Tourism City Management Optimization Model Based on Sustainable Development Concept

Jun Duan [1, *], Ke Xu [2]

[1] College of computer science and technology, Huaqiao University, Xiamen, China, 361021

[2] School of economics, Tongling University, Tongling, China, 244061

* Corresponding Author Email: duanjun_cn@163.com

Abstract. In response to the environmental degradation and increasing social pressures caused by over-tourism in some tourist cities in recent years, this paper developed a sustainable tourism optimization model. The model comprehensively considers three major factors: economic, environmental, and social aspects, covering six secondary indicators such as tourism revenue and water pollution index. First, this paper employed the DEMATEL-ANP hybrid method to analyze and calculate the global weights of these six secondary indicators. Next, based on indicator interrelationships, models for tourist numbers, economic development index, environmental & social pressure indices were built. Then, an optimized sustainable tourism development model was constructed using each indicator's global weight. Using the simulated annealing algorithm, this paper derived the optimal solution for the tourism sustainability index and conducted sensitivity analyses on each indicator. Research findings indicate that the impact of tourist volume and taxation is the most significant. Regarding visitor distribution across attractions, this paper developed a tourist flow optimization model and implemented it across five major attractions in Venice, Italy. The results showed that after optimization, the flow imbalance index dropped by about 64%, significantly improving visitor distribution and relieving pressure on individual attractions.

Keywords: Sustainable Tourism, Multi-objective optimization, Simulated Annealing Algorithm, Variance-Based Sensitivity Analysis.

1. Introduction

Under the background of global climate change and the intensification of resource constraints, sustainable tourism has become a core issue in international policies. The United Nations' "2030 Agenda for Sustainable Development" clearly states that it should promote the coordinated development of local economy, culture, and environment. The focus of sustainable tourism research is to mitigate or remedy the environmental, social, and economic impacts on the tourism industry [1]. Early foreign research focused on the "environmental carrying capacity" and the "stakeholder synergy theory". For example, Choi et al. (2006) constructed a 125 - item indicator system using the improved Delphi method [2]. Domestic scholars, from the perspectives of tourism geography and ecology, proposed that the tourism industry needs to balance ecological restoration and economic resilience. For instance, Guan (2024) analyzed the 2015 - 2019 coupling - coordination of Henan's tourism - economy resilience via an index system and entropy method [3].

In recent years, the construction of indicator systems has become a research hotspot. Baloch et al. (2023) took Pakistan as the research subject to study the relationship between tourism development and environmental sustainability and proposed a sustainable ecotourism framework [4]. Castanho et al. (2023) focused on the Azores Islands to explore the role of creative tourism in the sustainable development of island regions [5]. Based on the water footprint theory, Su (2023) compared different schemes to provide a decision - making basis for sustainable tourism development [6]. Garcês et al. (2024) analyzed the characteristics and well - being of tourists on Madeira Island, providing a new perspective [7]. Colasante et al. (2024) collected opinions, proposed sustainable tourism strategies, and emphasized the importance of policy intervention [8]. However, most of these studies are limited to a single dimension or static indicators and lack a comprehensive dynamic model to support multi - objective optimization decision - making.

This study breaks through the limitations of the traditional single - indicator system. By integrating indicators from the economic, environmental, and social dimensions, it constructs a multi - dimensional dynamic evaluation model that is closer to policy needs. The DEMATEL - ANP method is adopted to calculate the global weights of indicators, overcoming the shortcomings of the traditional Analytic Hierarchy Process (AHP). Combining with the simulated annealing algorithm, multi - objective optimization is achieved, improving the model's solution efficiency and stability. The main contents are as follows: 1) Establish an evaluation indicator system for the three dimensions based on literature and policy requirements; 2) Use the DEMATEL - ANP method to quantify the weights and establish a comprehensive model; 3) Use the simulated annealing algorithm to solve for the optimal index and analyze its sensitivity; 4) Verify the universality of the model through multi - scenic - spot cases, extend it to the tourist diversion scenario, and put forward optimization suggestions.

2. Methods

2.1. Dematel-ANP

In multi - attribute decision - making (MADM) problems, methods like AHP and entropy weight method often assume independent criteria, ignoring real - world feedback and dependence. DEMATEL, grounded in graph and matrix theory, quantifies relationships among complex - system factors to identify key elements and causal chains. ANP for multi - criterion decision - making accounts for factor interdependence and feedback for a more comprehensive perspective. The combined application of DEMATEL and ANP can enhance the scientificity and objectivity of research through a subjective - objective comprehensive weighting method [9]. This study uses their combination to quantify complex dependencies among tourism indicators and calculate weights.

2.1.1. Dematel Causal Relationship Modeling

First, construct the direct influence matrix by inviting experts in the tourism-related field to score the direct influence relationships between the constructed indicators, forming Matrix (1):

$$D = \left[d_{ij}\right]_{n\times n}, \tag{1}$$

Here, d_{ij} represents the direct influence intensity of indicator i on indicator j (0 = no influence, 4 = very strong influence).

Then, the direct influence matrix is normalized, and the matrix $X = \left[x_{ij}\right]_{n\times n}$ is calculated using the following formula:

$$x_{ij} = \frac{d_{ij}}{max\left(\sum_{j=1}^{n} d_{ij}, \sum_{i=1}^{n} d_{ij}\right)}, \tag{2}$$

Ensure that both the row and column sums of the matrix do not exceed 1, eliminating dimensional differences.

Then, calculate the Total Influence Matrix (T) by deriving the indirect influences through Markov chain theory, using the following formula:

$$T = X(I - X)^{-1}, \tag{3}$$

Where I is the identity matrix, and $(I - X)^{-1}$ is the Leontief inverse matrix, reflecting the cumulative effect of both direct and indirect influences.

Finally, calculate the centrality and causality degrees, defined as the row sum $R_i = \sum_{j=1}^{n} t_{ij}$ (the total influence of indicator i) and the column sum $C_j = \sum_{i=1}^{n} t_{ij}$ (the total influence received by indicator j).

2.1.2. ANP Network Weight Calculation

First, construct the ANP network structure. Based on the DEMATEL T matrix, categorize the indicators with $Q_i > 0$ as the cause set and those with $Q_i < 0$ as the effect set, forming a network model that includes dependency and feedback relationships.

Then, group the Total Influence Matrix T according to the ANP hierarchy. Using the eigenvector method, generate an unweighted supermatrix W, where the element ω_{ij} represents the relative influence weight of indicator i on indicator j:

$$\omega_{ij} = \frac{t_{ij}}{\sum_{k=1}^{n} t_{ik}}. \tag{4}$$

Finally, the limit supermatrix W^* is calculated using the power iteration method:

$$W^* = \lim_{k \to \infty} W^{2k+1}, \tag{5}$$

When the column vectors of the matrix converge to the same value, the global weights of the indicators are obtained as $\omega = [\omega_1, \omega_2, \dots, \omega_n]$.

2.2. Simulated Annealing Algorithm

The simulated annealing algorithm was first proposed by S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi in 1983 [10]. It is a general-purpose stochastic search optimization algorithm that effectively avoids falling into local optima by introducing probabilistic jump characteristics. The algorithm generates candidate solutions through the iteration of a domain function:

$$x' = x + \Delta x, \tag{6}$$

Here, x represents the current solution, x' is the newly generated candidate solution, and Δx is a random disturbance that follows a normal distribution with a mean of 0 and a standard deviation of σ. By this method, new solutions are randomly generated within the search space, increasing the likelihood of escaping local optima.

The acceptance probability of a solution is determined by the Metropolis criterion:

$$P(\Delta E, T) = \begin{cases} 1, & \Delta E < 0 \\ e^{-\Delta E/(k_B T)}, & \Delta E \geq 0' \end{cases} \tag{7}$$

Here, $\Delta E = E_{new} - E_{current}$ represents the difference in the objective function values between the new solution and the current solution, i.e., the energy difference. T Is the current temperature parameter, which decays during the execution of the algorithm according to the rule $T_{k+1} = \alpha T_k$, where the cooling rate α lies in the range $(0,1)$ When $\Delta E < 0$, it indicates that the new solution has a better objective function value, and the new solution is directly accepted. When $\Delta E \geq 0$, the new solution is accepted with a probability of $e^{-\Delta E/(k_B T)}$, where k_B is the Boltzmann constant.

2.3. Variance-Based Sensitivity Analysis

Variance-Based Sensitivity Analysis (VBSA) is a widely used technique in sensitivity analysis, suitable for assessing the contribution of input variables to the model output. It works by analyzing how changes in the input variables affect the variance of the output, thereby providing decision-makers with valuable information about the sensitivity of input variables. For a multi-input model, where the output $y = f(x_1, x_2, \dots, x_n)$ depends on multiple input variables $x_1, x_2, \dots, x_n$, the total variance of the model output can be decomposed using the following equation:

$$Var(y) = \sum_{i=1}^{n} Var(y|x_i) + \sum_{i<j} Var(y|x_i, x_j) + \cdots, \tag{8}$$

$Var(y)$ Is the total variance of the model output?

$Var(y|x_i)$ Is the contribution of the input variable x_i to the variance of the model output (i.e., the main effect of a single input variable);

$Var(y|x_i, x_j)$ Is the contribution of the interaction effect between input variables x_i and x_j to the variance of the output?

To quantitatively analyze the contribution of input variables to the model output, the following sensitivity indices can be used to evaluate the main effect contributions of each input variable:

$$S_i = \frac{Var(y|x_i)}{Var(y)}, \tag{9}$$

Where, S_i represents the contribution proportion of the input variable x_i to the model output. Variance-based sensitivity analysis not only calculates the contribution of individual input variables, but also evaluates the interaction between input variables by calculating their interaction effects.

3. Experimental

3.1. Data Sources

To develop a sustainable tourism model, this paper chooses Juneau, Alaska, USA as the research area. In recent years, a surge of tourists has brought economic vitality to Juneau, yet also worsened environmental degradation and increased social pressure. The renowned Mendenhall Glacier is melting due to over - tourism - induced temperature rise. Thus, establishing a sustainable tourism model for Juneau is crucial for local development. By leveraging Juneau's official website and government reports, this paper constructs a multi - dimensional evaluation system. Integrating the core concepts of sustainable tourism, it incorporates three dimensions (economic, environmental, and social) into the first - level indicator layer. Based on sustainability principles, the paper re - screens the indicators and finalizes six secondary indicators. See Table 1 for details:

Table 1. Basic State Variables Table.

Dimensions	Variable Names	Symbols
Economic	Initial Tourist Number	T_0
Economic	Per Capita Tourist Consumption	APC
Environmental	Water Pollution Index	WPI
Environmental	Solid Waste Index	SWI
Environmental	Carbon Footprint Index	CFI
Social	otal Tourist Capacity of the City	TC
Social	Basic Housing Cost	HC

3.2. Establishing Basic Relationship Models

3.2.1. Tourist Population Model

The number of tourists is crucial to the economic development of Juneau's tourism industry. While the increase in tourist numbers brings economic benefits to Juneau, it also intensifies environmental pollution and exerts greater pressure on urban infrastructure and the local population's quality of life. The index model is a common tool for growth prediction and is suitable for forecasting changes in tourist numbers. Its calculation formula can be expressed as follows:

$$V(t) = V_0 \cdot e^{rt}, \tag{10}$$

Where $V$the number of tourists per year is, r is the growth rate of tourist numbers, reflecting the rate at which the number of tourists changes over time. If$r > 0$, the number of tourists increases; if$r < 0$, the number of tourists decreases. t Represents time (in years), indicating the time period starting from the initial time.

3.2.2. Economic Development Index

This paper consider the tourism industry revenue of Juneau as a key economic indicator for measuring the development status of its sustainable tourism industry. The annual tourism industry revenue of Juneau is calculated and then normalized. The calculation formula can be expressed as follows:

$$G = \frac{APC \cdot T}{Gmax}, \tag{11}$$

Where G is the tourism industry revenue for the year, and $Gmax$ is the maximum tourism industry revenue in recent years in Juneau.

3.2.3. Environmental Pressure Index

This paper consider multiple environmental factors and consolidate them into an Environmental Pressure Index, which serves as an important indicator for evaluating the sustainability of Juneau's tourism industry. This index primarily covers three key aspects: water pollution, waste generation, and carbon emissions. The normalized calculation formulas can be expressed as follows:

$$W = \frac{WPI \cdot T}{Wmax}, \qquad R = \frac{SWI \cdot T}{Rmax}, \qquad C = \frac{CFI \cdot T}{Cmax}, \tag{12}$$

Where, W is the annual water pollution generated by tourists, and $Wmax$ is the maximum amount of water pollution generated by tourists in recent years. R Is the annual waste generated by tourists, and $Rmax$ is the maximum amount of waste generated by tourists in recent years. C Is the annual carbon emissions generated by tourists, and $Cmax$ is the maximum amount of carbon emissions generated by tourists in recent years?

3.2.4. Social Pressure Index

Based on the actual situation of Juneau, this paper consider tourist population carrying capacity and housing costs as important indicators for evaluating the sustainability of Juneau's tourism industry. The calculation formulas can be expressed as follows:

$$B = \frac{T}{TC}, \tag{13}$$

$$H = \frac{HC \cdot P \cdot T}{N \cdot Hmax}, \tag{14}$$

Where, B is the tourist carrying capacity coefficient, representing the current environmental pressure from the number of tourists? H Is the urban housing cost, P is the percentage by which the basic housing cost increases for every additional N tourists, N is the baseline number of tourists, $Hmax$ is the maximum housing cost in the region.

3.3. Construction of the Sustainable Tourism Development Optimization Model

The decision variables selected for the sustainable tourism industry model are as follows:

T : The number of tourists visiting Juneau City each year (unit: 10,000 people)
τ : The annual increase in hotel taxes by the government (unit: percentage)
G_1: The government funding for wastewater treatment (unit: USD)
G_2: The government funding for waste management (unit: USD)
G_3: The government funding for carbon emission management (unit: USD)
G_4: The government funding for infrastructure improvement (unit: USD)

Based on these decision variables, this paper derive the calculation formulas and constraints for each second-level indicator as follows (14):

$$\begin{cases} G_t = G_0 + \tau \cdot P_h \cdot T \\ W_t = W_0 - K_w \cdot G_1 \\ R_t = R_0 - K_R \cdot G_2 \\ C_t = C_0 - K_C \cdot G_3 \\ B_t = B_0 - K_B \cdot G_4 \\ T < 270 \\ 0 \le \tau \le 15 \\ G_{1+} G_{2+} G_{3+} G_4 \le G_{max} \\ G_1, G_2, G_3, G_4 \ge 0 \end{cases} \tag{15}$$

Objective function expression:

Based on the weights of each second-level indicator in the sustainable tourism evaluation system, this paper derive the calculation formula for the sustainability index as follows (16):

$$S_t = \begin{cases} 0 & \text{if } \mathrm{E}_n \ge 1 \\ k_1(G_0 + \tau \cdot P_h \cdot T) - k_2(W_0 - K_w \cdot G_1) - k_3(R_0 - K_R \cdot G_2) - k_4(C_0 - K_C \cdot G_3) - k_5(B_0 - K_B \cdot G_4) - k_6 H_t & \text{if } \mathrm{E}_n < 1 \end{cases} \tag{16}$$

3.4. Calculation of Indicator Weights in the Evaluation System

This paper use the DEMATEL method, combined with expert scoring, to calculate the influence relationships and strengths between the indicators. To quantify the relative importance of each indicator in the tourism and industry sustainability evaluation system, this paper first construct and test a judgment matrix to ensure logical consistency and decision-making rationality. Based on the network structure of the evaluation system, this paper use SuperDecision software to perform pairwise comparisons of the key indicators. After constructing and testing the judgment matrix, the software generates an unweighted supermatrix, reflecting the unweighted interrelationships and impact levels between the indicators. This paper then apply the weight information from the judgment matrix to weight the supermatrix, obtaining a weighted supermatrix. Finally, the weighted supermatrix is processed through limit normalization to derive a limit-weighted supermatrix that displays the global and local weights of each indicator. The specific calculation results are shown in Table 2:

Table 2. Weights of Each Indicator

Target Layer	Primary Indicator Layer	Secondary Indicator Layer	Local Weight	Global Weight
Optimization of Tourism Industry Structure	Economy	Tourism Industry Revenue	1.000	0.170
	Environment	Water Pollution from Tourists	0.320	0.158
		Waste Generated by Tourists	0.346	0.183
		Carbon Emissions from Tourists	0.334	0.180
	Society	Tourist Carrying Capacity	0.500	0.182
		Urban Housing Costs	0.500	0.127

3.5. Simulated Annealing Algorithm for Optimal Solution

3.5.1. Initial Value Setting

Here, this paper set the initial values for the initial temperature, termination temperature, and cooling coefficient in the simulated annealing process. The details are shown in Table 3:

Table 3. Initial Value Settings for Algorithm Parameters.

Variables Related to the Annealing Process	Values
Initial Temperature	10000.00
Termination Temperature	0.10
Cooling Coefficient	0.95

3.5.2. Algorithm Calculation Results

By observing the score and temperature changes during the annealing process (Figure 1), it can be seen that the sustainable development index gradually stabilizes after a certain number of iterations, showing no significant changes. This indicates that the factors influencing the sustainable development of the tourism industry have started to stabilize. Ultimately, the sustainable tourism index stabilizes around 1.76, indicating that the sustainable development of the tourism industry has reached a balanced state.

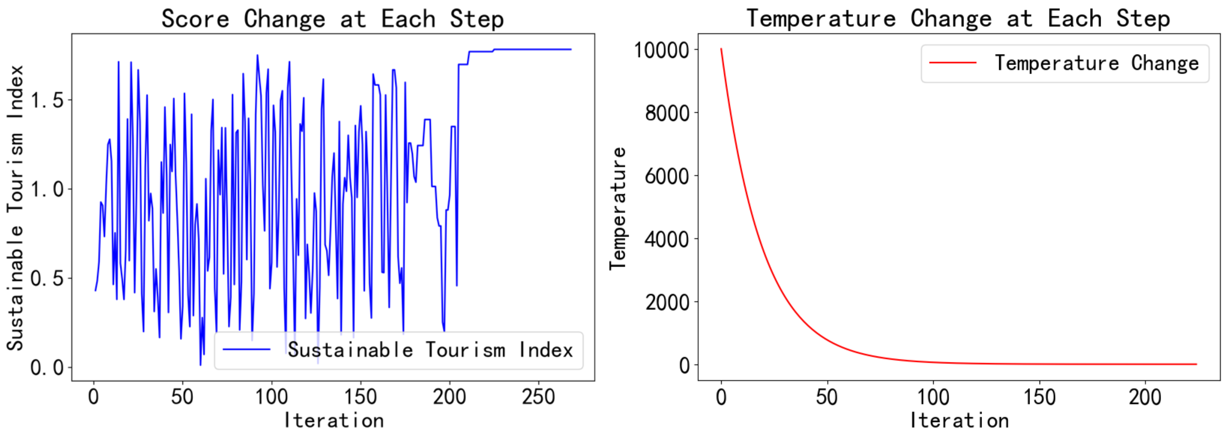

Figure 1. Change Trends in the Model Optimization Process.

3.6. Sensitivity Analysis

This paper calculated the first-order sensitivity indices for the six input variables using Sobol's variance-based sensitivity analysis. The specific calculation results are shown in Figure 2:

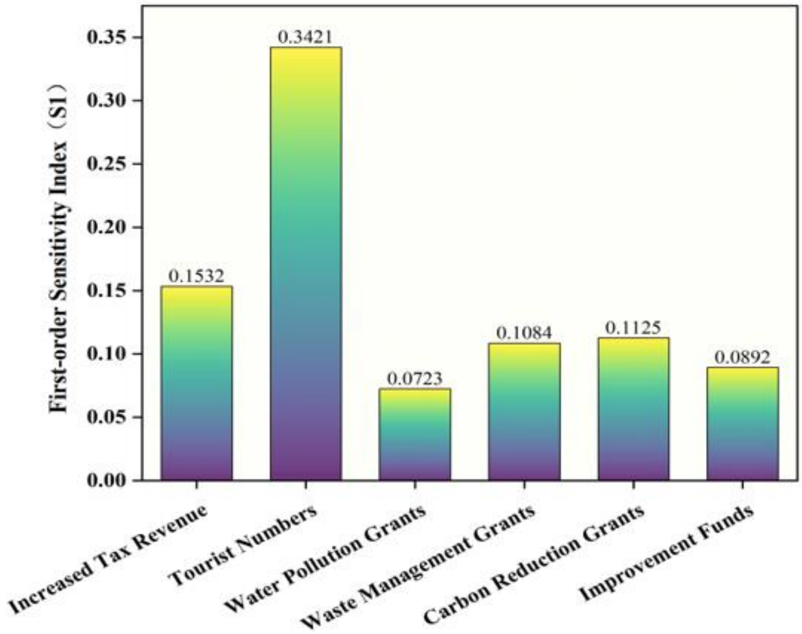

Figure 2. First-order Sensitivity Index of Each Parameter.

At the same time, this paper also calculated and displayed the second-order sensitivity index matrix, which shows the impact of the interaction between input variables on the sustainability tourism index. The results are shown in Figure 3:

Figure 3. Second-order Sensitivity Index Heatmap.

First - order and second - order sensitivity analyses indicate that the number of tourists is a key factor influencing the sustainable tourism index, having a significant impact on economic, environmental, and social sustainability. Therefore, controlling the number of tourists and managing tourist flows rationally are crucial for promoting the development of sustainable tourism. In addition, tax is also important as it indirectly supports sustainable development by providing funds for environmental protection and infrastructure construction. The interaction between the number of tourists and tax, especially in terms of fund allocation and management, directly affects the effectiveness of sustainable tourism.

3.7. Construction of the Tourist Diversion Optimization Mode

3.7.1. Construction of the Diversion Effect Function

In response to the imbalance of tourist numbers at different attractions, this paper established a tourist classification optimization model. The calculation formula for the diversion effect index is as follows:

$$TR = \sum_{i=1}^{n} (\frac{T_i - T_i^{opt}}{T_i^{opt}})^2 + \lambda \sum_{i=1}^{n} e^{0.02} \left(T_i - T_i^{opt}\right), \tag{17}$$

$$\sum_{i=1}^{n} T_i \leq T_{max}, \tag{18}$$

Where TR is the diversion effect index, T_i represents the number of tourists at the i-th attraction, T_i^{opt} represents the optimal number of tourists at the i-th attraction, m is the weight coefficient that controls the influence of the second term on the first term, and the second term is a penalty term used to promote the balance of tourist diversion. T_{max} Represents the maximum total number of tourists, and n is the number of attractions.

3.7.2. Construction of the Optimization Model

The optimization model for the flow - diversion effect index is based on the comprehensive goal of optimizing the distribution of tourist flow and the efficiency of resource utilization. The basic steps of its construction are shown in Figure 4:

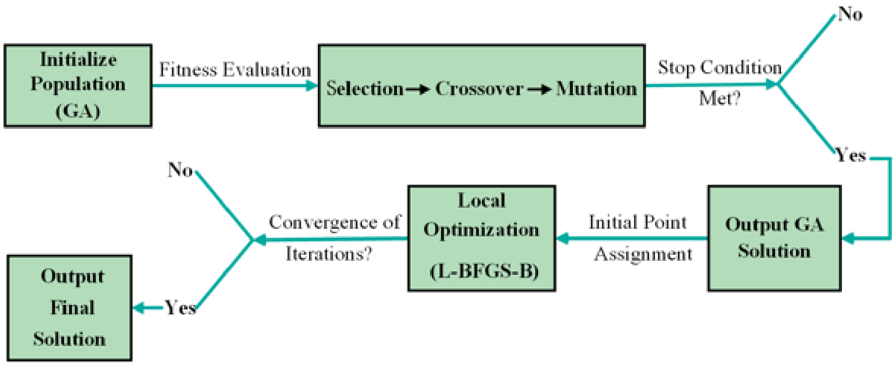

Figure 4. Diversion Effect Index Optimization Model Process.

3.7.3. Model Validation

To verify the specific effects of the diversion model, this paper selected Venice, a city with severe imbalance in tourist numbers at its attractions, to simulate the diversion model. The simulation results are shown in Table 4:

Table 4. Simulation Results.

Attractions	Original Average Daily Tourists	Optimized Tourists
St. Mark's Basilica	16000	18623
St. Mark's Square	45000	38795
Grand Canal of Venice	30000	28067
Doge's Palace	7000	11376
Rialto Bridge	12000	13139

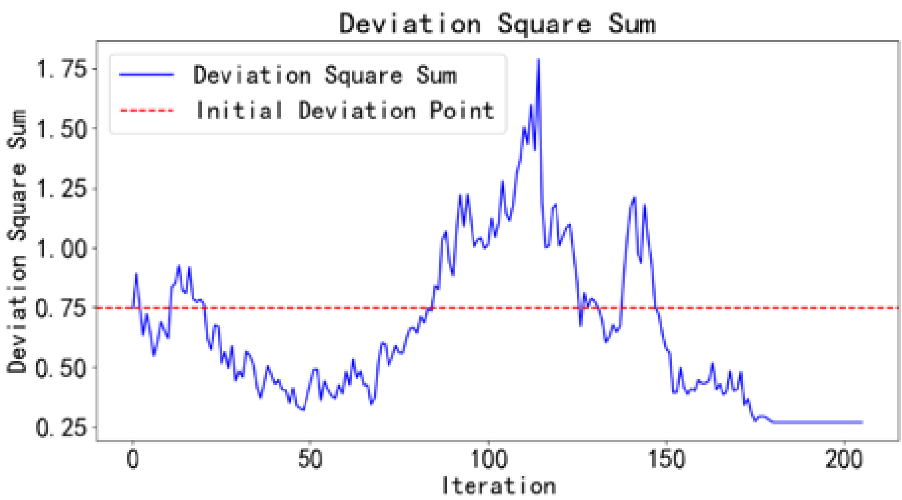

Figure 5. Simulation Results.

Through a detailed analysis of the simulation results (Figure 5), this paper found that the initial diversion effect index was 0.7458. This indicates that, without any diversion measures, the distribution of tourists between attractions was very uneven. This paper then applied the diversion model to reasonably adjust and allocate the number of tourists at each attraction. After applying this model, the diversion effect index significantly decreased to 0.2693, demonstrating the effectiveness of the diversion model in optimizing tourist distribution and alleviating pressure on the attractions.

4. Conclusions

This study integrates three major dimensions: economic, environmental, and social, to construct a comprehensive framework for assessing the sustainable tourism development of Juneau, Alaska, USA. Through DEMATEL-ANP analysis, this paper revealed significant cross-dimensional interactions, with the environmental pressure indicator (particularly the waste pollution index, with a global weight of 0.183) having the strongest impact on the overall sustainability index. By applying the simulated annealing algorithm, this paper derived the optimal solution for the sustainability tourism index while ensuring that environmental and social pressures remained within moderate ranges. Through sensitivity analysis, this paper found that the number of tourists had the greatest impact on the sustainability tourism index. In response to the number of tourists, this paper constructed a tourist diversion optimization model and applied it to the five major attractions in Venice. The results showed that after applying the tourist diversion optimization model, the pressure on tourist numbers at the five attractions in Venice was alleviated, providing feasible insights for balancing tourism growth, ecological protection, and social welfare.

Although this model is effective for evaluating tourism systems with clear structures and complete data, it still has certain limitations:

Limited applicability: For tourism cities with irregular structures and large dynamic data changes, the model may require frequent adjustments and updates to its parameters, affecting its stability and applicability.

Data sensitivity: If the input data contains noise or instability, or if the parameters are improperly selected, it could amplify data issues and reduce the model's robustness in complex tourism cities, impacting the reliability of decision-making.

In the future, we will address these limitations by studying the complex characteristics of tourism environments, developing adaptive model structures and algorithms. At the same time, we will apply data preprocessing techniques and combine intelligent algorithms to optimize parameter selection, improving the model's robustness to unstable data.

References

[1] Rahmadian E, Feitosa D, Zwitter A. A systematic literature review on the use of big data for sustainable tourism [J]. Current Issues in Tourism, 2022, 25(11): 1711-1730.

[2] Choi H S C, Sirakaya E. Sustainability indicators for managing community tourism [J]. Tourism management, 2006, 27(6): 1274-1289.

[3] Guan Mengjie. Research on the Coupling and Coordination between Tourism Industry Development and Economic Resilience: A Case Study of Henan Province [J]. Journal of Sanmenxia Polytechnic, 2024, 23(01): 105 - 114.

[4] Baloch Q B, Shah S N, Iqbal N, et al. Impact of tourism development upon environmental sustainability: a suggested framework for sustainable ecotourism [J]. Environmental Science and Pollution Research, 2023, 30(3): 5917-5930.

[5] Castanho R A, Santos C, Couto G. Creative tourism in islands and regional sustainable development: What can we learn from the pilot projects implemented in the Azores territory? [J]. Land, 2023, 12(2): 498.

[6] Su J. Water resources utilization and tourism environment assessment based on water footprint [J]. Open Geosciences, 2023, 15(1): 20220564.

[7] Garcês S, Pocinho M, de Jesus S N. Madeira Tourists Profile A Positive Psychology Approach [M]//Managing Destinations. Emerald Publishing Limited, 2024, 14: 69-83.

[8] Colasante A, D'Adamo I, De Massis A, et al. An exploratory study of stakeholder views on the sustainable development of mountain tourism [J]. Sustainable Development, 2024.

[9] Liu Jia, Hou Jiajia, Qi Ying. Research on the Optimization Evaluation of China's Tourism Industry Structure Based on the DEMATEL - ANP Model [J]. Geography and Geo - Information Science, 2021, 37(06): 102 - 112.

[10] Kirkpatrick S, Gelatt Jr C D, Vecchi M P. Optimization by simulated annealing [J]. Science, 1983, 220(4598): 671-680.