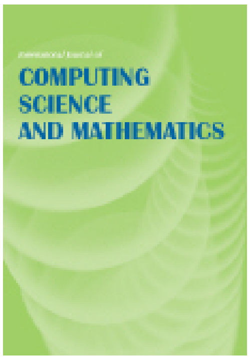

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Application of a hybrid genetic algorithm based on the travelling salesman problem in rural tourism route planning

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Abstract: It is very meaningful to integrate tourism resources, excavate valuable tourism information and develop a self-service tourism route planning system. In this study, a hybrid genetic algorithm (HGA) based on the travelling salesman problem (TSP) is proposed, and the proposed algorithm is simulated and case-analysed. The research shows that the HGA algorithm has better optimisation efficiency when the number of iterations is less; when there are many urban attractions and large distances, the HGA algorithm will show more cross-routes. After multiple iterations, the optimisation effect and results of the algorithm will be better. There is still much room for improvement in the method proposed in this study. In the next step, map technology can be used to design more detailed route display functions.

Keywords: TSP; travelling salesman problem; genetic algorithm; ant colony rural tourism; route planning.

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1 Introduction

With the rapid development of China's economy, people's living standards are also improving day by day. Tourism has become an important part of people's spiritual life (Zhang, 2019). At present, the proposal of 'smart tourism' makes people's travel more convenient. As a part of "smart tourism", rural tourism is also a new trend in tourism (Johannes et al., 2022). In recent years, the state has also advocated taking rural tourism and Internet construction as the development basis of the "Rural Revitalisation Strategy" to promote the rapid development of rural tourism. At present, the rapid development of artificial intelligence, big data and other technologies has promoted the information development of tourism (Uclea et al., 2020). Nowadays, great changes have taken place in the way of national tourism. People are gradually inclined to travel by self-driving and self-help. Therefore, tourists generally pay more attention to subjective factors such as travel consumption tendency and travel time, hoping to find a trip planning scheme with high cost performance (Arif and Du, 2019). Although each major network platform can provide some travel itinerary planning, it is only a simple route listing or short-distance combination between scenic spots, and tourists lack autonomy in the choice of travel routes (Qin et al., 2018). Therefore, it is very important to integrate tourism resources and tourism information and plan a scheme that can meet tourists' self-help tourism, which has great social significance. Many scholars have conducted in-depth research on tourism route planning for a long time. Wang and Qian (2019) improved the quality of the global optimal solution through the optimised ant colony (ACO) algorithm. The model was constructed according to the factors such as the road, waiting and tourists' interest in the scenic spot. The evaluation standard was determined by tourists' satisfaction. Finally, the application of ant colony optimisation algorithm in path planning was analysed, Finally, the tourism planning roadmap based on tourist satisfaction is obtained through ant colony optimisation algorithm, and the tourist satisfaction is significantly improved. Tao et al. (2019) and others used ant colony algorithm to optimise the genetic algorithm, optimised the re insertion offspring operation in the genetic algorithm, and applied it to the travelling salesman problem (TSP), improved the stability of the algorithm and obtained a better optimisation ability. Zou et al. (2008) took Lushan scenic spot as an example, combined with the popularity of the scenic spot and the residence time of the scenic spot, used the shortest path algorithm to recommend the one-day tour route of Lushan for tourists by improving the shortest path in GIS. Lu et al. (2008) combines multi-agent technology and interactive genetic algorithm to alleviate users' fatigue in the process of tourism evaluation by improving genetic algorithm. On the basis of genetic algorithm, Song Dan proposed top cultivation and phased strategy for TSP problem to strengthen population diversity (Song et al., 2004). Most scholars study tourism routes through various methods, but this is a simple combination of the shortest distance, without taking into account the personalised needs of tourists. Therefore, it is extremely urgent to provide tourists with a travel planning software to meet their needs.

The main contribution of this study is to propose a hybrid genetic algorithm (HGA) based on the TSP, propose a travel itinerary planning method on the HGA algorithm, and carry out simulation analysis on the improved genetic algorithm (GA). Finally, taking Pengyang County, Ningxia, as an example, 15 popular scenic spots in the county are used to build a local tourism route planning model, aiming to provide personalised tourism route planning services for tourists. This research is mainly divided into three parts, the first part is the introduction; The second part discusses the HGA based on the TSP and the travel planning problem, proposes the HGA for solving the TSP, and then proposes the travel planning method based on the HGA; The third part is the analysis of the experimental results, realising the simulation analysis of the fusion improved genetic algorithm and the route planning example analysis.

2 Hybrid genetic algorithm and travel planning based on travelling salesman problem (TSP)

2.1 Hybrid genetic algorithm for travelling salesman problem

As the scale of the problem increases, the premature convergence and poor local search ability of genetic algorithm greatly restrict the accuracy of the results when solving tourism path planning. Therefore, this chapter proposes an improved optimisation of the basic genetic algorithm for this problem. In view of the shortcomings of genetic algorithm, this paper proposes a new HGA based on genetic algorithm, which is called HGA for short.

Firstly, the natural number of scenic spots is coded by using the coding operation mode in combination with the characteristics of route planning, and the coding is connected into a string through the sequence of route arrival to construct the route chromosome individual. This coding method is more in line with the characteristics of forming a planning model. The fitness function f is used to judge the excellence of chromosome individuals. The selection of f will affect the search and convergence speed of the optimal solution of the algorithm. The travel planning problem belongs to the problem of minimising the objective function. Take the reciprocal of the objective function T_d to get f, that is, $f = 1/T_d$. The larger the f, the better the chromosome individual, and the shorter the total planning path.

When genetic algorithm initialises the population, it often generates the target population in a random form, and the initial solution set is composed of randomly generated individuals in the population. The initialisation of the population number is random, and after iteration, the initial solution set reaches the preset number. The size of the population also has an impact on the algorithm. If the population size is too large, the algorithm operation efficiency will be slow; if the population size is too small, it will lead to premature convergence. The population size of genetic algorithm is generally between [50500]. Within this range, the population size setting is large, which can increase population diversity. When crossover, mutation and other operators are selected, the initialisation population has a huge impact on the later search for the optimal solution. Due to the deviation of individual fitness and convergence of traditional genetic algorithm, ant colony algorithm is introduced to initialise the population. The initialisation population of ant colony algorithm will get more solution sets of optimal sub paths after iteration, which improves the solution space quality of genetic algorithm and improves the solution efficiency and accuracy of the algorithm. The specific algorithm steps are as follows. Step 1: use ant colony algorithm to initialise the parameters. The setting parameters include maximum iteration times (maxGEN), population size (PopSize), number of ant colonies (m), and information heuristic factor(α), Pheromone intensity (q), expected heuristic factor(β), It is encoded by path coding; step 2: solve the ant colony algorithm through the ant density system model and obtain the initial solution of genetic algorithm; step 3: take the result obtained by ant colony algorithm as the initial population of genetic algorithm.

The most commonly used genetic algorithm is the selection operator, but the selection operator has statistical errors, and even individuals with high fitness may be eliminated. In order to prevent the above problems, this study uses the expected value method to solve the TSP problem. The expected number N_i of individuals on each chromosome inherited to the next generation is calculated, as shown in formula (1).

$$N_i = \frac{f_i}{f_{avg}} = \frac{f_i * n}{\sum_{i=1}^{n} f_i} \tag{1}$$

In formula (1), f_i represents the fitness of individual i, $i = 1,2,..., n$. When chromosome individuals are selected, they will participate in the crossover operation of the next generation, $N_i = N_i - 0.5$; If not selected, $N_i = N_i - 1$. The calculation is continued until the N_i of chromosome individuals is lower than 0, then the elimination does not participate in the selection operation.

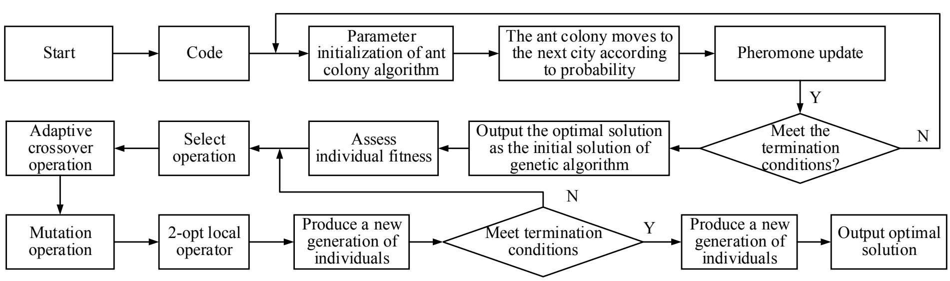
Considering that the number in TSP problem can not be repeated, this study uses sequential crossover operator (OX) for crossover operation. For example: F1 = (1-3 – | 5-2-8-6 | – 7-4), F2 = (2-5 – | 4-6-1-7 | – 3-8), first select two intersections in the parent generation, exchange the mating areas of F1 and F2 and place them at the front or last of them, then delete the same number in the two areas to realise that each scenic spot can only be traversed once, and finally get the result: Y1 = (4-6-1-7-3-5-2-8), F2 = (5-2-8-6-4-1-7-3).

In this study, the crossover probability is tested in the interval of [0.4,0.9], and according to the example of Eil51 dataset in TSPLIB international dataset, the final parameters are determined as follows: the mutation probability is 0.01, the number of iterations is 500, the population size is 50, the number of experiments is 20, and the international shortest path length is 426 (Luan et al., 2019; Liang and Wang, 2020). Finally, through 20 experiments, the shortest path length 423.7 is obtained when the crossing probability is 0.6, which is closest to the optimal solution 426 provided by international data (Santos et al., 2019; Du et al., 2019). In the early stage of population evolution, in order to improve the speed of individual generation, it is necessary to set a higher crossover probability for individuals. In the later stage of the algorithm, a lower crossover probability is set to improve the accuracy of the algorithm. The calculation of adaptive crossover probability P_c is shown in equation (2).

$$P_c = \begin{cases} \dfrac{k_1 \left(f_{\max} - f \right)}{f_{\max} - f_{avg}} & , \ f \geq f_{avg} \\ k_2 & , \ f < f_{avg} \end{cases} p1 \tag{2}$$

Finally, the local search algorithm (2-opt) is used to optimise two local elements (Bin et al., 2019). The specific algorithm steps of 2-opt to solve this problem are as follows: first, set the initialisation counter count to 0 and set the appropriate maximum number of iterations Gen; Secondly, a generated travel route is randomly selected, and the corresponding shortest path is min; Then select two unconnected loci in F1 and assume that C and G loci are randomly selected, and the new path is the flipped path; If the new path obtained by turning is shorter than the min path, the new path is min, set the count to 0, return and continue to select a travel route for calculation, otherwise set the count to 1, and when the count value is higher than gen, the algorithm ends. To sum up, the flow of fusion improved genetic algorithm proposed in this study is shown in Figure 1.

Figure 1 Process of fusion improved genetic algorithm



2.2 *Travel planning method based on hybrid genetic algorithm*

This study is based on self-help travel and integrates the improved genetic algorithm to construct the mathematical model of self-driving travel planning, in order to transform it into a specific self-help travel planning scheme. Tourism itinerary planning is to recommend suitable scenic spots to maximise tourists' tourism experience under certain departure, destination and constraints. Therefore, it is very necessary to build a mathematical model of recommended tourism itinerary (Oena et al., 2020). Generally, there are various influencing factors in the actual situation, which increases the complexity of solving the problem. Therefore, this study adopts reasonable assumptions and appropriately simplifies the problem model, and puts forward a total of 5 assumptions. First, the business hours of scenic spots are from 7:00 to 21:00; The second is to ignore the rest and catering time and combine these time into the scenic spot play time; Third, it is necessary to set the starting point and destination, and only pass through each scenic spot once; Fourth, in case of emergencies, the playing time should be within 10 days; Fifth, the tourism route planning is pre tourism planning, and there is no limit on the number of tourists during the business hours of the scenic spots.

Firstly, the travel planning model with single objective constraint is constructed. Suppose that there are n scenic spots that tourists need to visit, and the Min calculation is shown in equation (3).

$$\min z = \sum_{i \in M} \sum_{j \in M} Dist_{ij} \cdot x_{ij} \tag{3}$$

In equation (3), $Dist_{ij}$ is the distance between scenic spots x_i and x_j, in km. The constraint conditions are shown in equation (4).

$$s.t \begin{cases} \forall i \in M, \sum_{j \in M} x_{ij} = 1 & (1) \\ \forall j \in M, \sum_{i \in M} x_{ij} = 1 & (2) \\ u_j - u_i \geq n \cdot x_{ij} + 1 - n & (3) \end{cases} \tag{4}$$

In equation (4), M represents the city set $\{1,2,3, ..., n\}$, including each scenic spot x_i, where the starting and ending positions of the scenic spot are x_f and x_e respectively, and u_i represents a non negative variable of x_i. When x_i is 1 or 0, it means that tourists choose or do not choose scenic spot i; When x_{ij} is 1 or 0, it means that the path from scenic spots i to j is included or not included. The first two restrictions require that each scenic spot has only one access, that is, it can only be visited once; The third constraint is that there can be no sub cycle routes in the generated routes.

Secondly, the travel planning model with multi-objective constraints is constructed. The model mainly includes three constraints: travel cost, time and scenic spot heat.

For the travel cost constraint, first calculate the midway cost to the next scenic spot x_j, and the cost cannot be greater than the cost planned by tourists, as shown in equation (5).

$$TC = \sum_{i,j=1}^{n} LC_{ij} x_{ij} \leq TC_{\max} \tag{5}$$

In equation (5), TC represents the total cost of tourist attractions; LC represents the driving cost between two scenic spots; TC_{max} represents the maximum disposable cost of travel.

Then, judge whether the scenic spot x_i is the scenic spot on the planned optimal path. If x_{fi} is 1, the travel cost of x_i is the total travel cost TC_i, which is less than the set upper limit of travel cost; If x_{fi} is 0, x_i is not the optimal path subset. As shown in equation (6).

$$\forall i \in M : TC_i \leq TC_{\max} + \left(LC_{fi} - TC_{\max}\right) \cdot x_{fi} \tag{6}$$

The constraint in equation (7) is that each scenic spot can only be reached once, and there is and only one x_j after x_i.

$$\begin{cases} \forall j \in M : \sum_{i \in M} x_j = 1 \\ \forall i \in M : \sum_{j \in M} x_{ij} = 1 \end{cases} \tag{7}$$

In practice, the travel time of tourists is uncertain. In order to improve the utilisation of the total time constraint, the generated path needs to meet equation (8).

$$\mathrm{Cos}\,t(Rr) = \min\left(\frac{TC_{\max} - TC}{TC_{\max}}\right) \tag{8}$$

In equation (8), Rr is the tourism route set $\{x_1, x_2, ..., x_n\}$, $x_i \in R \in M$.

For the travel time constraint, first calculate the midway time to the next scenic spot x_j, and the time cannot be greater than the time planned by tourists, as shown in equation (9).

$$TT = \sum\nolimits_{i=1}^{n} ST_i x_i + \sum\nolimits_{i,j=1}^{n} LT_{ij} x_{ij} \le TT_{\max} \tag{9}$$

In equation (9), TT represents the total time of tourist attractions, ST represents the time spent on tourist attractions, LT represents the midway time, and TT_{max} represents the maximum disposable time of travel. In fact, tourists will be affected by uncertain factors such as scenic spot passenger flow, traffic congestion and waiting time. In order to improve the utilisation of travel for total time constraints, the generated path needs to meet equation (10).

$$Time(Rr) = \min\left(\frac{1}{TT_{\max} - TT}\right) \tag{10}$$

Equation (10) reflects the time constraint. The smaller the value of Time(Rr), the more satisfied the tourists are.

For the scenic spot heat constraint, first calculate the tourists' interest $I(Rr)$ in the generated route Rr. The higher $I(Rr)$, the higher the tourists' satisfaction. As shown in equation (11).

$$I(Rr) = \frac{\sum\nolimits_{i=1}^{n} f_i x_i}{\sum\nolimits_{i=1}^{n} f_i} \tag{11}$$

In equation (11), f_i represents the heat of the ith scenic spot.

According to the above analysis, the multi-objective constraints of cost, time and scenic spot heat are comprehensively considered, and the $Value(Rr)$ is used to evaluate the travel experience of tourists, as shown in equation (12).

$$Value(Rr) = A \cdot \frac{TC}{TC_{\max}} + B \cdot \frac{TT}{TT_{\max}} + C \cdot \frac{\sum\nolimits_{i=1}^{n} f_i x_i}{\sum\nolimits_{i=1}^{n} f_i} \tag{12}$$

In equation (12), the three parameters A + B + C = 1. The specific setting will change at any time according to the tourist flow and tourist demand of the scenic spot. This study uses the ratio of 3 : 3 : 4 to set the three parameters.

3 Simulation analysis and route planning implementation of fusion improved genetic algorithm

3.1 Simulation analysis of fusion improved genetic algorithm

The parameters of genetic algorithm mainly include population size PopSize, maximum iteration times maxGEN, crossover probability Pm and mutation probability Pc. These parameters must be tuned to get appropriate values. In this study, the optimal parameters of each parameter experiment are taken as the parameter settings of the improved algorithm, as shown in Table 1. Among them, α Represents the information heuristic factor, β Represents the expected heuristic factor, ρ Indicates pheromone volatilisation coefficient.

Table 1 Improved algorithm parameter setting

Parameter name	*Parameter value*	*Parameter name*	*Parameter value*
MaxGEN	500	*A*	1
PopSize	100	*B*	5
Pm	0.04	*P*	0.1

This study compares the traditional particle swarm optimisation (PSO) algorithm, GA algorithm and the improved HGA algorithm proposed in this study through four groups of examples: Oliver 30, att48, eil76 and kroa100 in TSPLIB dataset. The parameters of each algorithm are consistent with those of the algorithm proposed in this study.

Firstly, the formula in Yue (2022) is used to calculate the quality of the optimal solution of the algorithm to verify the effectiveness of the algorithm. The higher the quality values of the optimal solution, the worse the optimisation efficiency. After 50 experiments, the results are shown in Table 2.

Table 2 Comparison of test example results for solving TSP problem

TSP model	*TSPLIB optimal solution*	*Algorithm name*	*Calculate the optimal solution*	*Quality of optimal solution* (%)
Oliver30	420	GA	423.852	0.89
		PSO	423.8516	0.89
		HGA	423.852	0.89
Att48	33522	GA	33867.513	1.04
		PSO	34267.361	2.33
		HGA	**33646.494**	**0.38**
Eil76	538	GA	574.848	6.97
		PSO	552.863	2.88
		HGA	**540.614**	**0.55**
kroA100	21282	GA	23084.960	8.85
		PSO	22414.446	5.41
		HGA	**21400.631**	**0.56**

It can be seen from Table 2 that in addition to the consistency of the quality values of the optimal solutions of the three algorithms in the Oliver30 dataset, the quality values of the optimal solutions of the HGA algorithm are far lower than those of the PSO and GA algorithms in the other three datasets, indicating that HGA can get better results or even closer to the optimal solution when solving the TSP problem.

Simulated annealing algorithm (VFSA) and traditional simulated annealing algorithm (BMSA) based on K-means clustering algorithm are introduced to compare their performance with the algorithm model proposed in this study. Among them, 8 clusters are classified. The solution time of each algorithm in different datasets is compared through the time spent corresponding to the best result in 50 experiments. See Table 3.

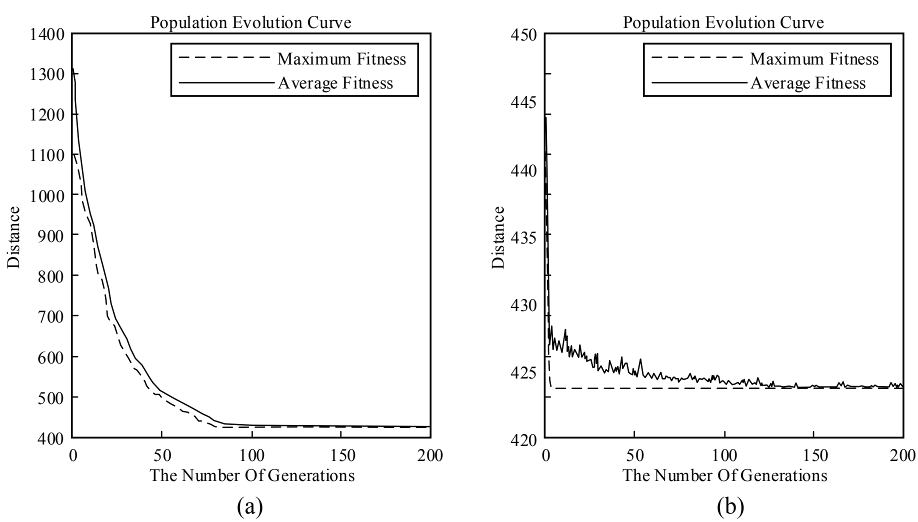
Table 3 Time comparison of test examples for solving TSP problem (s)

Algorithm name	*Oliver30*	*Att48*	*Eil76*	*kroA100*
GA	4.3	6.85	14.73	20.66
PSO	13.88	29	35.92	74.86
HGA	**11.33**	**21.64**	**29.28**	**65.82**
VFSA	12.46	24.69	30.83	68.70
BMSA	13.14	25.17	32.47	70.42

It can be seen from Table 3 that although the solution accuracy of HGA algorithm is higher than that of PSO and GA algorithm, the time spent by HGA algorithm is lower than that of GA, but higher than that of PSO algorithm, reflecting that HGA algorithm combines the advantages of GA and PSO. HGA algorithm takes less time than VFSA and BMSA algorithm, which shows that this algorithm is superior to other algorithms in performance.

In order to compare the optimisation ability of GA algorithm before and after improvement, this study takes Oliver30 dataset as an example to compare the population fitness of the algorithm during iteration before and after improvement, so as to judge the optimisation ability of the algorithm, as shown in Figure 2.

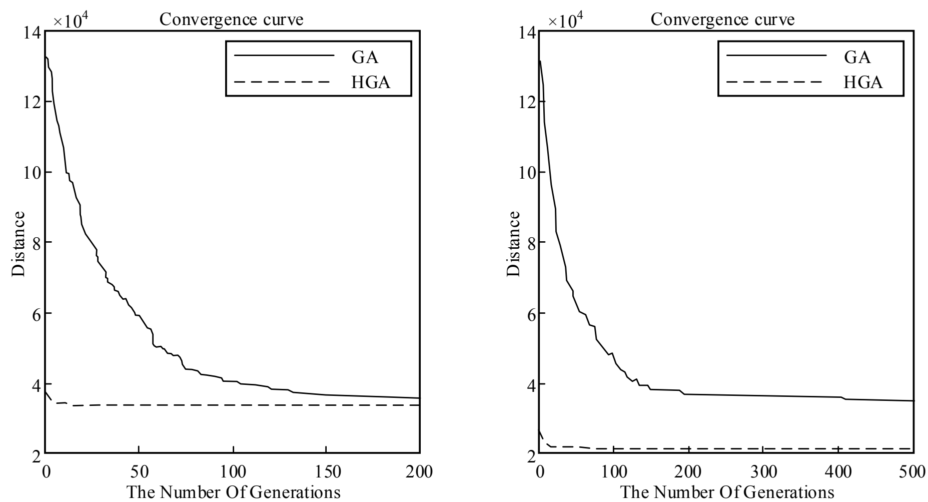
Figure 2 Fitness evolution curve of Oliver 30 population: (a) genetic algorithm population fitness evolution and (b) population fitness evolution of hybrid genetic algorithm



It can be seen from Figure 2 that the improved GA algorithm can make the average population fitness closer to the maximum population fitness under the condition of less iterations, which reflects that the improved algorithm effectively improves the population fitness ability and has strong ability to search the optimal solution. However, the adaptability of the initial population of the traditional GA algorithm is poor. After many iterations, the adaptability is improved. The results show that the solution space ability of the improved genetic algorithm is obviously better than the traditional genetic algorithm, and has better optimisation efficiency.

In order to better compare the convergence speed of GA algorithm before and after optimisation, verify the convergence process of the two algorithms in eil51 and Oliver 30 datasets, as shown in Figure 3.

Figure 3 Convergence curves of Att48 and Kroa100: (a) Att48 convergence curve and (b) Kroa100 convergence curve

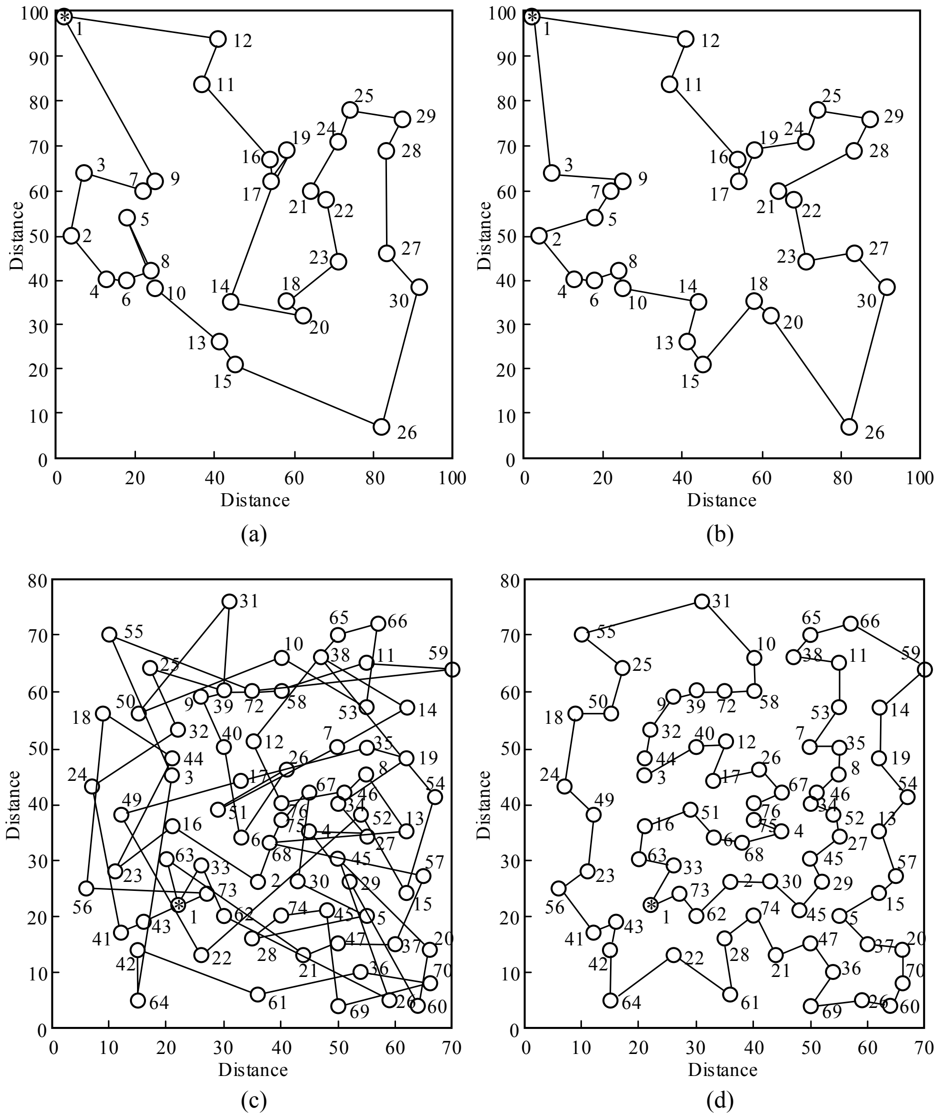


(a) (b)

As can be seen from Figure 3(a), when there are few urban scenic spots and a large distance, the convergence curve of the optimised GA algorithm decreases significantly in the initial stage, but the traditional GA algorithm needs more than 100 iterations to find the optimal solution, but the accuracy is not as good as the optimised GA algorithm. As can be seen from Figure 3(b), when there are many urban scenic spots and large distances, the optimised GA algorithm converges faster, which is significantly higher than the traditional GA algorithm. Therefore, the HGA algorithm proposed in this study has better optimisation ability and search efficiency.

In order to verify the optimisation ability of the algorithm, the HGA algorithm proposed in this study is applied to find the optimal travel route map. The results are shown in Figure 4.

Figure 4 Path optimisation results of Oliver30 and eil76: (a) initialisation path of Oliver30; (b) optimal path of Oliver30; (c) initialisation path of eil76 and (a) optimal path of eil76



The HGA algorithm proposed in this study is used to solve the optimal path of Eil76 and Oliver30 datasets. Where (a) and (c) are Eil76 and Oliver30 respectively, and (b) and (d) are the optimal path results solved by Eil76 and Oliver30 respectively. Compared with (a) and (c), the optimised HGA algorithm can obtain the optimal solution when there are few urban scenic spots and the distance is small, the initialisation path effect of the optimised HGA algorithm is better, and the number of iterations is small. When there are many scenic spots in the city and the distance is large, applying HGA algorithm to initialise the path will show more cross routes. After multiple iterations, the optimisation effect and result of the algorithm are also better.

3.2 Route planning and realisation

This study takes Pengyang County of Ningxia as an example, this study constructs the local tourism route planning model with 15 popular scenic spots in the county, and locates the longitude and latitude coordinates of each scenic spot through the network map in order to obtain the distance between each scenic spot. According to the distance solution formula in document (Am et al., 2022), the actual distance between scenic spots is solved through the longitude and latitude of scenic spots.

In order to verify the effectiveness of the mathematical model with multi-objective constraints in this experiment, the play time of each scenic spot needs to be used, but the play time is affected by many factors. Therefore, this study refers to the data of major tourism websites and summarises the average play time and average score of each scenic spot, as shown in Table 4.

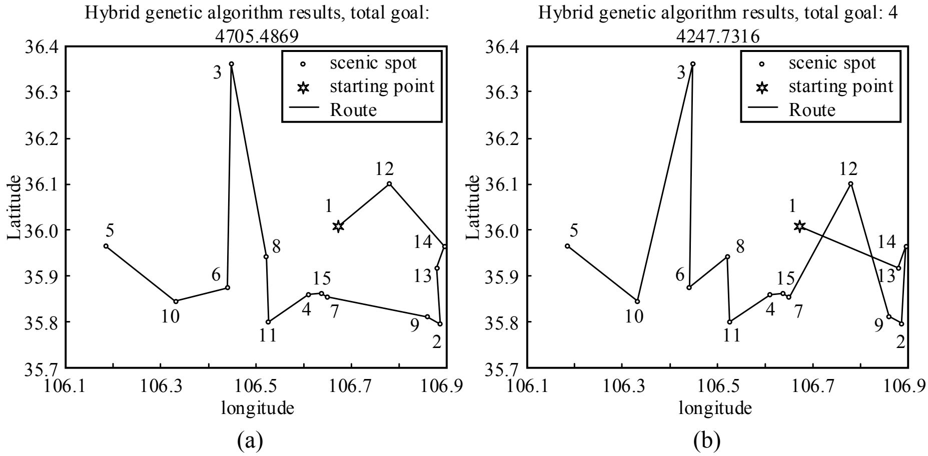
Table 4 Recommended visiting time and rating of scenic spots

Scenic spot serial number	*Recommended travel time*	*Scenic spot rating*	*Scenic spot serial number*	*Recommended travel time*	*Scenic spot rating*
1	100	3	9	40	1
2	100	3	10	40	2
3	50	2	11	30	1
4	100	3	12	20	1
5	30	1	13	80	3
6	40	2	14	30	1
7	50	2	15	100	3
8	30	2	\	\	\

Because most of the scenic spots are located in the countryside and the geographical environment is complex, this study ignores the reasons such as roads and weather, abstracts the roads as an undirected graph, and defaults that the back and forth distance between scenic spots is the same. The optimal route map satisfying the conditions is simulated by MATLAB, hoping to provide passengers with a comfortable travel route. Firstly, the longitude and latitude coordinates of all 15 scenic spots are imported into the algorithm, and the fitness function is selected as the path length, which is solved by the HGA algorithm proposed in this study. The results are shown in Figure 5.

Based on HGA, the optimal path for solving single objective constraints in Figure 5 (a) is 1-12-14-13-2-9-7-15-4-11-8-3-6-10-5 and the distance is 4705km. In Figure 5 (b), the optimal path for solving multi-objective constraints is 1-13-14-2-9-12-7-15-4-11-8-6-3-10-5, with a distance of 4247 km. The multi-objective constraint problem comprehensively considers the time, cost and popularity of scenic spots. The ratio of 3:3:4 is used to allocate time, cost and score, and finally the results are recommended to tourists.

Figure 5 Single objective and multi-objective constraint solution results of hybrid genetic algorithm: (a) single objective constraint solving and (b) multi-objectiveconstraint solving



4 Conclusion

In this study, a HGA algorithm based on TSP is proposed for rural tourism route planning. The HGA algorithm is simulated and analysed, and 15 popular scenic spots in Pengyang County are used to build the local tourism route planning model. The results show that the improved HGA not only reduces the number of iterations, but also shortens the path search time when solving the TSP. Secondly, the improved HGA is superior to the traditional genetic algorithm in terms of population diversity, solution accuracy and optimisation ability. Taking Pengyang County, Ningxia, as an example, a more reasonable tourism route that meets the needs of tourists is obtained, which lays an algorithm and theoretical foundation for the realisation of the tourism route recommendation and customisation function of Pengyang County's rural tourism system. This paper only considers the route planning between scenic spots, and the planning within scenic spots has not been considered, which needs further research and improvement.

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