Multi-objective Route Planning of Museum Guide based on an Improved NSGA-II Algorithm

Yuhan Xu, Qing Guo*, Aopin Tan, Liying Xu, Yiwei Tu and Shuang Liu

College of Information Science and Technology Beijing University of Chemical Technology Beijing, China

*Email: guoqing@mail.buct.edu.cn

Abstract. Museums have become a hot spot of tourism. However, the uneven distribution of passenger flow makes it difficult for tourists to find out the shortest and most comfortable tour route. The multi-objective route planning strategy is proposed for the design of museum tour route. This paper presents an improved version of the NSGA-II algorithm, named adaptive 2-opt integrated non-dominated sorting genetic (AONSGA) algorithm. Based on NSGA-II algorithm, the adaptive probability and 2-opt local search strategy is introduced. Then the computation results on benchmark multi-objective problems show that the AONSGA algorithm has better convergence and diversity performance than the NSGA-II. Whereafter, taking the Palace Museum as an example, a map is established and AONSGA is applied to carry out multi-objective guide route planning. Finally, according to different requirements of tourists, three kinds of specific schemes of the guide route in the Palace Museum are recommended.

1. Introduction

In recent years, museums have become a tourist hotspot. However, during the peak period of museum visits, due to the uneven distribution of the passenger flow in space and the unfamiliarity of tourists with the museum, it is difficult for tourists to find the shortest and most comfortable route. Therefore, how to effectively carry out multi-objective museum guide path planning to ensure that the tourists feel comfortable and the path is short enough, has become the mainly problem to be solved.

In many optimization problems in science and engineering, it is often necessary to optimize multiple objectives that are generally conflicting with each other [1]. Since Schaffer [2] firstly attempt to solve multi-objective optimization problems, a variety of multi-objective evolutionary algorithms (MOEAs), ranging from traditional evolutionary algorithms to newly developed techniques, have been proposed and widely used in different applications [3]. Among them, genetic algorithm searches the population composed of gene coding individuals. The search range is wide and comprehensive, and when dealing with all kinds of constraints and objective functions, it is rarely related to mathematical forms. Its emergence provides theoretical support for multi-objective optimization problems. On the basis of genetic algorithm, scholars have proposed multi-objective evolutionary algorithm (MOEA). Among them, non-dominated sorting genetic algorithm (NSGA) proposed by Deb and Srinivas is the most representative. It is based on the theory of non-dominated sorting. After that, Deb and other scholars improved on the basis of NSGA and proposed a non-dominated sorting genetic algorithm with elite strategy (NSGA-II) [4].

In this paper, based on the NSGA-II algorithm, the crossover probability and mutation probability are adaptively optimized, and 2-opt local search algorithm is introduced. We named the new algorithm AONSGA. Then, we compare the new algorithm with the traditional NSGA-II algorithm by benchmark
multi-objective problems. Finally, taking the Palace Museum as an example, we used AONSGA algorithm to guide path planning of the museum. To ensure that the tourists feel comfortable and the path is short enough, several schemes are given for tourists to choose.

2. AONSGA Algorithm

2.1. Local Search Strategy 2-opt Algorithm
The 2-opt(2-optimization) algorithm is one of the local search algorithms [5]. Figure 1 describes the principle of 2-opt algorithm. When solving combinatorial optimization problems, the local search can help the algorithm jump out of the local optimum. The process of applying the 2-opt algorithm to the route planning of museum tour guides is as follows: Starting with an arbitrary route, the 2-Opt heuristic repeatedly replaces two edges of the route by two other edges, as long as this yields a shorter route. The 2-Opt heuristic stops when no further improvement can be made this way. A route that the 2-Opt heuristic cannot improve is called 2-optimal [6]. This paper will use the 2-opt algorithm to perform a local search on the newly generated population of each generation of the NSGA-II algorithm.

![2-opt schematic diagram](image1)

2.2. Adaptive Crossover Probability and Mutation Probability Adjustment Mechanism
In the simple genetic algorithm, the crossover probability $p_c$ and the mutation probability $p_m$ are fixed during the evolution process, but actual research shows that they are the key to the performance of the genetic algorithm. This article respectively makes adjustments to the crossover probability and mutation probability.

2.2.1. Adaptive Crossover Probability Adjustment Mechanism. The size of the crossover probability $p_c$ determines the update rate of the population individuals. Large $p_c$ will destroy the excellent genetic pattern, whereas small $p_c$ make the search speed slower and the population difficult to evolve. In the early period of evolution, in order to expand the overall search range and speed up the update of population, $p_c$ should be increased. However, in the later period of evolution, the overall solution set of the population tends to be stable. In order to maintain the excellent gene structure, $p_c$ should be appropriately lowered. In addition, the crossover operator can change or even destroy the gene structure. Therefore, more participation in the crossover operation can promote their continuous optimization for individuals with poor fitness. As a result, a higher value of $p_c$ should be given. Based on the above considerations, the following adjustment mechanisms are set up:

$$p_c = \begin{cases} p_{c_{\text{max}}}, & f_i < \bar{f} \; \text{or} \; f_i \geq \bar{f} \; \text{or} \; \Delta f_i \geq \frac{G(f_{\text{max}} - \bar{f})}{2G(f_{\text{max}} - f)} \; \text{or} \; G \geq \frac{3G}{2} \; \text{or} \; g \geq G/2; \\ \frac{p_{c_{\text{max}}}}{p_{c_{\text{max}}}} + \frac{\Delta f_i}{G(f_{\text{max}} - f)}, & \end{cases}$$

$$p_{c_{\text{max}}} = \begin{cases} 19/20, & G \leq G/4; \\ 17/20, & G/4 < g \leq 3G/4; \\ 3/4, & 3G/4 < g \leq G. \end{cases}$$

(1)

Where $G$ is the maximum number of generations; $g$ is the current number of iterations. $p_c$ is the crossover probability of $i$; $p_{c_{\text{max}}}$ is adjusted with the number of generations, $p_{c_{\text{max}}}$ equals to 0.7 and
\( \Delta p_m = p_{c_{\text{max}}} - p_{c_{\text{min}}} \); \( f_i \) is the fitness function value of individual \( i \); \( f_{\text{max}} \) is the current maximum fitness of all individuals; \( \bar{f} \) is the average fitness value of the current population.

2.2.2. Adaptive Mutation Probability Adjustment Mechanism. The appropriate mutation of an individual can maintain the diversity of the population and prevent it from falling into a local optimum. However, if the probability of mutation \( p_m \) is too large, the algorithm is similar to random search and loses the characteristics of genetic evolution. In the early period of evolution, the possibility of individual mutation is relatively small. At the end of evolution, increasing the probability of individual mutation operations in the population is conducive to expanding the search range and jumping out of the local optimum. In addition, individuals with smaller fitness are less likely to mutate, which leads to the result that individuals tend to have similar genetic structures as the number of iterations increases, and at this time they are likely to fall into a local optimum. In order to avoid it, \( p_m \) should be appropriately increased to maintain individual diversity. Considering both genetic evolution generations and fitness function value of individual, we establish the adjustment formula for the mutation probability:

\[
P_{m_i} = \begin{cases} 
p_{m_{\text{min}}}, & f_i < \bar{f} \\
p_{m_{\text{min}}} + \frac{\Delta p_m [G(f_i - f) + 2g(f_{\text{max}} - f)]}{2G(f_{\text{max}} - f)}, & f_i \geq \bar{f}.
\end{cases}
\]

\[P_{m_{\text{min}}} = \begin{cases}
1/20, & 0 < g \leq G/4; \\
3/20, & G/4 < g \leq 3G/4; \\
1/4, & 3G/4 < g \leq G.
\end{cases}
\]

Where \( P_{m_i} \) is the probability of mutation, \( p_{m_{\text{max}}} \) equals to 0.30, \( p_{m_{\text{min}}} \) is adjusted with the number of generations and \( \Delta p_m \) equals to \( p_{m_{\text{max}}} - p_{m_{\text{min}}} \).

2.3. The Process of AONSGA Algorithm

The program flow chart of the AONSGA algorithm is as Figure 2:
Step 1: Initialize decision variables, and randomly generate an initial parent population $P_t(0)$ of size $N$ according to constraints.

Step 2: Perform non-dominated sorting and crowding degree sorting for $P_t(0)$.

Step 3: For $P_t(t = 0)$, random league selection is performed according to the individual's non-dominated order and crowdedness value, and then binary crossover and polynomial mutation are used to generate the offspring population $Q_t$.

Step 4: Merge the parent population $P_t$ and the offspring population $Q_t$ to form an intermediate population $R_t$, then perform fast non-dominated sorting and calculation of crowdedness value for $R_t$, and select $N$ individuals to form the next generation of parents $P_{t+1}$ according to the non-dominated order and crowdedness value.

Step 5: Perform a 2-opt local search for the newly generated parent population $P_{t+1}$.

Step 6: First let $t$ equal to $t+1$ and then judge whether it is greater than the maximum number of iterations $G$. If yes, terminate the algorithm and output the central non-dominated solution as the Pareto optimal solution set. Otherwise, return to Step 3.

2.4. Algorithm Performance Testing and Analysis

2.4.1. The Method of Algorithm Performance Testing. In order to intuitively and specifically compare the distribution of NSGA-II and the AONSGA algorithm proposed in this paper in solving multi-
objective optimization problems, this study will refer to Schott’s evaluation method [7] to compare the diversity of population distribution in the evolutionary process, and the evaluation function is as follows:

$$SP = \left( \frac{1}{n-1} \sum_{i=1}^{n} (d - d_i)^2 \right)^{1/2}$$

$$d_i = \min_j \left( \sum_{k=1}^{m} \left| f^k(x) - P^j(x) \right| \right)$$  \hspace{1cm} (3)

where $d$ is the average value of all $d_i$, $n$ is the number of individuals in the solution set, $f^k(x)$ is the optimal solution set of pareto obtained by experiment, $P^j(x)$ is the set of solutions uniformly collected by the front surface of real Pareto, and $d_i$ is the Eucalyptus distance between the pareto solution set obtained by experiment and the nearest real Pareto solution. The smaller the SP value is, the more uniform the population distribution is.

In addition, generation distance (GD) represents the distance between the obtained solution set and the true Pareto optimal solution set. The smaller GD value is, the optimal solution set converges to the true Pareto optimal solution set. It can be calculated by:

$$GD = \frac{1}{n} \left( \sum_{i=1}^{n} d_i^2 \right)^{1/2}$$  \hspace{1cm} (4)

2.4.2. The Results of Algorithm Performance Testing. Using ZDT1–ZDT3 [8] and SCH to conduct comparative experiments between basic NSGA-II and AONSGA. Each test function performs 60 sets of experiments, with the maximum, minimum and average values of SP index and GD index calculated.

![Graphs of ZDT1, ZDT2, ZDT3, and SCH](image)

**Figure 3.** The test curve of the ZDT1.

**Figure 4.** The test curve of the ZDT2.

**Figure 5.** The test curve of the ZDT3.

**Figure 6.** The test curve of the SCH.

**Table 1.** The SP values of the two algorithms.

| function | NSGA-II | AONSGA |
|----------|---------|--------|
| ZDT1 | 0.0189 | 0.0078 | 0.0131 | 0.0172 | 0.0072 | 0.0116 |
| ZDT2 | 0.0261 | 0.0000 | 0.0050 | 0.0185 | 0.0002 | 0.0047 |
| ZDT3 | 0.0457 | 0.0131 | 0.0247 | 0.0277 | 0.0149 | 0.0208 |
| SCH | 1.73E-04 | 1.26E-04 | 1.40E-04 | 1.68E-04 | 1.21E-04 | 1.40E-04 |

**Table 2.** The GD values of the two algorithms.

| function | NSGA-II | AONSGA |
|----------|---------|--------|
| ZDT1 | | | | | | |
| ZDT2 | | | | | | |
| ZDT3 | | | | | | |
| SCH | | | | | | |
It can be seen from Figures 3~6 that the Pareto front of AONSGA algorithm has better distribution and accuracy. Caused by Pareto uneven distribution of the optimal solution, there are obvious “discontinuities” in some areas. Although AONSGA algorithm still exists some uneven distribution, it obviously improves this shortcoming and fits the standard value better than the original algorithm. This phenomenon can be explained as the adaptive crossover and mutation probability makes the population update rate in the evolutionary process more reasonable, and thus avoiding the local optimum collaborated with 2-opt algorithm.

Table 1 shows the statistics value of SP obtained by running the two algorithms 60 times under different test functions. It reveals that AONSGA algorithm is superior to NSGA-II algorithm in both the extreme value and the average value, which indicates that the improved algorithm has a more uniform distribution. Table 2 shows the statistics value of GD which indicates that AONSGA algorithm is superior to NSGA-II algorithm in terms of convergence efficiency.

|     | GD-max | GD-min | GD-aver | GD-max | GD-min | GD-aver |
|-----|--------|--------|---------|--------|--------|---------|
| ZDT1| 0.0749 | 0.0332 | 0.0533  | 0.0638 | 0.0033 | 0.0049  |
| ZDT2| 0.1435 | 0.0668 | 0.1034  | 0.1034 | 0.0466 | 0.0748  |
| ZDT3| 0.0778 | 0.0204 | 0.0419  | 0.0419 | 0.0247 | 0.0327  |
| SCH | 2.48E-04 | 1.95E-04 | 2.25E-04 | 2.58E-04 | 1.98E-04 | 2.23E-04 |

Figure 7. The differences of the SP value between two algorithms.

Figure 7 shows the changes of SP value when both two algorithms run 20 times of the ZDT1 function. It is obvious that the SP value of AONSGA always fluctuates up and down at a lower value than of NSGA-II, and the fluctuation range is relatively small, indicating that the new algorithm has stronger stability, better robustness and adaptability.

In order to further verify the stability of the new algorithm in the evolution process, the SP value is calculated every 50 generations in the evolution process. The right of Figure 7 shows the SP values of the two algorithms in the evolution process under the ZDT1 function. Through comparison, it can be found that under the same algebraic evolution, the SP value of the new algorithm decreases faster and remains more stable.

3. Multi-objective Tour Guide Path Planning Based on AONSGA Algorithm

3.1. Problem Description and Modeling
There are two objectives in the museum path planning, one is the length of the path, the other is the congestion degree. In this paper, we select the Palace Museum as the research object. We choose 32 famous pavilions and mark them in the panorama of the Palace Museum. After transformation, the coordinates of each scenic spot are obtained, and the distance matrix is generated by calculating the distance between any two scenic spots. The degree of congestion is generated randomly, and the symmetric congestion matrix with the size of 32 * 32 and the range of 1 ~ 200 is generated by MATLAB program.
The distance between the n pavilions and the congestion of the paths are known. Visitors must to visit the pavilion once. According to the actual situation of the Palace Museum, the starting point of tourists is noon gate and the end is Shen-Wu gate. How to make the tour path short and the tourists comfortable is the main problem of this study.

$d_{ij}$ is the distance matrix between the vertices and $q_{ij}$ is the crowdedness matrix between the vertices. If a visit order of the exhibition hall $B = \{b_1, b_2, b_3, \cdots, b_n \}$ is $S = \{s_1, s_2, s_3, \cdots, s_n \}$ ($s_i \in V(i = 1, 2, 3, \cdots, n)$), and $s_i, s_n$ are fixed, then the mathematical model of the multi-objective Museum shortest guide path planning problem is as follows:

$$\begin{align*}
\min D &= \sum_{i=1}^{n} d_{b_i,b_{i+1}} \\
\min Q &= \sum_{i=1}^{n} q_{b_i,b_{i+1}}
\end{align*}$$

(5)

3.2. Multi Objective Tour Guide Path Planning Experiment in the Palace Museum

In this paper, AONSGA algorithm is applied to optimize the multi-objective guide path planning of the Palace Museum. The experimental conditions are as Figure 8.

**Figure 8.** Initial parameters of AONSGA.  **Figure 9.** Pareto optimal front of AONSGA.

The input of the experiment is the map of the Palace Museum and the randomly generated symmetry matrix of crowding degree. The output is the Pareto optimal frontier of the multi-objective guide path planning problem, as shown in Figure 9. Next, according to the specific needs of tourists, we design the tour guide path scheme. Taking the tourists who regard the length of the route and the degree of congestion as equally important, we provide three feasible schemes, as shown in Figure 10. Tourists can further choose according to their preferences.
Figure 10. The three feasible solutions.

4. Conclusion
To improve the efficiency and comfort of tourists' tours, this paper has presented an improved NSGA-II algorithm which is applied to multi-objective route planning in museums. The adaptive crossover probability and mutation probability are introduced and 2-opt local search strategy are integrated with traditional NSGA-II algorithm. By such means would we propose a new algorithm AONSGA. Compared with NSGA-II, AONSGA has better distribution and it fits the standard value better. Finally, the new algorithm is applied to the multi-objective guide route planning of the Palace Museum, and an effective and feasible plan is given. In the future, we will continue to think about how to improve the efficiency of AONSGA algorithm and try to put it into real museum environment as soon as possible.

References
[1] Tang L and Wang X 2012 A Hybrid Multiobjective Evolutionary Algorithm for Multiobjective Optimization Problems IEEE Transactions on Evolutionary Computation, 2012, 17(1) 20-45
[2] Schaffer J D 1985 Multiple objective optimization with vector evaluated genetic algorithms,” Proc. 1st Int. Conf. Genet. Algorithms 1985 93–100
[3] Coello C A C, Veldhuizen D A V, and Lamont G B 2002 Evolutionary Algorithms for Solving Multiobjective Problems (Norwell, MA: Kluwer) pp 61-121
[4] Deb K, et al 2002 A fast and elitist multi-objective genetic algorithm: NSGA-II IEEE Transactions on Evolutionary Computation 6(2) 82-197
[5] Croes G A 1958 A Method for Solving Traveling-Salesman Problems Operations Research, 6(6) 791-812
[6] Hougardy S, Zaiser F, Zhong X 2020 The approximation ratio of the 2-Opt Heuristic for the metric Traveling Salesman Problem Operations Research Letters 48 401–4
[7] Schott J R 1995 Fault Tolerant design using single and multicriteria genetic algorithm optimization Cellular Immunology 37(1) 1-13
[8] Zitzler E, Deb K, Thiele L 2000 Comparison of multiobjective evolutionary algorithms,” Empirical Results. Evol Comput 8(2) 173–195