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Research on sustainable carrying capacity of urban tourism environment based on multi objective optimization algorithm

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ABSTRACT

As tourism becomes more and more strategic in the development of modern cities, the state and government are paying more attention to the tourism environment than ever before. The development of the tourism environment involves many interests such as residents, local government and enterprises, which can cause serious harm to the city's economy and environment if not handled properly. Therefore, it is necessary to optimize the carrying capacity of the tourism environment. The study improves the crossover, mutation and elite strategies of non-dominated sorting genetic algorithm II (NSGA-II), and establishes a multi-objective optimization model of urban tourism environment based on this. The results showed that the improved algorithm had a faster convergence speed and the resulting solutions were more uniformly distributed for both the variance probability of 0.005 and 0.05. Compared with the traditional NSGA-II algorithm and the multi-objective genetic algorithm, the Pareto solution set obtained does not appear to be missing in the interval [0,1] and is more widely distributed. In the tests of the DTLZ1 and DTLZ2 functions, the IGD variance values of the improved algorithm were 1.745 E+01 and 3.315E-03, respectively, which showed strong stability. In the empirical analysis, the optimization results obtained by the improved algorithm in the peak, low and flat tourism seasons are more reasonable and maintain a high degree of balance, indicating that it can provide effective guidance for the sustainable development of the urban tourism environment.

1. Introduction

Tourism is an important driving industry for national economic development, with good economic and ecological functions, and is indispensable in the sustainable development of cities. The tourism environment is the basis on which tourism activities can be carried out, and with the rapid development of urbanisation and tourism, a number of problems such as ecological degradation, severe traffic congestion and overcrowding during peak seasons have emerged, causing serious damage to the sustainable development of the tourism environment [1]. To realize the sustainable development of urban tourism, it is necessary to optimize the carrying capacity of tourism environment. Zhang et al. established an urban resource and environmental carrying capacity index system based on ecological civilisation in order to solve the contradiction between urban resources and the environment, and applied it to the sustainable development planning of Tianjin, and the results showed that the index system not only reflected the current situation of the urban carrying capacity better, but also could describe The results showed that the index system not only reflects the current situation of urban carrying capacity better, but also can describe the changes of urban carrying capacity increment [2]. The current indicator system is useful for reference, but in practical problems, multi-objective optimization algorithms need to be used to achieve optimal results. Therefore, the study improves the NSGA-II algorithm in the multi-objective optimization algorithm and applies it to the process of optimizing the carrying capacity of the tourism environment, with a view to achieving optimal results for the sustainable development of urban tourism. By improving the NSGA-II algorithm and applying it to the sustainable carrying capacity of urban tourism environment, the main contribution of the study is, firstly, to improve the multi-objective optimization algorithm of NSGA-II according to the characteristics and needs of the sustainable carrying capacity of urban tourism environment, improve the search ability and convergence rate of the algorithm, so as to better solve the sustainable carrying capacity of urban tourism environment. Second, to optimize the sustainable carrying capacity of urban tourism environment. The improved NSGA-II algorithm is used to find the optimal decision scheme within the range of determined decision variables to achieve the goal of maximizing tourism income,

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minimizing environmental pressure and maximizing social benefits, so as to achieve sustainable management of the urban tourism environment. Finally, provide decision support. According to the optimization results, provide decision support for urban tourism managers, including suggestions and measures on rational planning and management of urban tourism resources, optimization of tourism infrastructure layout, and promotion of sustainable tourism development, so as to promote the sustainable development of urban tourism.

2. Related work

The sustainable development of urban tourism is closely related to the environmental carrying capacity, and the multi-objective optimization of the environmental carrying capacity of tourism in a city can provide reliable support for the sustainable development of urban tourism. In recent years, the improvement of multi-objective optimization algorithms has provided a useful reference for solving this problem. Zhou et al. proposed a spatial optimization analysis framework based on the water environment carrying capacity, combining water environment information and economic information, and integrated the water environment based on multi-objective system, information entropy method and The results showed that it could achieve fine management of the water environment and effectively help local governments achieve sustainable planning goals [3]. Wan's team developed an evolutionary multi-objective optimization algorithm for the topic of cyber-physical social systems and applied it to layout planning, and the results showed that its success rate reached et al. proposed a congestion control algorithm based on a multi-objective optimization algorithm for solving the congestion problem in wireless sensor networks, which uses a multi-objective optimization function that considers node energy in the fitness function and compares it with an adaptive cuckoo search algorithm, and the experimental results showed that it had better performance [4]. Wu et al. proposed a batch optimization algorithm with inverse scheduling to deal with the flexible job shop scheduling problem with variable batch sizes, and increased the diversity of the population by updating the dynamic clustering algorithm of the population and controlling the threshold of neighbourhood updates, and the results showed that it effectively ensured the diversity of Pareto solutions [5]. Zuo et al. developed an improved ant colony algorithm to adjust the quality of solutions for solving the task scheduling problem in cloud computing, and used a multi-objective optimization scheduling method to achieve multi-objective optimization of performance and cost, which was shown to improve the performance by 56.6% in the best case [6]. Chao et al. addressed the processing time controllable sequencing problem, a multi-objective discrete virus optimization algorithm was proposed with the aim of minimizing the total extra resource consumption and the maximum completion time, and the results showed that the algorithm has good operational performance [7].

Chen Dong et al. proposed an improved immune clone selection algorithm for the multi-objective trajectory planning problem, and evaluated the performance of the planned trajectory by three technical indicators: production cost, assembly efficiency and motion smoothness, and the experimental results showed that the algorithm could meet the requirements of the assembly task [8]. Chen's team, in order to improve the power control scheme diversity and boundary search capability, a multiple swarm co-evolutionary dynamic multi-objective particle swarm power control algorithm based on congestion distance profile management was developed and a corresponding dynamic response scheme was proposed, which was shown to have higher stability [9]. In order to reduce the cost of cold chain logistics distribution, Zhao et al. designed a combined multi-improved ant colony algorithm combining multi-objective heuristic functions and applied it to solve the vehicle path model for multi-objective optimization, and the results showed that it produced more Pareto optimal solutions and improved the algorithm's performance in finding the best [10]. Ho-Huu et al. developed a multi-objective optimization algorithm for dealing with the limited performance of complex Pareto fronts in order to cope with a multi-objective evolutionary algorithm for bi-objective optimization and modeled the optimal design of truss structures, and the results showed that it improved the efficiency and applicability of the optimization search [11]. Jian et al. designed a multi-independent population genetic algorithm incorporating sub-domain mazes for the optimization of surface-mounted permanent synchronous motors, and used it to build an accurate system dynamics model, and the results verified the superior performance of the algorithm (Jian G et al., 2018) [12]. Paknejad et al. in order to solve the workflow scheduling problem caused by computational resources, designed a multi-objective optimization model that applies workflows to service providers and user requirements, and incorporated an improved fitness function to improve the performance of the algorithm, and the results proved the effectiveness of the algorithm [13].

In summary, most researchers use multi-objective optimization algorithms and improve them accordingly to achieve optimal results when faced with problems influenced by multiple factors. This provides a methodological reference for dealing with multi-objective optimization of environmental carrying capacity. However, the current multi-objective optimization algorithm is difficult to meet the requirements of sustainable carrying capacity of Urban tourism environment in terms of efficiency, performance, etc. Therefore, the research mainly explores the sustainable carrying capacity of Urban tourism environment through the improved NSGA-II multi-objective optimization algorithm. The research gives the specific indicator system of Urban tourism environmental sustainable carrying capacity from the perspective of the core interest subject, and points out three specific goals to achieve the sustainable carrying capacity of Urban tourism environment in combination with the specific requirements of Urban tourism development planning and the interest demands of the core interest subject, and uses the idea of multi-objective optimization to build a multi-objective optimization model of Urban tourism environmental sustainable carrying capacity. The purpose of the study is to provide scientific decision support to policy makers, promote the sustainable development of urban tourism, and enhance the benefits of tourism and environmental protection. The study aims to provide theoretical and methodological support for urban tourism planning, resource allocation and management, and to promote the sustainable development of urban tourism.

3. A sustainable development model for urban tourism based on multi-objective optimization of environmental carrying capacity

3.1. Multi-objective optimization based on improved NSGA-II algorithm

In practical engineering applications, decisions on a solution are often constrained by several factors, i.e. they can only be accomplished with a multi-objective design. For multiple objectives, there are often certain differences, so it is necessary to find the most optimal design that satisfies multiple criteria, i.e. a multi-objective optimization problem. Traditional multi-objective optimization algorithms are mostly single-objective optimization with strong limitations [14]. Non-dominated Sorting Genetic Algorithm II (NSGA-II), as one of the more widely used traditional multi-objective optimization algorithms, has the advantages of stable results of multiple calculations and high solution accuracy, but it has the problems of poor global search ability, large randomness of results, and premature convergence of the algorithm. The NSGA-II algorithm first randomly generates the initial population and processes the initial population in the solution space by crossover, variation and other operations to obtain the corresponding subpopulation. Then the two parts of the subpopulations are combined, i.e. the child subpopulation and the parent subpopulation. The new generation population is then obtained by evaluating individuals using the crowding comparison operator and non-dominated sorting methods, and using an elite strategy to filter the population, thereby recovering the population size. Finally, the NSGA II algorithm is compared with the termination condition to decide whether to stop the operation.

From the flowchart of the NSGA-II algorithm in Fig. 1, it is clear that the crossover, variance and elite strategies are the main parts that affect the performance of the algorithm. Therefore, the study improves the algorithm accordingly while retaining the crowding comparison operator, crowding and fast dominance ranking methods. The crossover variation probabilities in the NSGA-II algorithm are set in the same way as in the genetic algorithm and are invariant, which greatly increases the probability that the results obtained by the algorithm fall into a local optimum [15]. To avoid the computational errors caused by fixed parameters, an adaptive approach is adopted to adjust accordingly, and the adaptive crossover probability formula is shown in equation (1).

$$P_{(o)}(g) = P_{oamx} - (P_{o\ \max} - P_{o\ \min}) * \frac{g}{gen} \tag{1}$$

In equation (1), $P_{(o)}(g)$ is the crossover probability, g represents the current evolutionary generation, gen is the total number of evolved generations, and $P_{o\ \max}$ and $P_{o\ \min}$ are the predetermined upper and lower limits of the crossover probability, respectively. It can be seen that this adaptive crossover probability method does not closely link the current population information to the evolutionary algebra, increasing the likelihood that individuals with poor solution characteristics will be retained at a later stage. To enhance the relevance of the population individuals to the adaptive adjustment, the resulting adjustment formula for the adaptive crossover probability is shown in equation (2).

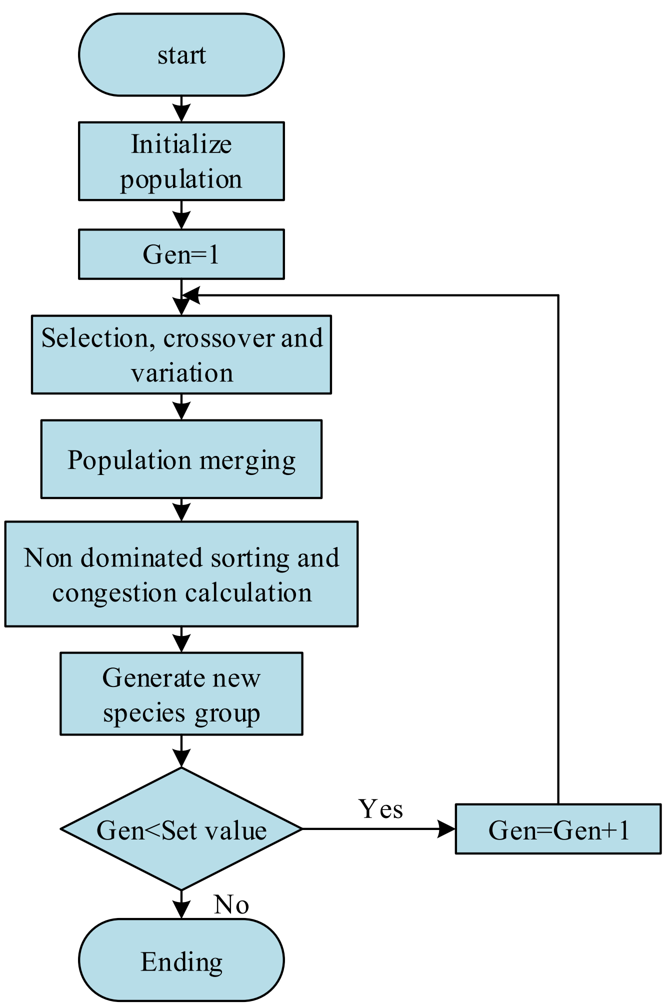


Fig. 1. Flow chart of NSGA-II algorithm.

$$P_o = \begin{cases} P_{o\ \min} - \dfrac{f_{\max} - f_{avg}}{f_{\max} - f_{\min}} * (P_{o\ \max} - P_{o\ \min}), else \\ P_{o\ \max}, f_{\min} = f_{avg} \end{cases} \tag{2}$$

In equation (2), $f_{\min}$ and $f_{\max}$ are the minimum and maximum values of the objective function corresponding to the individuals in the population, respectively, while f_{avg} represents the average value of the objective function corresponding to all individuals in the population. The adaptive variation probability formula is shown in equation (3).

$$P_v(g) = P_{v\ \max} - (P_{v\ \max} - P_{v\ \min}) * \frac{g}{gen} \tag{3}$$

In equation (3), $P_v(g)$ represents the mutation probability, and $P_{v\ \max}$ and $P_{v\ \min}$ are the upper and lower limits of the established probability of variation. In order to combine the probability of variation with information about the individuals in the population, the adjusted variation probability formula is shown in equation (4).

$$P_v = \begin{cases} P_{o\ \min} - \dfrac{f_{\max} - f_{avg}}{f_{\max} - f_{\min}} * (P_{v\ \max} - P_{v\ \min}), else \\ P_{v\ \max}, f_{\min} = f_{avg} \end{cases} \tag{4}$$

In equation (4), P_v represents the adjusted probability of variation. According to the adjusted cross-variance probability formula, it can be seen that at the early stage of algorithm evolution, the difference between individuals is expressed through the objective function value, while the maximum and minimum values are different at this time, and the average objective function value is equivalent to the average of the two. Therefore, the probability of cross-variance is larger at the beginning of the algorithm and finding the optimal solution set becomes easier at the beginning. At the later stages of the algorithm, the number of individuals with larger objective function values is extremely small, again facilitating the search for the optimal solution set. The variational operator of the NSGA-II algorithm is then improved, as the variational operator of the NSGA-II algorithm is more stochastic in its local search for the optimal set, as it has no dependence on the information of other individuals in the population. It is therefore improved by introducing a differential evolution algorithm, as shown in equation (5).

$$x_i(1+g) = (x_{r_1}(g) - x_{r_2}(g)) * F + x_{best}(g) \tag{5}$$

In equation (5), F represents the scaling factor, g is the number of evolutionary generations, and $x_{best}(g)$ is the best individual in the generation with the sequence g. The formula for defining the crossover operator of the NSGA-II algorithm is shown in equation (6).

$$\begin{cases} X_A^{t+!} = (1-\alpha) * X_B^t + \alpha X_A^t \\ X_B^{t+!} = (1-\alpha) * X_A^t + \alpha X_B^t \end{cases} \tag{6}$$

In equation (6), α represents the crossover factor, which is a deterministic constant. $X_A^{t+!}$, $X_B^{t+!}$ represents two parent individuals, and X_A^t and X_B^t correspond to the chromosomes of the two parent individuals. The children in the current crossover operator inherit the best individuals from their parents, but the global search performance remains weak, resulting in overpopulation of the best solutions and a lack of population diversity. Therefore, the value of α was redefined to retain individuals of high rank, as shown in equation (7).

$$\alpha = \frac{rankA}{rankB + rankA} \tag{7}$$

In equation (7), $rankA$ is the non-dominated ranking level of individual A and $rankB$ is the non-dominated ranking level of individual B. By combining α with the non-dominated ranking levels, the diversity is enriched and individuals with high-ranking levels are retained. The final refinement of the elite strategy was carried out. The retention of individuals by the original elite strategy was done through the non-dominated hierarchy, i.e. if the initial population size exceeded the number of individuals in the first hierarchy, individuals with excellent crowding characteristics were derived from the next hierarchy until the original population size was reached after the population was populated. However, the selection of populations is prone to the problem that individuals in populations in tiers other than the first are not very different, thus affecting the local search for excellence. Therefore, a deeper enrichment of the diversity of the populations is required, the rationale for which is shown in Fig. 2.

The modified elite strategy selects individuals in the other tiers proportionally on the basis of retaining the individuals in the first tier, i.e. the smallest individuals in the non-dominated tier, as shown in equation (8).

$$N_i = \frac{2(1+M-i)(N-N_1)}{(M-1)(2+M)} \tag{8}$$

In equation (8), M represents the maximum value in the non-dominated stratum, N represents the population size, i represents the stratum number, and N_i represents the number of individuals selected from the stratum i. The improved elite strategy starts with selection from the second stratum, which entails retaining as many individuals from populations lower in the ranking stratum as possible, which results in different ratios of individuals selected in other strata, enriching the diversity of the population and further enhancing the local search for excellence.

3.2. A multi-objective optimization-based model of the carrying capacity of the urban tourism environment

After the improvement of the NSGA-II algorithm, the sustainability indicators of environmental carrying capacity should be determined. The construction of the indicator system should be centered on the core interest subjects, and among the core interest subjects of the urban tourism environment, the government, urban residents, tourism enterprises and tourists occupy a dominant position [16]. The government is the regulator of urban tourism, and its influence on the sustainable conditions that the urban tourism environment can bear is mainly through legislation, planning and policy regulation, i.e. at the macro level, balancing economic interests and livelihood issues. The tourist, as the real feelers and claimants of the tourist, has an interest in a high-quality tourism environment under reasonable passenger flow conditions. Urban residents both enjoy the benefits of tourism and experience tourism activities, while tourism enterprises take on the role of planning and implementing tourism activities, both of which are also core subjects of interest. Therefore, according to the interests of the core subjects, the indicators obtained include the natural tourism environment, social tourism environment and economic tourism environment, as shown in Fig. 3.

Based on the core interest subjects and indicator system, the sustainable objectives of environmental carrying are identified as maximized economic income, maximized number of urban residents and tourists, and maximized employment rate of urban residents, and the objective function is constructed from this (Fang R. 2019) [17]. The maximized economic income is the maximization of the income received by the tourism site and is closely related to the number of tourists, as shown in equation (9).

$$\max_{z1} = F_{a1} + F_{a2} \tag{9}$$

In equation (9), $z1$ represents tourism receipts, $a1$ and F_{a1} represent the number of mainland tourists and tourism receipts respectively, and $a2$ and F_{a2} represent the number of overseas tourists and tourism receipts respectively. The relationship between $a1$, F_{a1}, $a2$, and F_{a2} is shown in equation (10).

$$\begin{cases} F_{a1} = a1 \times \mu \\ F_{a2} = a2 \times \zeta \end{cases} \tag{10}$$

In Formula (10), μ represents the tourism income brought by each unit of tourists in the mainland, and ζ represents the tourism income brought by each unit of overseas tourists. The maximized urban employment rate is the maximum share of employment in the urban population due to the tourism activities of overseas and mainland tourists, as shown in equation (11).

$$\max_{z2} = \frac{(b_1 + b_2) \times c_3}{b_3} \tag{11}$$

In equation (11), $z2$ represents the employment rate of urban residents, b_3 represents the number of urban residents and $c3$ represents the increase in employment per unit of tourist induced, b_1, b_2 represents the number of overseas and mainland tourists respectively. The maximum number of subjects in the tourism environment is the maximum population accommodated, as shown in equation (12).

$$\max_{z3} = a1 + a2 + b_3 \tag{12}$$

In equation (12), $z3$ is the number of subjects to be accommodated. Through a system of indicators for the tourism environment, taking into account both economic incomes, the number of subjects accommodated and the employment rate of urban residents, the general constraint is obtained as shown in equation (13).

$$\sum_{j=1}^{n} \left(\frac{1}{\lambda_{ij}} \cdot x_{ij} \cdot a_{ij} \right) \geq [\theta_i(1-e_i) + e_i] \cdot D_i \cdot h_i \tag{13}$$

In equation (13), a_{ij} represents the per capita resource use, D_i is the total amount of the first resource, λ_{ij} represents the satisfaction of town residents and tourists, x_{ij} is the number of the first j tourist, e is the actual utilization rate, θ is the degree of resource use, and h_i is the resource turnover rate. Therefore, the study established a specific indicator system for the sustainable carrying capacity of urban tourism environment based on the perspective of the core interest subjects, pointed out three specific goals to achieve the sustainable carrying capacity of urban tourism environment in combination with the specific requirements of China's urban tourism development planning and the interest demands of the core interest subjects, and constructed a multi-objective optimization model for the sustainable carrying capacity of urban tourism environment. Finally, the research can use the improved NSGA-II algorithm to solve the multi-objective optimization model, so as to achieve the multi-objective optimization of the sustainable carrying capacity of Urban tourism environment. The improved NSGA-II algorithm sets parameters in the initialisation process to be based on the number of overseas tourists, mainland tourists and town residents, and the initialised individual information is generated randomly. The crowding distance comparison operator makes the populations of environmental carrying capacity seeking with diversity and distribution, and the crowding distance formula is shown in equation (14).

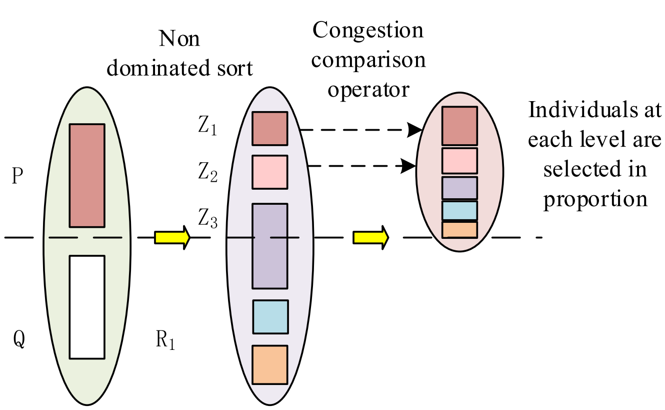


Fig. 2. Schematic diagram of improving elite strategy.

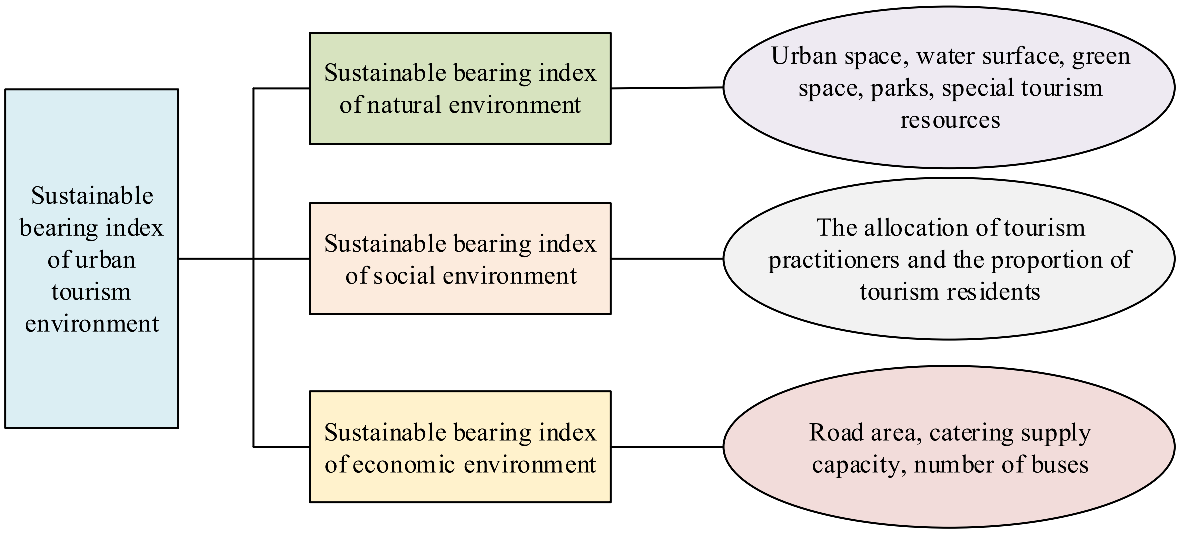


Fig. 3. Sustainable bearing index of urban tourism environment.

$$P[i]_{dis\tan ce} = \sum_{n=1}^{r} (f_n[1+i] \cdot P - f_n[i-1] \cdot P) \tag{14}$$

In equation (14), n represents the number of objective functions, $P[i]_{dis\tan ce}$ is the crowding distance and r is the number of sub-objective functions. The individuals in the population have crowding distances and non-dominance ranks, and the ranking is based on the dominance relationships exhibited between individuals, as shown in Fig. 4.

The improved NSGA-II algorithm uses the biased order relationship as the basis for classification and its dominance relationship is shown in equation (15).

$$i \succ_n j, if\left(i_{rank} = j_{rank} or i_{rank} < j_{rank} and P[i]_{dis\tan ce} > P[j]_{dis\tan ce}\right) \tag{15}$$

In equation (15), *rank* represents the non-dominance rank. Where non-dominance ranks differ, the lower party has priority. In the case of the same non-dominance rank, priority is given to individuals with low congestion density or large distance. Therefore, the improved NSGA-II algorithm in urban tourism environment carrying capacity needs to firstly obtain the decision variables by means of real number coding, then calculate the values of individuals on the constructed objective function, then perform the merit search and judge whether the generated objective function meets the established requirements, and finally check whether it meets the termination conditions to decide whether to output the Pareto solution set. The expression of the affiliation function under the tourism environment constraint is shown in equation (16).

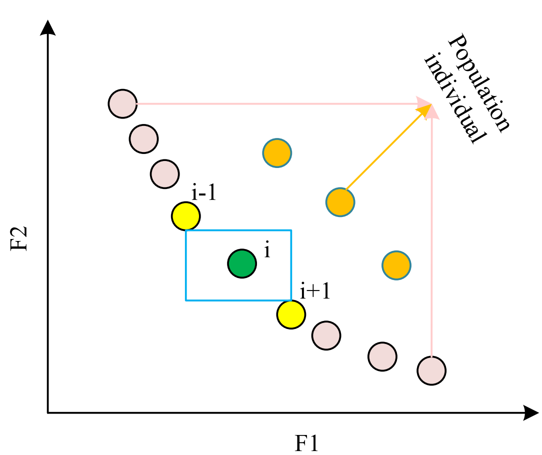


Fig. 4. Congestion distance map.

$$U_F(Z_0(x_i)) = \begin{cases} 1, d_0 < Z_0(x_i) \\ 1 - \theta_i, d_0 - \theta_{e_0} < Z_0(x_i) \quad (0 \le t \le 1) \\ 0, d_0 - e_0 > Z_0(x_i) \end{cases} \tag{16}$$

In equation (16), θ_i represents the ratio between dissatisfaction with tourism benefits and dissatisfaction under multiple subjects, Z_i represents the objective function, d_0 represents the maximum expectation, and $d_0 - e_0$ is the minimum expectation. Since the values of the parameters affecting the factors of tourism environmental carrying capacity have different distribution patterns, linear affiliation was used to clearly describe the increasing and decreasing relationship exhibited by the affiliation function (Zhang R et al., 2018) [18]. In the construction process of the model, the expectation values of multiple subjects are obtained, and according to the different values taken by θ_i, the optimal decision is made to achieve the balance of demand among the core subjects, as shown in Fig. 5.

4. Analysis of application effects

The improved NSGA-II algorithm first needs to be tested for performance. In order to verify the superior performance of the improved al-

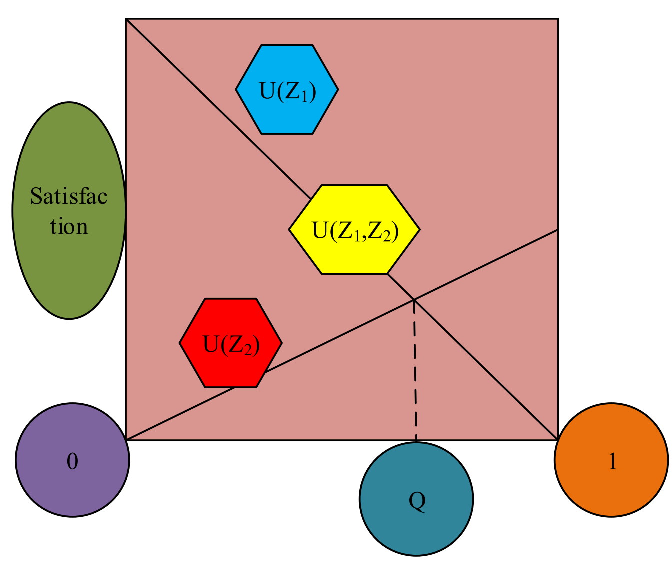


Fig. 5. Optimization process chart under satisfaction.

gorithm, simulation experiments for solving the minimum were carried out using the adapted adaptive variational approach and the polynomial variational principle, respectively, using the nonlinear functions $y = \sum_{i=1}^{20} x_i^2 + 0.5$, $x_i \in [0, 100]$. The evolutionary procedure was carried out by means of real number coding, arithmetic crossover and deterministic sampling options, keeping the remaining parameters consistent. The evolutionary algebra was set to 250, the crossover probability to 0.9 and the population size to 100. Regarding the setting of the average probability, the study referred to the setting of the average probability in Ref. [19], with values of 0.05 and 0.005, respectively. The reason is that if the average probability value is too small, the application rate of crossover and mutation operations will be reduced, resulting in a slower rate of convergence of the algorithm, which may fall into a local optimal solution. Conversely, if the average probability value is too large, the application rate of crossover and mutation operations will increase, leading to a decrease in population diversity, which may cause the algorithm to fall into local optima too early. According to the test results in the literature [19], it is confirmed that 0.05 and 0.005 are appropriate average probability values that can maintain the convergence rate of the algorithm while preserving the diversity of the population. The convergence curves of the NSGA II algorithm under two average probability values are shown in Fig. 6.

As can be seen from Fig. 6(a), when the average variation probability is 0.005, the adapted adaptive variation approach converges faster and has a smaller value of the optimal individual function than the traditional polynomial variation approach. As can be seen from Fig. 6(b), the improved variational approach still has a faster convergence rate and a more uniform distribution of solutions for an average probability of 0.05, indicating that it better overcomes the paradox of choosing variational probabilities and has a stronger performance advantage. To further verify the merit-taking characteristics of the improved NSGA-II algorithm, it was compared with NSGA-II and Multi Objective Genetic Algorithm (MOGA), and different sets of Pareto solutions were obtained through the process of genetic coding and crossover, and their distribution and merit-taking characteristics were analysed. The maximum number of evolutionary generations set for the experiment was 1000, and the population size was 500. The three algorithms were genetically manipulated in turn according to the evolutionary process, and the results obtained are shown in Fig. 7.

As can be seen from Fig. 7, the distribution interval of Pareto obtained by the NSGA-II algorithm is relatively small, less evenly distributed and more dense. The Pareto obtained by the MOGA algorithm has a significant deficiency between 0.4 and 0.6, and the distribution is equally less dense and even, and slightly inferior to the NSGA-II algorithm. The improved algorithm, on the other hand, has a relatively wide distribution interval, a smoother and more uniform Pareto boundary, and the best performance. The three algorithms were then tested in two test functions, DTLZ1 and DTLZ2. The DTLZ1 function makes it more difficult for the algorithm to converge to the Pareto frontier, leading to local optimum problems, while the DTLZ2 function has no redundant objectives. Therefore, the number of iterations was set to 250, the crossover probability to 0.9 and the population size to 300. The study further verified the performance of the three methods by comparing Inverted Generational Distance (IGD) and Hypervolume. Among them, the IGD index mainly evaluates the overall performance of the algorithm, namely the distribution and convergence. The Hypervolume metric is a metric used to evaluate the performance of multi-objective optimization algorithms, which measures the volume size dominated by the optimization solution in the multi-dimensional target space. For hypervolume metrics, bigger is better. At the same time, a limited number of experimental runs can lead to higher randomness in the results obtained. Therefore, the study first improves the stability of the results by increasing the number of experimental runs, thereby reducing the impact of randomness on the results. In addition, statistical analysis methods are used to assess the reliability of the results by calculating statistical indicators such as mean and variance, and to compare and infer the results. The three algorithms were run independently 100 times in the DTLZ1 and DTLZ2 test functions and the IGD and Hypervolume indicators obtained are shown in Table 1.

As can be seen from Table 1, the improved algorithm obtained a minimum value of 2.124 E+00 for IGD in DTLZ1, compared to 4.327 E+00 and 3.071 E+01 for the MOGA and NSGA-II algorithms, respectively, and a minimum value of 3.187E-02 for the improved algorithm in

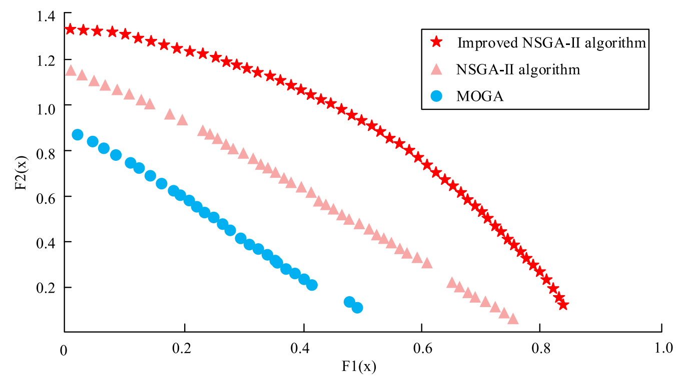
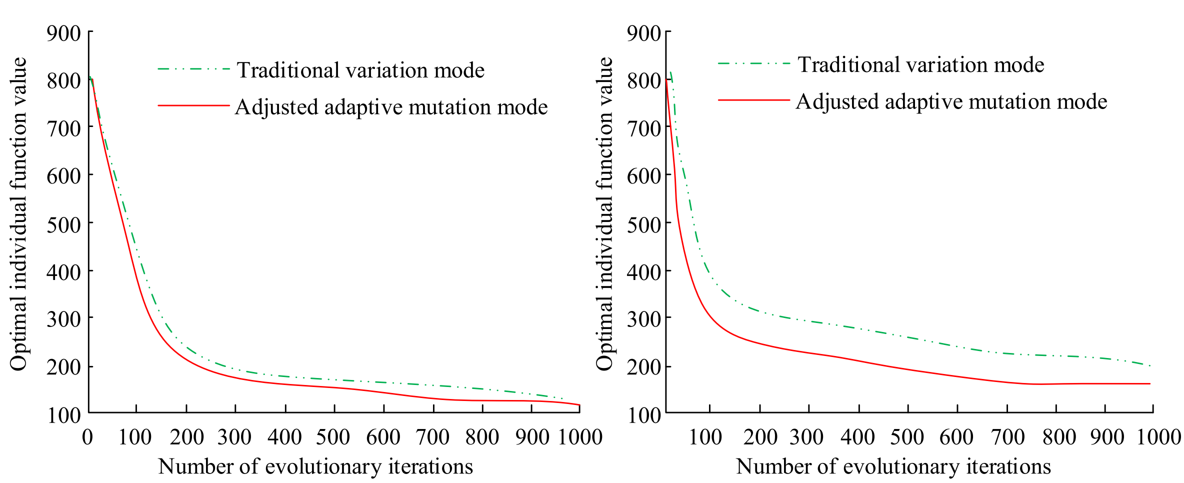


Fig. 7. Comparison diagram of solution distribution of MOGA algorithm of three algorithms.



(a) The average probability of variation is 0.005 (b) The average probability of variation is 0.05

Fig. 6. The function value of the optimal individual increases with the evolution algebra change curve.

Table 1
Comparison of IGD and Hypervolume index results of the three algorithms.

Category	Algorithm	Min	Mean	Variance	Hypervolume
DTLZ1	MOGA	4.327 E+00	5.123 E+01	2.193 E+01	3.1739
	NSGA-II	3.071 E+01	5.962 E+01	2.421 E+01	3.1625
	Improved NSGA-II	2.124 E+00	3.654 E+01	1.745 E+01	6.0063
DTLZ2	MOGA	4.261E-00	4.503E-02	4.503E-02	6.2034
	NSGA-II	3.765E-02	4.177E-02	4.184E-02	6.2377
	Improved NSGA-II	3.187E-02	4.093E-02	3.315E-03	9.0072

DTLZ2, compared to 4.261E-00 and 3.765 E-for the other two algorithms, respectively. 02, indicating that the improved algorithm outperforms the other two algorithms in terms of minimum values in both test functions. Meanwhile, the variance values of IGD indicators obtained by the improved algorithm are 1.745 E+01 and 3.315E-03 respectively, which are smaller than the other two algorithms, indicating that they are more stable. In addition, in the comparison of hypervolume indicators, the improved NSGA-II algorithm was 6.0063 and 9.0072 respectively, significantly higher than the two selected methods, indicating that the improved NSGA-II algorithm found more high quality solutions, and these solutions have better distribution and performance in the target space. Finally, the improved algorithm was empirically analysed. The peak tourism season of Yantai City in 2019 was chosen for the optimal solution of the environmental carrying capacity. The population size and evolutionary generation were 200, and the ranking method was chosen as binary tournament, and the optimized solution set for 2019 was obtained as shown in Fig. 8.

Fig. 8 shows the results of the environmental carrying capacity search for the 2019 peak tourism season in Yantai City, with the three axes being the employment rate of urban residents, economic income and the number of subjects that the tourism environment can accommodate. From Fig. 8, it can be seen that the number of subjects accommodated obtained by the improved algorithm is steadily increasing, up to more than 2.5×10^7 people, while the economic income is gradually increasing, up to 1.088×10^{11} yuan. As for the employment rate of urban residents, it shows smaller fluctuations, but still maintains a high level of employment rate, stable at around 8.75×10^{-3}. It can be seen that the model established by the improved algorithm can obtain a reasonable distribution of optimal solutions. To further verify the effectiveness of the algorithm, it is then applied to Yantai's tourism off-season and peacetime in 2019 to optimize the carrying capacity, and compared with MOGA and NSGA-II algorithms. The results are shown in Fig. 9.

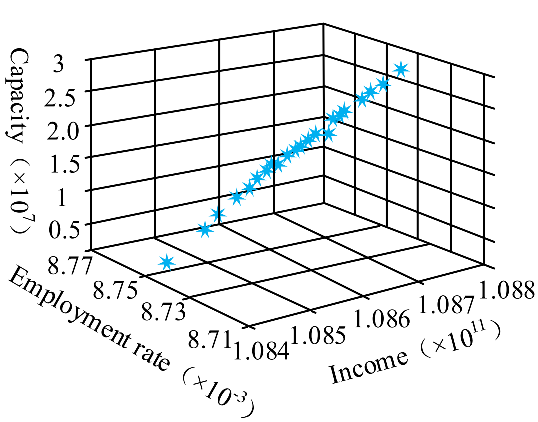


Fig. 8. 2019 peak tourism season optimization solution set result chart.

As can be seen from Fig. 9(a), in the shoulder season of tourism in Yantai City, the number of people obtained by the improved NSGA-II algorithm decreases within the range of 2.24 × 107∼2.27 × 107, and the tourism revenue also shows a small fluctuation, but it is still above 3.18 × 1010 yuan. MOGA and NSGA-II algorithms have lower benefits than the improved NSGA-II algorithm. As shown in Fig. 9(b), the employment rate of urban residents obtained by the improved NSGA-II algorithm is in the range of 0.18 × 10–3∼0.19 × 10–3 in the tourism off-season. As the tourism capacity decreases, the tourism income fluctuates slightly and remains in the range of 3.18 × 1010∼3.21 × 1010. MOGA and NSGA-II algorithm have lower tourism income and employment rate. Combined with Fig. 9, it can be seen that from peak season to shoulder season and off-season, the number of tourists accommodated in Yantai City gradually decreases, and the tourism income and employment rate of urban residents also decrease significantly. However, the results obtained by the improved NSGA-II algorithm are more reasonable.

Based on the optimization results and the actual situation of the region, the suggestions proposed in the study mainly come from the key stakeholders. On the government side, efforts should be made to innovate tourism technology, increase investment in tourism science and technology, improve the efficiency of tourism resource utilization, and optimize the existing spatial structure of the tourism environment; increase the development and investment of new tourism resources, strengthen the development of characteristic tourism resources, and enhance the attractiveness of the urban tourism environment; Strengthen the promotion of civilized travel and green travel, and create a good image of urban tourism; strengthen the construction of urban infrastructure, especially investment in transportation, accommodation, health care and environmental protection. At the same time, formulate relevant tourism policies and encourage more people to invest in tourism activities. Tourists should improve their environmental awareness and refrain from doing anything that damages the tourism environment during tourism activities; Secondly, tourists should know the current situation of the urban tourism environment in advance, such as what tourism resources there are in the city, the periods of off-season, normal season and peak season, and make a tourism plan that meets their own tourism needs in combination with these specific situations. For example, try to stagger the peak season as much as possible, determine your own travel route and transportation, book a hotel before accommodation, understand the specific unknowns and opening hours of the scenic area, etc. As for urban residents, firstly, cities and towns should strive to learn about tourism environment protection and actively participate in tourism education of the urban tourism environment; secondly, cities and towns should actively participate in environmental protection publicity activities and contribute to the protection of the tourism environment from their own perspective. As for tourism enterprises, they should devote themselves to the development of urban tourism resources with urban characteristics, and increase the attractiveness of the urban tourism environment for tourists; Secondly, fully consider the interests and needs of foreign tourists, and build and develop some tourism characteristic resources or products that are more attractive to foreign tourists; In addition, tourism enterprises should increase the development of tourism resources in off-season and peacetime, strengthen the cooperation between tourism regions and stakeholders in the urban tourism environment, so as to promote the diversion of tourists in the urban tourism environment.

5. Conclusion

The urban tourism environment is the basis for the development of urban tourism. The sustainable carrying capacity of the tourism environment is influenced by many factors such as economic, natural and social factors, and how to achieve a balance between economic and environmental benefits is the focus of current research in this field. The study applies the improved NSGA-II algorithm to optimize the carrying

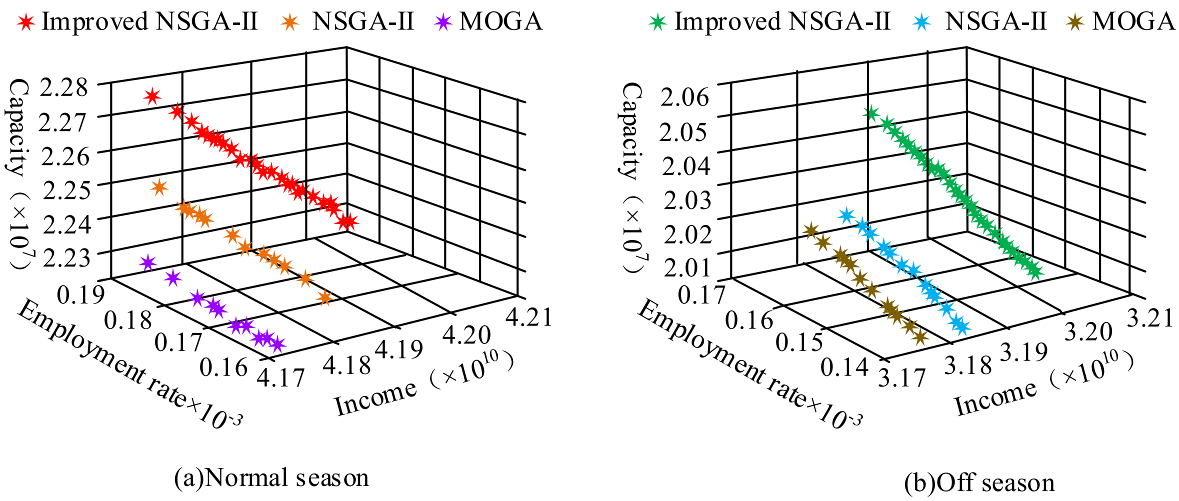


Fig. 9. 2019 tourism off-season and flat season optimization solution set result chart.

capacity of the tourism environment in order to scientifically and effectively improve the level of environmental carrying capacity. The experimental results showed that the adaptive variational approach of the improved algorithm converged faster than the traditional variational approach in the average probability of 0.005 and 0.05, and the solutions of the distribution were more uniform, which had better performance advantages. In the genetic manipulation experiments, the MOGA algorithm's Pareto had significant deficiencies within 0.4–0.6 and was less dense and uniform, while the improved algorithm's solution set had a wider distribution interval and a smoother and more uniform distribution. In the experiments with test functions DTLZ1 and DTLZ2, the minimum values of the improved algorithm are 2.124 E+00 and 3.187E-02 respectively, and the variances are 1.745 E+01 and 3.315E-03 respectively, both of which are better than the MOGA and the original NSGA-II algorithm. In the empirical analysis, the optimization results obtained by the improved algorithm for the employment rate of urban residents, the number of people accommodated and the economic income are more reasonable, indicating that the algorithm can improve the sustainability of the urban tourism environment. However, the study does not confirm the range of constraints, so the method of selecting the range of parameters has to be further explored.

CRediT authorship contribution statement

Qihong Tan: Conceptualization, Methodology, Formal analysis, Supervision, Investigation, Data curation, Resources, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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