To help tourism companies effectively obtain tourist interest information, Cheunkamon et al. synthesized TAM, TPB, and trust and satisfaction factors for developing a model of the relationship between structural factors. Research has shown that this model helped develop tourism marketing strategies and support sustainable competition [15].

Table 1 summarizes the key features, performance indicators, and limitations of these studies. Table 1 illustrates the advantages and potential for improvement of the proposed algorithm in the context of tourism interest point recommendation and itinerary planning, as compared to existing algorithms. The incorporation of a weak correlation adaptive evolutionary algorithm and an archiving strategy has led to a notable enhancement in the precision of recommendations and the efficacy of trip planning.

Table 1: Related literature review table

Algorithm name	Key feature	Performance indicators	limitation
Qiao et al. 's adaptive hybrid evolutionary immune multi-target algorithm [6]	Adaptive hybrid evolutionary immune algorithm based on uniform distribution selection	High convergence speed, effectively avoid local optimization	No specific mention of big data processing capabilities
Wang's team proposed a MO path planning model combining energy recharge and data acquisition [7]	Energy replenishment and data acquisition for wireless rechargeable sensor networks	Significant improvement in data collection target value	Tourism application scenarios are not mentioned
MO niche hybrid particle swarm optimization algorithm proposed by	MO optimization design for composite sandwich sandwich board	The performance is better than other algorithms, but it is not	Travel recommendations or itinerary planning are

Gholami et al. [8]		quantified	not involved
MO Volleyball Super League algorithm proposed by Moghdani et al. [9]	Solve global optimization problems for multiple objective functions	Excellent performance on a number of benchmark issues	Not directly used in the field of tourism
Multi-layer interactive preference decomposition MOEA proposed by Liu's team [10]	MO optimization based on multi-layer interactive preferences	Using preference information effectively to deal with MO optimization problems	Real-time performance in specific application scenarios is not mentioned
Gil team used GIS search engine to analyze the frequency of tourist attractions [11]	Use search engine data to analyze the frequency of tourist attractions	Provide effective information on tourist attractions and visitor preferences	Lack of real-time recommendation and trip planning capabilities
New negative sampling method proposed by Liu et al. [12]	Improve the accuracy of point of interest recommendations, taking into account geographical distance and POI classification distance	F1 scores and NCG scores improved significantly	No mention of large-scale data processing capabilities
Chen et al. integrated different types of interest point data and remote sensing data [13]	A 3D model was constructed to explore the relationship between geographic predictor and heat source	Improve the accuracy of AHF mapping	Not directly applied to travel recommendations
WAEA model is proposed in this study	MO optimization based on weak correlation adaptive evolutionary algorithm	Improved recommendation accuracy	/

3 Application of improved MO algorithm in tourism interest points and itinerary planning

To address the issues of accuracy and rationality of travel interest point recommendations in tourism services, this study is based on the MOEA and introduces weakly correlated adaptive evolutionary algorithms to improve [16]. The aim is to construct a tourism interest point recommendation system. Simultaneously incorporating the archiving strategy into the MO ACA aims to construct a travel planning optimization model.

3.1 MO evolutionary algorithm optimization strategy for tourism interest point recommendation

With the improvement of economy and living standards, tourism has become one of the important leisure and entertainment methods for people. However, traditional tourism recommendation methods cannot meet the personalized needs of tourists, cannot reflect market conditions in a timely manner, and it is also difficult to explore user interests and hobbies. The MO evolutionary algorithm combines multiple objective functions to comprehensively consider multiple factors and can solve MO optimization problems [17]. Therefore, this study is based on the MO algorithms to achieve recommendation of tourism interest points. The recommended objective function in the MO algorithm is shown in equation (1).

$$M\inf(X) = (f_1(X), f_2(X), ..., f_m(X)) \quad (1)$$

In equation (1), m is the total of multiple factors. X is the recommended solution. $f_m(X)$ is the function value of the recommended solution. The expression formula for the objective function value is shown in equation (2).

$$\mathrm{f}\, i = d(X, A_i) \quad (2)$$

In equation (2), A_i is the recommendation result considering the i -type factor in the recommendation function. d is the Euclidean distance in the recommended solution and the i -class factor. However, a single MO algorithm lacks real-time analysis of data and is difficult to handle data sparsity. The weak association-based adaptive evolutionary algorithm (WAEA) can adapt to market changes and user needs through continuous learning and optimization, achieve dynamic recommendations, and improve the intelligence and accuracy of recommendations. This study introduces the WAEA on the basis of MO algorithms to achieve improvements. In the WAEA, the habitat angle of the target space needs to be calculated first, and its expression is shown in equation (3).

$$a = \underset{i\in\{1,2,...,N\}}{median}\left\{\min_{j\in\{1,2,...,N\}} across(Vi, Vj)\right\} \quad (3)$$

In equation (3), V is the unit reference vector. j

is a constant value. a represents the perspective of the subspace habitat. Correspondingly, the angle subspace of the target space can be obtained, as expressed in equation (4).

$$C_i = \left\{ o \in R^m \left| \langle o, V_i \rangle = \frac{a}{2}, \forall i = 1, 2, ..., N \right. \right\} \quad (4)$$

In equation (4), o is the boundary vector. After generating the subspace, the original target space is divided to form a habitat with a consistent range, where the solution of the target is associated with the reference vector. Figure 1 is a schematic diagram of sub-association and multi-association generation in a two-dimensional target space.

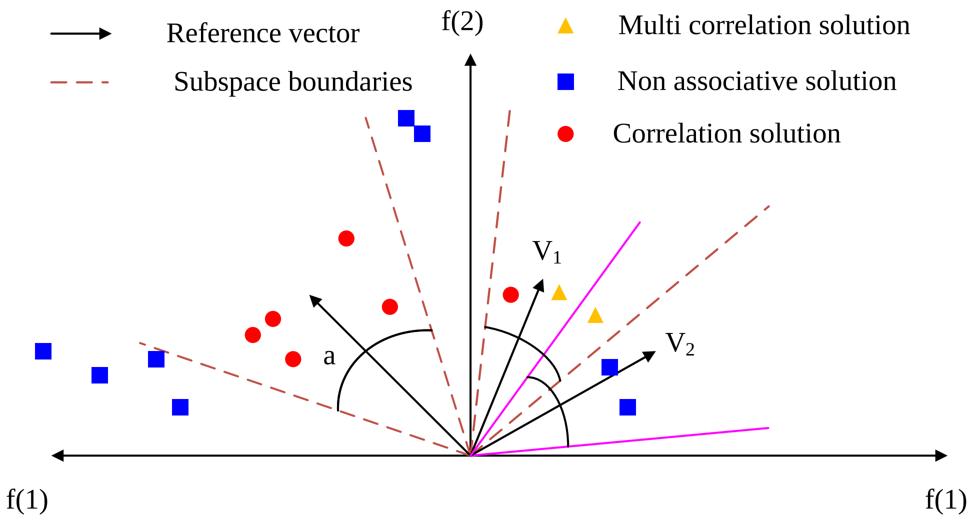


Figure 1: Generation of target sub-spaces and multiple association solutions in 2D space

As shown in Figure 1, in the two-dimensional target space, a sub-association can be represented as an association rule, where some variables have direct or indirect dependencies between them. The existence of this seed association can help us better understand the relationships between variables in the target space and provide more accurate prediction and classification capabilities. Multiple associations can take into account the interactions and dependencies between multiple variables, thus providing more comprehensive and accurate association rules. Next, it considers the angle between solutions in the habitat space, and its expression is shown in equation (5).

$$Angle(s, V_i) = ar\cos\left(\frac{f(s) \cdot V_i}{\| f(s) \|}\right) \quad (5)$$

In equation (5), s is the solution in the habitat space population. To further optimize the global selection strategy, a bimodal scalar function is utilizing for optimizing the MO problem, and its expression is shown in equation (6).

$$\min F(s, V_i) = \begin{cases} con(s) + \theta * d_2(s, V_i), s \in P_{vi} \\ con(s) + \theta * d_2(s, V_i) * R(s, V_i), s \notin P_{vi} \end{cases} \quad (6)$$

In equation (6), $R(s,V_i)$ is the angle ratio factor. $con(s)$ is the sum of target values for each dimension. θ is the penalty parameter. The expression for the sum of the target values of each dimension is shown in equation (7).

$$con(s) = \sum_{i=1}^{M} f_i(s) \quad (7)$$

Furthermore, the expression for d_2 can be obtained as shown in equation (8).

$$d_2 = \left\| f(s) - Z^* - d_1 \frac{V}{\|V\|} \right\| \quad (8)$$

In equation (8), Z^* is the minimum value of each target. To handle different types of high-dimensional MO problems, the penalty parameter θ is designed, and two major criteria, BSF and PBI, are used for parameter tuning. The parameter tuning process is shown in Figure 2.

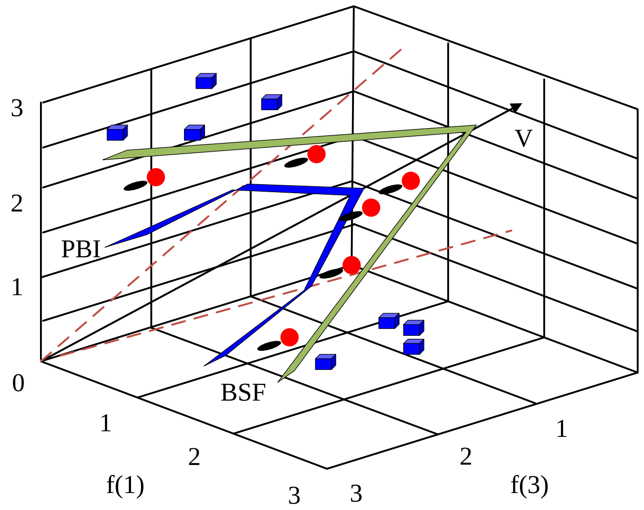


Figure 2: High dimensional MO optimization process

As shown in Figure 2, BSF and PBI criteria are used to evaluate the stability of the solving process and determine the optimal value of penalty parameters when dealing with high-dimensional MO problems [18]. Due to the complexity of high-dimensional MO problems, the solution process may become very unstable, resulting in inaccurate solution results. Therefore, calculating the rate of change of model function energy using the BSF criterion can evaluate the stability of the solving process and determine appropriate termination or convergence conditions [19]. In MO optimization problems, there are usually multiple conflicting objectives that require the use of penalty functions to transform into one objective function for optimization. The PBI criterion can select the optimal penalty parameter by comparing the values of the objective function under different penalty parameters, thereby facilitating the attainment of superior optimization results. In summary, by introducing the WAEA to improve MO algorithms, the objective function is continuously optimized and adjusted during the solving process of evolutionary algorithms to achieve better recommendation results.

3.2 Design of MO ACA for journey planning based on the archive strategy fusion

In tourism, MO algorithms can not only be applied to recommendation of tourism interest points, but also to travel itinerary planning [20]. In tourism itinerary planning, there are six elements of tourism, namely food, accommodation, transportation, travel, shopping, and entertainment. It is necessary to consider the conflict of multiple elements, and a single objective algorithm is difficult to obtain high-quality solutions. Therefore, this study introduces an archiving strategy to obtain better approximate Pareto frontiers and optimal solutions through two stages of evolutionary operations. Firstly, it calculates the number of explorations of tourists' travel modes between two places, and its expression is shown in equation (9).

$$N = \frac{1}{e^{\frac{x}{3}} * p} \tag{9}$$

In equation (9), p represents the iterative process of the ACA. x is the search record or archive record. Figure 3 shows the MO ACA for the archiving strategy.

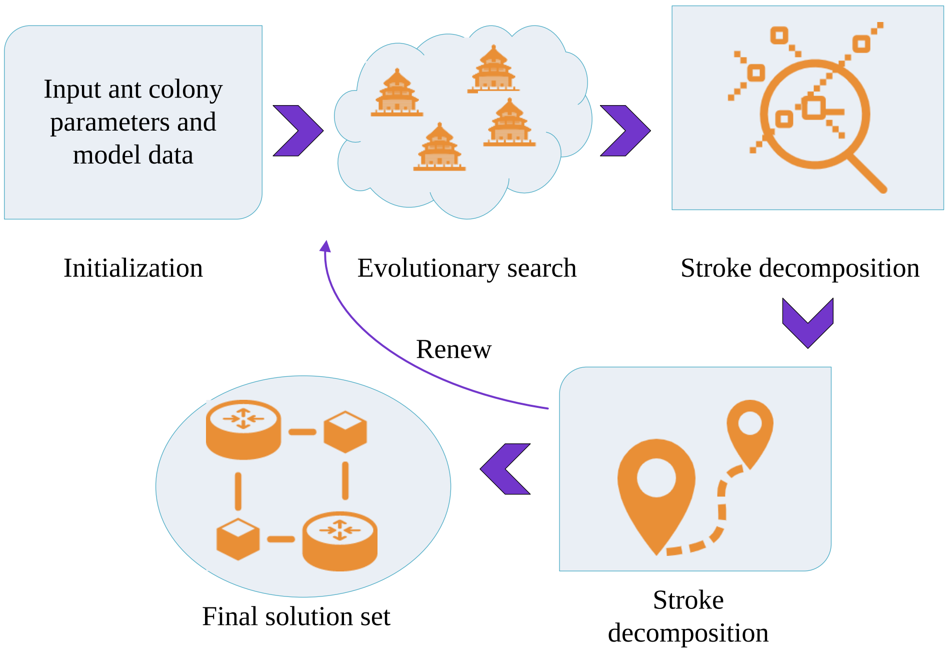


Figure 3: Flow of MO ACA based on the archive strategy

As shown in Figure 3, this study first sets parameters such as the quantity of ants, quantity of iterations, and pheromone volatilization rate, and initializes the pheromone matrix. Next, it aggregates the scenic spots and constructs a solution space on the ground of the problem definition of tourism itinerary planning. Each solution is represented as a travel route, completing the decomposition of the itinerary. Then, according to certain rules, it initializes the solutions in the solution space as an archive strategy, and calculates the attractiveness of each node. It updates the pheromone concentration of the node based on the pheromone matrix and attractiveness, and finally outputs the final solution set. In the integration of scenic spots, equation (10) is used to calculate them to avoid duplication.

$$P_{ij}^{k}=\begin{cases}\dfrac{\tau_{ij}(t)\eta_{j}(t)}{\sum s\in c\tau_{ij}(t)\eta s(t)},\ j\in c\\ 0,\ j\notin c\end{cases} \quad (10)$$

In equation (10), c is the collection of scenic spots. τ_{ij} is the pheromone between two scenic spots. η_j is the inspiration information. When updating pheromones, equation (11) is used for calculation.

$$\Delta\tau_{ij}(t)=\begin{cases}\dfrac{Q}{time(i,j)*\cos t(i,j)},(i,j)\in\rho\\ 0,(i,j)\notin\rho\end{cases} \quad (11)$$

In equation (11), Q is the intensity of pheromones. ρ is the volatilization coefficient of pheromones. ρ is the number of iterations. This indicates that the formula for calculating the next iteration of pheromones is shown in equation (12).

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\rho\Delta\tau_{ij}(t) \quad (12)$$

In equation (12), $1-\rho$ is the pheromone residue factor. Figure 4 shows the process of exploring the travel modes between two places in the final design.

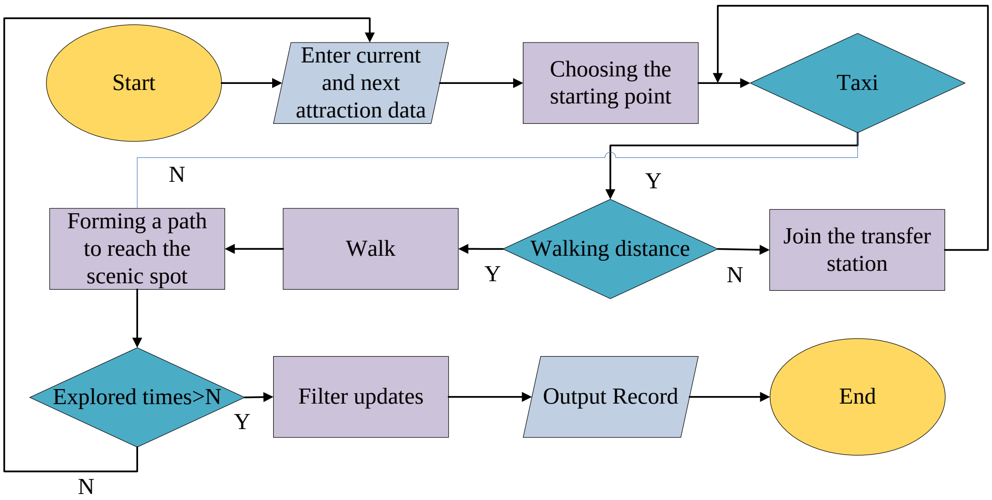


Figure 4: Process of exploring travel modes between two places

In the MO ACA based on archive strategy, the data and exploration times of the current and next attractions are first input, followed by the starting point and transportation. If they choose taxis as transportation, they will reach the next scenic spot, forming a new path. Otherwise, they will choose other public transportation methods or walk to reach the next scenic spot. If the exploration exceeds a certain limit, non-dominant modes of travel will be selected in the number of choices, and random selection will be made before output. Otherwise, a new mode of transportation will be selected. To verify the convergence and diversity of the algorithm, the HV index is selected to evaluate the coverage and convergence diversity of the MO ACA based on the archiving strategy in the target space. To estimate uncertain parameters, confidence intervals are used for sample extraction, and the expression is shown in equation (13).

$$P(a < x` < b) = a \qquad (13)$$

In equation (13), $x`$ is the variable. a and b are probability intervals. The quantile expression of a in the confidence interval is shown in equation (14).

$$P(x < Z_{(a)}) = a \qquad (14)$$

In equation (14), $Z_{(a)}$ is the quantile. Next, the probability density function is used to calculate the traffic time between two scenic spots.

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(t-\sigma)^2}{2\sigma^2}) \qquad (15)$$

In equation (15), σ is the standard deviation. The final tourism itinerary planning framework based on the MO ACA with archiving strategy is shown in Figure 5.

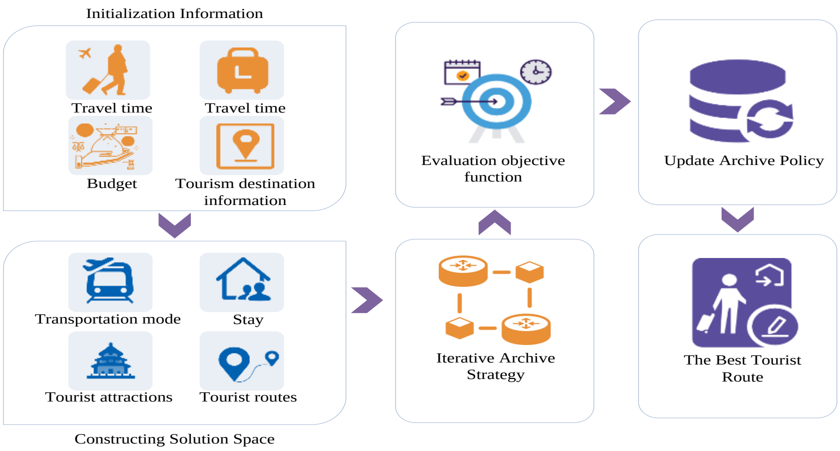


Figure 5: Tourism itinerary planning framework on the ground of MO ACA with archive strategy

The tourism itinerary planning framework based on the archive strategy MO ACA can be divided into the following parts. Firstly, the tourism destination information, travel time, budget and other constraints, as well as the preferences and needs of tourists, are inputted into the tourism itinerary planning. Based on the problem definition of tourism itinerary planning, a solution space is constructed using appropriate coding methods. Each solution represents a tourist route, including tourist attractions, transportation methods, accommodation, etc. Next, it initializes the archive strategy, initializing some of the solutions in the solution space as the archive strategy according to certain rules. The archive strategy can include solutions that have already been explored, as well as some initial solutions. Then it uses MO ACA for iterative search and continuously updates the archiving strategy. In each iteration, the ant selects a path based on the archiving strategy as the current path, and updates the pheromone concentration of the path based on the pheromone matrix and attractiveness. It selects the next node based on the updated pheromone concentration and probability. It repeats this process until it reaches the endpoint or reaches the maximum number of iterations. It adds each path to the archive policy. Next, it evaluates the quality of each solution in the archiving strategy based on the objective function of tourism itinerary planning, which includes travel time, cost, scenic spot tour integrity, etc. It continues to update the archiving strategy based on the evaluation results of the objective function, and adds solutions with good evaluation results to the archiving strategy, while deleting solutions with poor evaluation results. Finally, the optimal solution in the archive strategy is output as the result of tourism itinerary planning. This is defined as the tourism route that aligns with the needs and constraints of tourists, while also exhibiting the optimal objective function value. In summary, a tourism itinerary planning framework based on MO ACA with archive strategy is utilized for obtaining tourism routes that meet the needs and constraints of tourists. This can improve the efficiency and accuracy of tourism itinerary planning.

4 Application evaluation of MO optimization algorithms in tourism recommendation and itinerary planning

To verify the superiority of the WAEA MO algorithm model for tourism interest point recommendation, this study collected relevant scenic spot information for scenic spot feature recommendation value analysis, and compared it with relevant algorithm models. To verify the effectiveness of the MO recommendation ACA model in tourism itinerary planning, this study selected the maximum total utility of the route, the minimum total cost of the route, and the minimum maximum travel time in the route to analyze the performance of the model.

4.1 Experimental environment settings

The computer configuration used in the experiment is as follows: the processor is Intel Core i9-9900K CPU @ 3.60GHz, with 8 cores and 16 threads. The memory is 64GB DDR4 RAM and the frequency is 3200MHz. The storage is 1TB NVMe SSD, which is used for fast read and write of operating system and experimental data. The operating system is Windows 10 Pro 64-bit. The programming language and tools are Python 3.8, implemented using scientific computing libraries such as NumPy, Pandas, Scikit-learn, and custom MOEA and ACA algorithms. To verify the effectiveness of the proposed algorithm, a dataset containing information about tourist attractions in multiple cities is constructed. The dataset is drawn from multiple publicly available tourism data sources, including government tourism authorities, online travel platforms, and social media. It is about 5GB in size and contains more than 100,000 records. Each record contains multiple dimensions such as location, opening hours, ticket prices, user reviews, social media mentions, and popularity ratings. To comprehensively evaluate the performance of the proposed algorithm, the evaluation indexes such as recommendation accuracy, over-volume, maximum total route utility, minimum total route cost, minimum maximum travel time, convergence speed, and path length optimization are used.

4.2 Performance evaluation of intelligent tourism interest point recommendation system

To verify the recommendation effect of the MO algorithm introduced by WAEA in smart tourism interest points, this study first selects 10 tourist attractions in a certain city for recommendation value analysis of a single feature factor. The parameters of WAEA-MOEA algorithm are set as follows: The population size is set to 100. The crossover rate is set to 0.8. The variation rate is set to 0.05. The maximum number of iterations is set to 1000. The convergence criterion is that the algorithm is considered to converge when the change of the optimal solution is less than 0.01% in 10 successive generations. The temporal complexity of WAEA-MOEA is mainly composed of population size, number of objective functions, crossover operation, variation operation and fitness evaluation. For each iteration, the time complexity is roughly O (N*M*G), where N is the population size, M is the number of objective functions, and G is the number of iterations. The outcomes are shown in Table 2.

Table 2: Recommended values of characteristic factors of different scenic spots

Scenic spot number	Correlation feature	Synergistic feature	Heat characteristic	Social networking is extremely high
1	87	92	78	79
2	67	56	46	57
3	68	47	57	46
4	57	76	47	63
5	57	56	43	62
6	46	46	57	73
7	35	36	36	74
8	78	47	36	52
9	53	57	37	74
10	67	68	65	51

Table 2 shows the recommended value analysis of feature factors for scenic spots based on the WAEA MO algorithm. The feature factors for each scenic spot are selected as correlation features, collaborative features, popularity features, and social network features. Then, the feature factors are combined based on different user preferences and the optimal solution is obtained. Among them, attraction 1 has the highest recommendation value for each feature, with a collaborative feature recommendation value of 92. Then, to verify the recommendation accuracy of the MO algorithm based on WAEA, the recommendation values of the correlation features, collaborative features, popularity features, and social network features of the scenic spots are compared before and after the improvement of the algorithm. The results are shown in Figure 6.

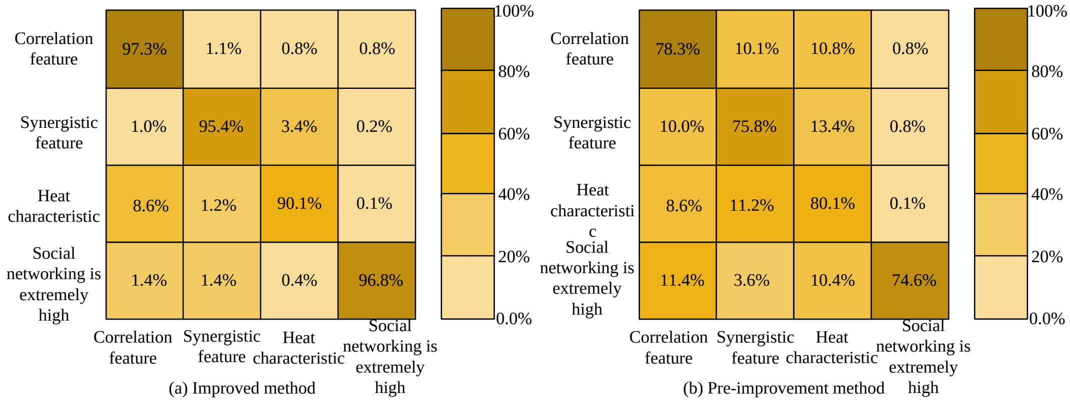


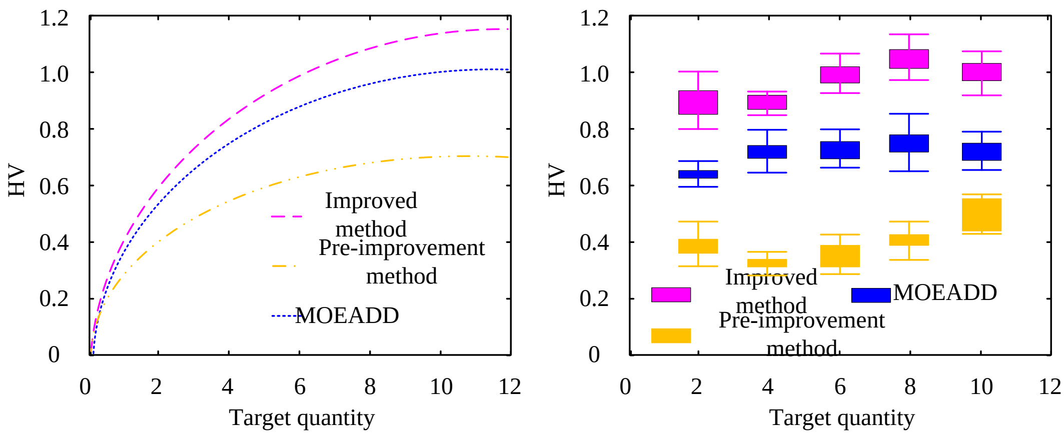
Figure 6: Comparison of accuracy of landscape feature recommendation values

Figure 6 shows the accuracy comparison outcomes of the recommended values for the four feature factors of scenic spots. It demonstrates that the average recommendation accuracy of the improved WAEA-based MO algorithm is over 90%. The accuracy of the recommended values for scenic spot related features is the highest at 97.3%, which is 19% higher than the accuracy of the recommendations before improvement. In the accuracy comparison of collaborative feature recommendation values, the research algorithm is 19.6% higher than the improved algorithm. In the analysis of the accuracy of recommended values for tourist attraction heat characteristics, the research algorithm is 10% higher than the improved algorithm. In the accuracy analysis of social network features in scenic spots, the research algorithm is 22.2% higher than the improved algorithm. This indicates that the WAEA-based MO algorithm has a higher accuracy in extracting feature factors from various scenic spots, which is conducive to providing more accurate recommendation services for tourists. In addition, the standard deviation and 95% confidence interval for each feature recommendation accuracy are calculated. The results are shown in Table 3. Standard deviation and 95% confidence interval data can better illustrate the stability of algorithm performance.

Table 3: Standard deviation and 95% confidence interval of feature recommendation accuracy

Feature type	Average recommendation accuracy	Standard deviation	95% confidence interval
Correlation feature	97.3%	0.5%	[96.8%, 97.8%]
Synergistic feature	96.9%	0.6%	[96.3%, 97.5%]
Heat characteristic	91.2%	0.7%	[90.5%, 91.9%]
Social network characteristics	92.5%	0.4%	[92.1%, 92.9%]

Table 3 shows that WAEA-MOEA algorithm has stable and reliable performance. For example, the correlation feature recommendation accuracy is as high as 97.3% and the standard deviation is only 0.5%, showing high precision stability. The narrow confidence interval of the recommendation accuracy of each feature indicates that the algorithm performs consistently in different situations, effectively improving the accuracy and credibility of the recommendation of tourism interest points. Secondly, functional test sets of DTLZ and WFG are selected to compare the performance of the WAEA-based MO algorithm with the improved algorithm, as well as the decomposition-based MO evolutionary algorithm (MOEAD) in solving target problems for different scenic spots and tourists. The results are shown in Figure 7.



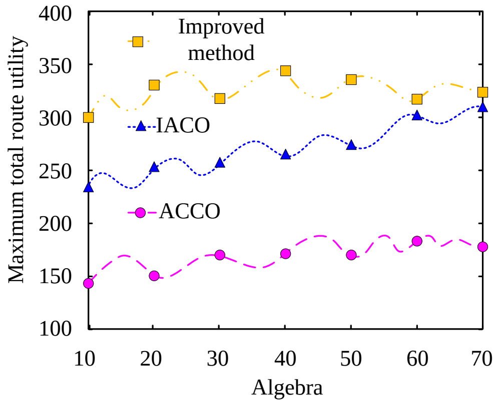
(a) DTLZ function data set (b) WFG function data set

Figure 7: Comparison results of HV values under different targets

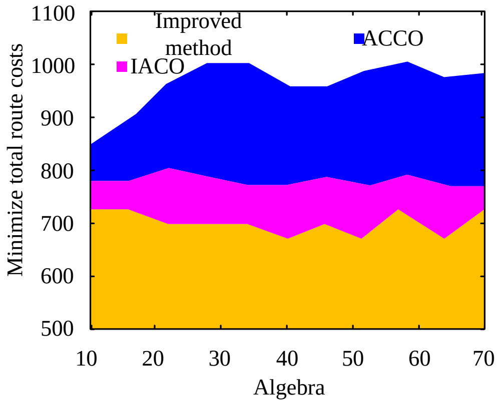
Figure 7 (a) shows the comparison results of HV values of various algorithms under the DTLZ function test set. As the target values of tourism interest points increase in Figure 7 (a), the HV value of the MO evolutionary algorithm based on WAEA also increases, and the HV value of the research algorithm always remains the highest under any number of targets. When the target number of tourist attractions is 8, the HV value of the research algorithm is 0.42 and 0.16 higher than that of the improved algorithm and MOEADD algorithm. Figure 7 (b) shows the comparison of HV values of different algorithms under the WFG function test set, where the HV values of the research algorithms are also at the leading level. When the target number of tourism interest points is 8, the maximum HV value of the research algorithm reaches 1.1, which is 0.53 and 0.24 higher than the HV values of the improved algorithm and MOEADD algorithm, respectively. The higher the HV value, the more excellent the overall performance of the solution set on the ground of this algorithm. In summary, the research algorithm not only effectively extracts the feature values of tourist attractions, but also has higher recommendation accuracy for different tourist attractions.

4.3 Analysis of the itinerary planning effect of MO ACA on the ground of archive strategy

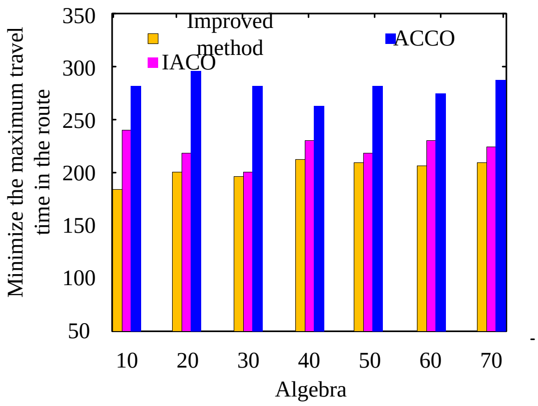
To verify the recommendation effect of MO ACA based on archive strategy in tourism itinerary planning, three indicators are considered: maximum route total utility, minimum route total cost, and minimum maximum travel time in the route. It compares the research model with the Interactive Ant Colony Optimization (IACO) and Adaptive Harmony Search Algorithm (ACCO) models. The parameters of the MO ACA algorithm are set as follows: The number of ants is set to 50. The number of iterations is set to 100. Pheromone volatilization rate is set to 0.1. In the archive policy, the archive size is set to 50. Convergence criteria: By monitoring the changes in the super volume values, it is possible to determine whether the algorithm is converging. The time complexity of MO ACA algorithm is not only composed of population size, number of objective functions, cross-operation, mutation operation, and fitness evaluation, but also involves pheromone renewal and path selection. Its time complexity also includes the number of ants and the cost of updating pheromone matrix. Its time complexity is close to O (N*G), where N represents the combined effect of the number of ants and the number of iterations. The results are shown in Figure 8.



(a) Maximum route total utility comparison



(b) Minimize total route cost comparison



(c) Minimize the maximum travel time comparison in the route

Figure 8: Recommendation effect of travel planning index

Figure 8 (a) shows the comparison results of the maximum route total utility of three models. The MO ACA model based on archive strategy studied has an increasing optimization ability as the quantity of iterations grows. Compared with the IACO and ACCO algorithm models, the average value of the maximum route total utility in its travel planning is 50-100 values higher. Figure 8 (b) shows the comparison results of the total cost of minimizing the route for three models. The MO ACA model based on archive strategy, compared with the IACO and ACCO algorithm models, maintains a minimum total cost of 700 and performs well. Figure 8 (c) shows the comparison results of the maximum travel time among the minimized routes of the three models. Figure 8 (c) shows that the time required to study the algorithm model is minimal and remains basically below 200. This indicates that the algorithm model studied in this study has the highest overall utility in travel planning, with the lowest cost and time for planning travel. Next, it compares the total utility of travel planning among the three algorithm models, and the results are shown in Figure 9.

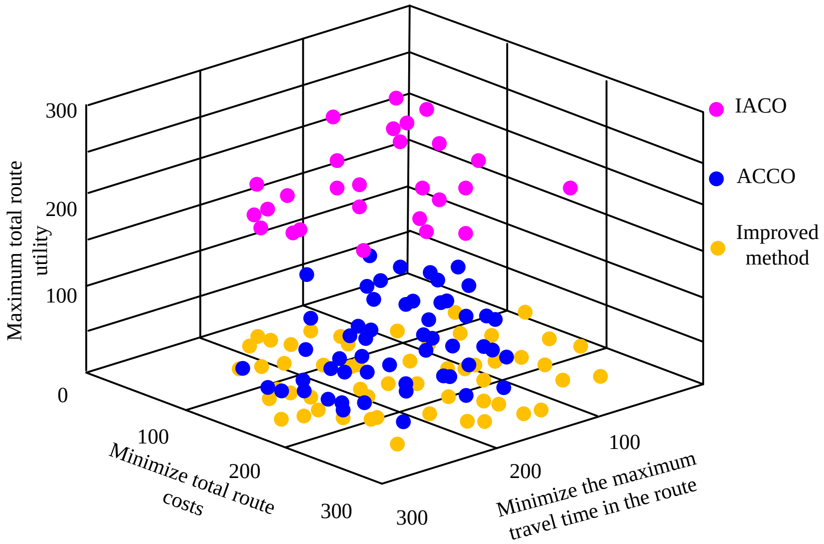


Figure 9: Comparison of MO optimization results in trip planning

The MO ACA model based on archive strategy studied in Figure 9 performs well, specifically in the MO solution of tourism itinerary. The solution is mainly concentrated below the target space, within the range of 100 to 200 units between minimizing the total cost of the route and minimizing the maximum travel time in the route. This indicates that the research algorithm has advantages in minimizing the total cost of the route and minimizing the maximum travel time in the route planning. The solutions of the IACO and ACCO algorithm models are more dispersed, and their advantages are not obvious. Next, the research algorithm model is applied to tourism itinerary planning, and the results are shown in Figure 10.

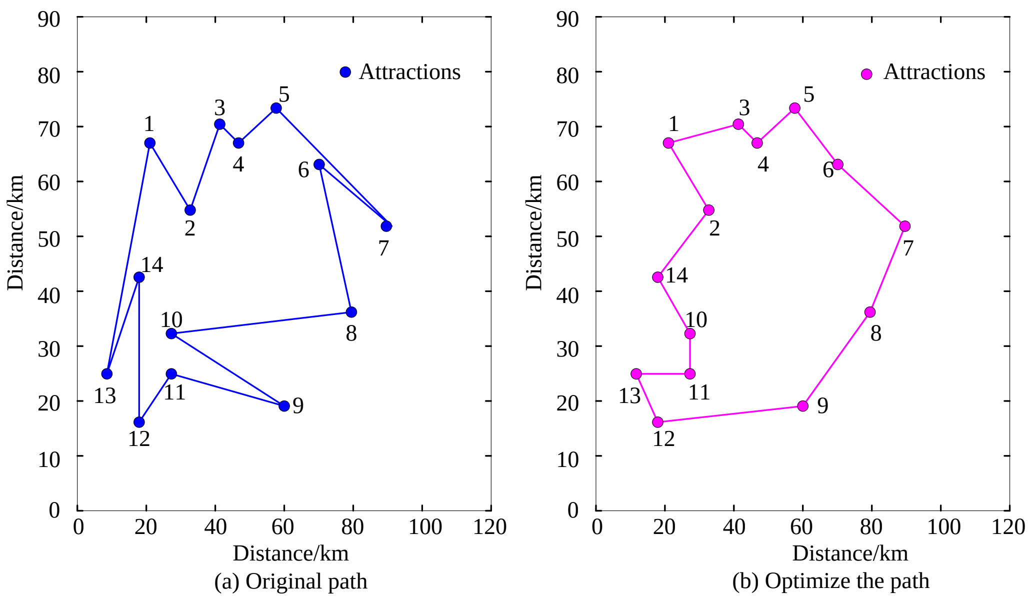


Figure 10: Optimization results of travel itinerary path

Figure 10 shows the results of a MO ACA model based on archive strategy in tourism itinerary planning. Figure 10 shows a total of 14 tourist attractions involved in the tourism itinerary planning, with a total length of 213.4 km in the original itinerary. After studying the algorithm model and optimizing the path, the total length of the travel itinerary is 170.2 km, which reduces the travel by about 43.2 km and effectively reduces unnecessary distance in the itinerary. This indicates that the algorithm model in this study can find the best travel itinerary. Finally, the optimization results of the research algorithm model at various distances are shown in Figure 11.

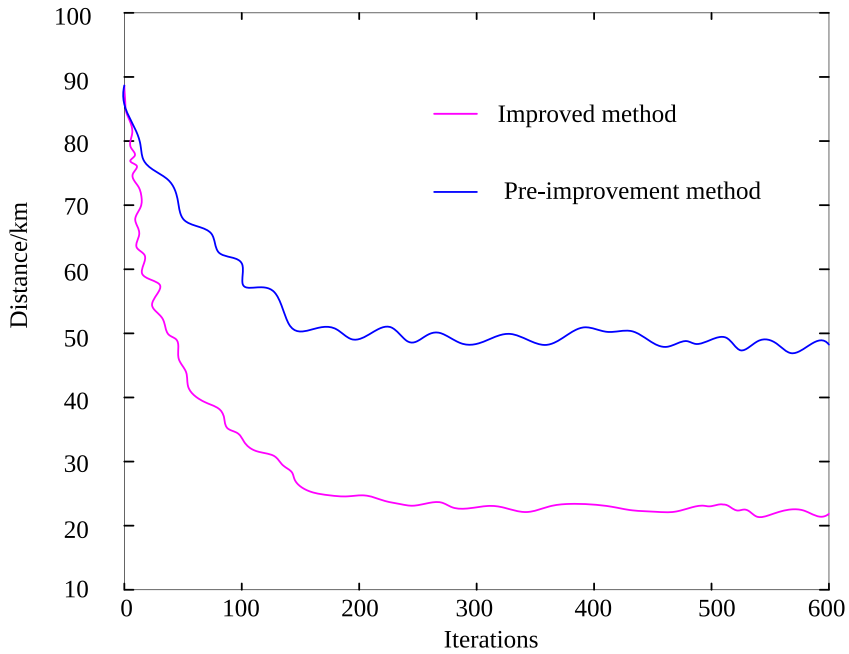


Figure 11: Convergence curve of the number of tourist attractions and travel distance

When the number of cities in Figure 11 is small but the journey is long, the convergence speed of the research algorithm is faster, and the optimal solution can be found within 100. However, traditional algorithms require 140 iterations for finding the optimal solution, indicating that the research algorithm is markedly more excellent than the MO algorithm before improvement. This indicates that the study of MO ACA based on archive strategy can achieve the highest total utility in travel itinerary planning, minimize the cost and time of planning itinerary, and simultaneously plan the optimal route.

4.4 Performance of the algorithm in different tourism cases

To further enhance the applicability and persuasiveness of the paper, case studies of the proposed algorithm in different tourism environments will be presented, mainly including actual cases of different scenarios such as urban and rural, cultural and adventure tourism. These case studies not only verify the wide applicability of the algorithm, but also demonstrate its superior performance in different situations. The specific case analysis is shown in Table 4.

Table 4: Details of the case analysis

Case type	Background description	Experimental design	Experimental result
City tourism	Famous tourist city in China, rich in historical and cultural relics, modern shopping centers and food streets	WAEA-MOEA algorithm is used to recommend personalized points of interest, and MO ACA algorithm is combined to plan the optimal itinerary	Recommended points of interest with high accuracy, in line with individual needs; Trip optimization reduces the total travel distance by about 20%
Rural tourism	Countryside with beautiful natural scenery, featuring pastoral scenery, rural culture and farmhouse music	Adjust the weight of WAEA-MOEA algorithm, focusing on natural scenery and parent-child activity recommendation; Plan an itinerary that includes multiple modes of transportation	Recommended points of interest combine natural scenery with parent-child activities, reasonable schedule, reduce travel costs
Cultural tourism	A famous historical and cultural city with rich historical sites, museums and	Use WAEA-MOEA algorithm to recommend historical and culture-related attractions and	Recommended cultural interest points are well loved, itinerary design

	traditional cultural performances	activities; Plan a reasonable tour route	improves tourist satisfaction, and fully experience the cultural atmosphere
Adventure travel	Famous outdoor adventure destination with steep mountains, fast-flowing rivers and lush forests	Combining WAEA-MOEA algorithm to recommend adventure activities; Plan an itinerary that includes multiple adventure activities	Recommend adventure activities to meet challenges and ensure safety; Reasonable schedule to ensure tourists rest and recovery

From Table 4, the proposed algorithm performs well in a variety of situations, verifying its wide applicability and superior performance. These case studies not only enhance the persuasiveness of the paper, but also provide valuable references for practical applications.

5 Discussion

MOEA based on WAEA and MO ACA based on archiving strategy presented in the study show significant performance improvement in the recommendation of travel interest points and itinerary planning. Compared with existing SOTA methods, the above algorithm shows advantages in many aspects [21]. First of all, in terms of the recommendation of tourist interest points, WAEA-MOEA algorithm shows higher accuracy in extracting feature values of scenic spots. The experimental results demonstrate that the recommendation accuracy of WAEA-MOEA for the correlation features, collaborative features, heat features, and social network features of scenic spots is significantly higher than that of the improved algorithm. Notably, the recommendation accuracy for correlation features reaches 97.3%, which is 19% higher than that of the improved algorithm. This is primarily attributable to the fact that WAEA can adapt to market changes and user requirements, and is thus able to generate recommendations that are continuously updated and optimized, thereby enhancing the precision and sophistication of the recommendations provided. Secondly, in terms of trip planning, the archiving strategy-based MO ACA algorithm is also superior to traditional algorithms in convergence speed and optimization effect [22]. The experimental results show that the algorithm can find the optimal solution within 100 iterations, while the traditional algorithm needs 140 iterations. In addition, by optimizing the path, the algorithm shortens the total travel length from 213.4 km to 170.2 km, effectively reducing unnecessary travel distances. This is mainly due to the application of archiving strategy, which makes the algorithm more effectively retain the good solutions and eliminate the bad ones, thus improving the search efficiency and the quality of the final solutions.

The innovation of this study lies in the two new algorithm models for the recommendation of tourism interest points and itinerary planning. First of all, WAEA-MOEA algorithm realizes dynamic adaptation to market changes and user needs by introducing weak correlation adaptive evolution mechanism, and improves the accuracy and intelligence level of recommendation. Secondly, MO ACA algorithm based on archiving strategy combines archiving strategy and MO optimization technology to realize efficient solution of travel itinerary planning problems. These two algorithm models not only solve the limitations of traditional methods in dealing with MO optimization problems, but also significantly improve the quality and efficiency of the solution by introducing new optimization strategies and technical means. Although the proposed algorithm has achieved remarkable results in the recommendation of tourism interest points and itinerary planning, there are still some potential limitations and areas for improvement. This research mainly focuses on the recommendation and planning of individual tourists without fully considering the interests and preferences of tourism groups. In the future, the research scope can be further expanded to recommend and analyze tourism groups. Secondly, the proposed algorithm needs to be optimized in processing large-scale data and real-time recommendation. With the continuous growth of tourism data and the increase of real-time recommendation demand, how to further improve the real-time and scalability of the algorithm will become the focus of future research. In addition, future work can also consider combining the research algorithm with other advanced artificial intelligence technologies, such as deep learning, reinforcement learning, etc., to achieve more intelligent and personalized travel recommendation and planning services.

6 Conclusion

With the increasing personalized demand for tourist attractions, traditional tourist attraction recommendations cannot meet the diverse needs of tourists and cannot provide the best travel itinerary for them. Therefore, this study enhanced the MO evolutionary algorithm in two key areas: tourism interest points and itinerary planning. It developed a MO tourism interest point recommendation model based on WAEA and a MO ant colony itinerary planning model based on archive strategy. Experiments have shown that the research model could effectively extract correlation features, collaborative features, popularity features, and social network features of scenic spots. Among them, the accuracy of recommendation values for scenic spot correlation features was the highest at 97.3%, which was 19% higher than the accuracy before improvement. In the comparison results of HV values between different algorithms, when the target number of tourist attractions was 8, the HV values of the research algorithm were 0.42 and 0.16 higher than those of the improved algorithm and MOEADD algorithm, respectively. In comparison to the IACO and ACCO algorithm models, the average value of the maximum route total utility of the research model's travel planning was found to be between 50 and 100 values higher. After studying the algorithm model and optimizing the path, the total length of the travel itinerary was 170.2 km, resulting in a reduction of approximately 43.2 km. This indicates that the two proposed algorithm models can effectively recommend tourist interest points and design the optimal itinerary. The drawback of this study is that it did not consider the interest preferences of tourist groups and only analyzed individual tourists. In the future, research recommendations and analysis can be conducted for group tourists.

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