Multi-Objective Optimization Study on Tourism Destination Sustainable Development Based On NSGA-II

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Abstract. Against the backdrop of the booming global tourism industry, how to crack the development dilemma of tourism destinations between economic benefits, environmental protection and residents' well-being has become a key issue to be solved. In this study, a multi-objective dynamic optimization model based on the Non-dominated Sorting Genetic Algorithm (NSGA-II) is constructed for the city of Akureyri, Iceland, as a typical case, in response to the composite challenges of glacier recession, out-migration of residents and financial pressure triggered by the surge of its cruise tourism. By integrating 12 key indicators in the three dimensions of tourism income, carbon emission, and residents' satisfaction from 2007 to 2022, and combining the hierarchical analysis method to determine the weighting system of economy (α=0.5), environment (β=0.3), and society (γ=0.2), the model reveals that the number of tourists and the per capita consumption price are the key sensitivity parameters, where a change in the number of tourists by ±10% will lead to fluctuations in income ± 15.8% and carbon emission change ±7.3%. The model validation shows that the dynamic regulation of attraction diversion strategy and seasonal price adjustment mechanism provides a quantifiable decision-making framework for global tourist cities to solve the triangle paradox of "development-ecology-livelihood".

Keywords: Sustainable Tourism, Multi-Objective Optimization, Tourist Destination Management, NSGA-II.

1. Introduction

With the rapid development of global tourism, the issue of sustainable development of tourism destinations has become increasingly prominent. While pursuing economic benefits, how to balance the multidimensional goals of ecological and environmental carrying capacity, residents' well-being and tourism growth has become an important challenge to current tourism development. The traditional tourism development model is often oriented to a single economic indicator, ignoring environmental costs and social impacts, leading to ecological degradation and social conflicts in many tourist destinations. Especially in the global context of carbon peak carbon neutrality, the issue of carbon emissions from tourism activities has attracted much attention. In Akureyri, Iceland, the surge of tourists brought by glacier tours has created economic benefits but accelerated glacier melting and triggered a chain reaction of out-migration of residents and overloaded infrastructures. This phenomenon reveals the urgency of a paradigm shift in tourism development: it is necessary to build a dynamic regulatory mechanism to ensure economic vitality while solving the complex dilemma of ecological threshold breakthroughs, declining social satisfaction, and financial pressure on the government.

This study takes the city of Akureyri, Iceland, as an empirical object, and intends to explore the sustainable development path of tourism through the method of mathematical modeling. First, we systematically integrate the historical data of the city's tourism revenue, carbon emission intensity, and residents' satisfaction, and use the least squares method to analyze the linear correlation between the variables, to establish the framework of the multi-objective dynamic optimization model. Second, the solution strategy is designed based on the non-dominated sorting genetic algorithm (NSGA-II), and the weighting relationships among economic, environmental, and social objectives are quantified by the hierarchical analysis method (AHP), and the sensitivity test is introduced to identify the key regulatory parameters. Further, a synergistic mechanism of attraction diversion and dynamic pricing is proposed to be constructed by combining the climate cycle and tourists' behavioral characteristics, so as to form a decision support system for sustainable development that takes into account both science and operability.

2. Multi-objective Optimization Methodology

2.1. Multi-objective optimization model construction and key algorithms

This study constructs a multi-objective optimization framework based on the Non-dominated Sorting Genetic Algorithm (NSGA-II), as shown in Figure 1. The algorithm maintains population diversity through non-dominated sorting, combines with congestion calculation to realize the uniform distribution of Pareto frontiers, and effectively balances the competitive relationship between multiple objectives[1].

In the process of establishing the optimization model, the linear regression method is firstly used to quantitatively analyze the historical dataset to reveal the mathematical correlation between the influencing factors and the comprehensive utility. The contradiction between resource allocation and constraints in multi-objective optimization is systematically dealt with through the introduction of max-min function, which shows unique mathematical advantages in scheduling optimization and game equilibrium analysis[2].

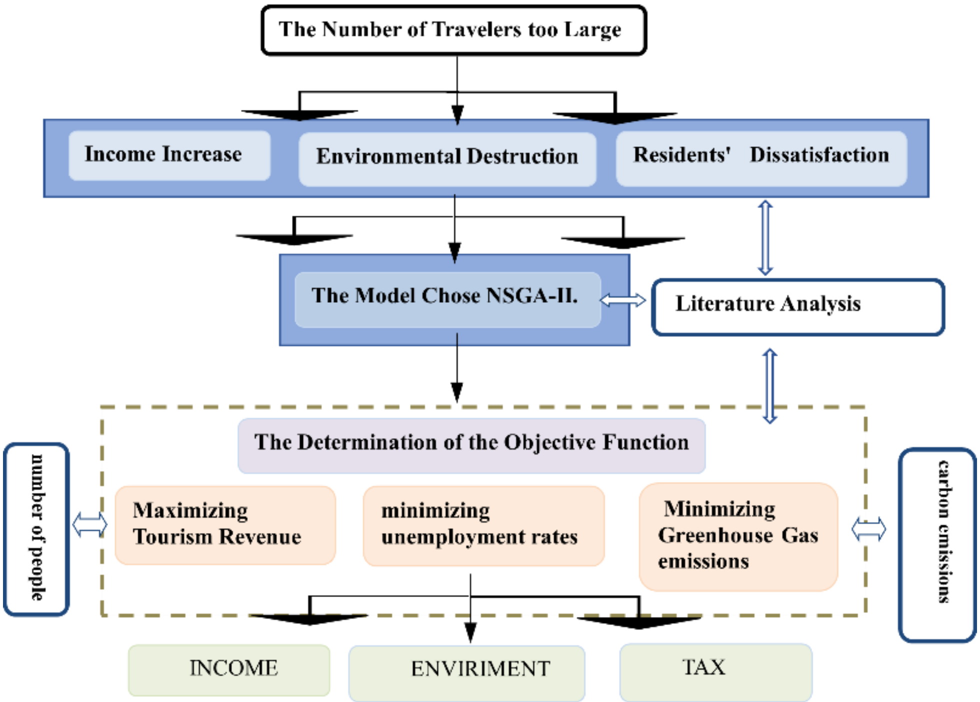

Figure 1. The Multi-objective Optimization Methodology

2.2. Dynamic weight optimization and sensitivity study

In the optimization stage of model parameters, the hierarchical analysis method is used to establish the dynamic weight adjustment mechanism. By constructing a recursive hierarchical structure, the relative importance of each element is quantitatively assessed, and the adaptive updating of the weights of the objective function is realized.

Especially, developing a sensitivity analysis module based on Monte Carlo simulation systematically investigated the marginal impact of different parameter combinations on the optimization results[3]. Through the establishment of a three-dimensional response surface model, the nonlinear relationship between the key parameters and the optimization objectives is visualized, providing decision makers with a multi-dimensional basis for the selection of solutions. This composite analysis method not only improves the robustness of the optimization results, but also effectively identifies the vulnerable links in the system operation.

3. Multi-objective Modeling for Sustainable Tourism Development

3.1. Multi-objective optimization model construction

3.1.1 Underlying assumptions of the model

Considering that the multidimensional interaction between ecological protection and tourism development is highly complex and characterized by dynamic evolution, this study makes the following key assumptions in order to construct an operational multi-objective optimization model, while ensuring the integrity of the core scientific issues:

First, to address the difficulty of quantifying the value of ecosystem services, this study adopts carbon equivalent as a comprehensive metric. Specifically, taking the glacier tourism scenario in the Akureyri region as an empirical object, multiple ecological impacts such as ecological footprints and biodiversity loss are uniformly converted into carbon consumption equivalents for accounting (data source: https://ust.is). The assumption is based on the IPCC greenhouse gas accounting methodology framework, and the monetized assessment of ecological impacts is realized by establishing a quantitative relationship model between the glacier ablation rate and tourists' carbon footprint[4].

Second, at the level of multi-objective optimization system architecture, it is assumed that the three core elements, namely economic benefits, ecological costs and social benefits, have fully elastic adjustment characteristics. That is, the weighting coefficients between different objective functions can be dynamically adjusted according to real-time monitoring data, and the adjustment process does not generate additional conversion costs[5]. This setting enables the model to effectively capture the dynamic equilibrium point of each stakeholder's demand through parameter sensitivity analysis, providing theoretical support for the formulation of tourism management programs that take sustainable development into account.

3.1.2 Quantitative analysis of the objective function

First of all, in the process of maximizing the multi-objective subjective benefits using NSGA-II, it is necessary to analyze what are the crucial factors that will have positive and negative benefit effects on the total benefits based on a large number of readings of the literature, the total objective benefit function of this paper is then positioned to maximize the income (f_1), minimize the emissions (f_2), and increase the satisfaction of the residents (f_3)[6].

(1) Quantification of tourism revenues: According to economic principles, revenues are equal to the price multiplied by the number of people, and the cost can be expressed in terms of spending per capita as follows (data source: https://www.ferdamalastofa.is/):

$$f_1 = N \times P \tag{1}$$

(2) Quantification of ecological costs: this can be quantified as the carbon emissions of the population multiplied by the total number of people traveling, using the formula:

$$f_2 = 0.0729 \times N \tag{2}$$

(3). Resident satisfaction quantification: according to the reading material, can be quantified: satisfaction with per capita income, satisfaction with population density, satisfaction with taxation, satisfaction with the environmental impact, the specific formula (data source: https://statice.is/):

$$f_3 = min\left(S_{\text{income}}, S_{\text{environmental}}, S_{\text{density}}, S_{\text{tax}}\right) \tag{3}$$

The impact factor of resident satisfaction is modeled as:

Per capita income satisfaction:

$$S_{\text{income}} = \frac{\text{real income } - \text{ min income}}{\text{max income } - \text{ min income}} \tag{4}$$

(Note: The number of residents does not very much in the historical data, which varies by less than double the standard deviation, so reasonable assumptions were made to establish the historical data as a fixed value, and the historical mean was chosen as the value for the number of residents.)

Environmental satisfaction:

$$S_{\text{environmental}} = \frac{f_{2\text{max}} - f_{2\text{real}}}{f_{2\text{max}} - f_{2\text{min}}} \tag{5}$$

Population density satisfaction:

$$S_{\text{density}} = \frac{\text{max density } - \text{ real density}}{\text{max density } - \text{ min density}} \tag{6}$$

Tax satisfaction:

$$S_{\text{tax}} = \frac{\text{real tax } - \text{ min tax}}{\text{max tax} - \text{min tax}} \tag{7}$$

3.1.3 Model constraint setting

And it is obtained based on historical data regression: supply and demand constraints:

$$N \leq 2{,}896{,}560.5 - 640.5P \tag{8}$$

Emission cap constraints:

$$\mathrm{f}_2 = 0.0729 \times \mathrm{N} \leq 113{,}587(\text{Maximum emissions 2012}) \Rightarrow \mathrm{N} \leq 2{,}227{,}196 \tag{9}$$

3.2. Utility function design for sustainability

According to the max-min algorithm, the sliding window method calculates the historical mean value of 0.605 based on the historical data of residents' satisfaction. Statistical tests show that this value can effectively characterize the level of satisfaction under regular operation. Thus, a sustainable development utility function is established to determine the optimal solution between multiple objectives quantitatively[7].

$$y = \alpha \cdot \frac{f_1 - f_{1\text{min}}}{f_{1\text{max}} - f_{1\text{min}}} - \beta \cdot \frac{f_{2max} - f_2}{f_{2\text{max}} - f_{2\text{min}}} + \gamma \cdot f_3 \tag{10}$$

where $\alpha, \beta, \gamma \geq 0$, and $\alpha + \beta + \gamma = 1$.

The core purpose of introducing standardization in the utility function of sustainable development is to eliminate the heterogeneity of the scale and the conflict of the target direction, to normalize the multiple targets to the [0,1] interval through linear mapping, to ensure the fairness of the trade-offs between the economic, environmental, and social targets, and to enhance the scientific and balanced decision-making of the multi-attribute decision-making.

3.3. Hierarchical analysis method of weight determination

The weights of the objective function $y = \alpha \cdot f_1 - \beta \cdot f_2 + \gamma \cdot f_3$ were scientifically assigned by the hierarchical analysis method (AHP)[8].

(1) Hierarchical construction

The objective layer is constructed to maximize the combined utility of sustainable tourism. The guideline layer has tourism revenue, carbon emissions,

Resident Satisfaction. The program layer represents the strategy choices under different combinations of weights.

(2) Judgement matrix building

A two-by-two comparison of guideline level importance (1 - 9 scale method):

$$\begin{array}{cccc} & f_1 & f_2 & f_3 \\ f_1 & 1 & 3 & 5 \\ f_2 & 1/3 & 1 & 2 \\ f_3 & 1/5 & 1/2 & 1 \end{array} \tag{11}$$

f_1 Significantly more important than f_2(scale 3) in regional development, where the urgency of economic growth is significantly higher than environmental constraints (e.g., pressure to lift people out of poverty, employment needs)[9].

f_1Extremely important (scale 5) than f_3, reflecting the fact that short-term economic gains may be prioritized over long-term social benefits (e.g., resident satisfaction needs to be gradually increased through the monetary base) and that growth of the local economy is usually the primary goal of government.

f_2 Slightly more important than f_3 (Scale 2), it is clear that environmental issues (e.g., carbon emissions). However, secondary to the economy, it needs to be controlled through policy and technical means to avoid ecological collapse that could have a backlash on social stability. For example, excessive carbon emissions may lead to health problems for the population or degradation of tourism resources.

(3) Weighting and consistency tests

The eigenvector method calculates the weights:

$$\alpha = 0.557, \beta = 0.320, \gamma = 0.123 \tag{12}$$

Normalization process: the weights were fine-tuned to enhance interpretability in the context of the study and finally rounded to:

$$\alpha = 0.5, \beta = 0.3, \gamma = 0.2 \tag{13}$$

Consistency test: Maximum eigenvalue $\lambda_{\max} = 3.024$, consistency ratio $CR = 0.021 < 0.1$, passes the test.

(4) Rationalization of weights

Economic income is weighted at $\alpha = 0.5$, which needs to be prioritized; environmental constraints are weighted second at $\beta = 0.3$, with carbon emission control as the key constraint; social equilibrium is weighted at $\gamma = 0.2$, with resident satisfaction reflecting long-term stability, which has the lowest weight but cannot be ignored.

3.4. NSGA-II Algorithm Implementation and Optimization

3.4.1 Pareto Frontier Solution Mechanism

Pareto Frontier Solutions for NSGA-II is a core concept in multi-objective optimization problems, and NSGA-II is an efficient algorithm for solving Pareto frontier solutions.

Least squares linear regression is a classic statistical method for modeling the linear relationship between the dependent (target) variable and one or more independent variables (features). It is one of the most basic and widely used data analysis and machine learning techniques. The core rationale for using the non-dominated sorting genetic algorithm (NSGA-II) in the multi-objective optimization model for sustainable tourism lies in its ability to handle complex multi-objective conflicts and solution-set diversity and constraints systematically.

3.4.2 NSGA-II Algorithm Flow Design

Genetic Algorithm (NSGA-II) Initialization of stocks for the number of travelers.

First, determine the range of variables on the number of travelers and price[10]:

$$\mathrm{N} \in [117{,}000\,, 2{,}227{,}196], \mathrm{P} \in [2{,}334\,, 5{,}000] \tag{14}$$

Population size: generate M = 150 individuals, use Latin hypercube sampling to ensure a uniform distribution and make a rejection check for individuals that do not satisfy the constraints. Adaptation multi-objective function values were calculated for each individual, including utility values and constraint penalty terms.

Second, solve(x) dominance solution(y) according to the dominance relation, if and only if:

$$(\forall k \in \{1,2,3\}, f_k(x) \geq f_k(y)) \text{ (for maximization goals)}, (\exists j, f_j(x) > f_j(y) \tag{15}$$

Divide the population into frontiers, where Front 1 is the optimal non-dominated solution.

Normalized to the target values,

$$\widetilde{f_k} = \frac{f_k - f_{k\min}}{f_{k\max} - f_{k\min}}, \mathrm{k} = 1,2,3. \tag{16}$$

Third, calculate the crowding distance for each individual:

$$\mathrm{Distance(i)} = \sum_{\mathrm{k}=1}^{3} \left(\widetilde{\mathrm{f_k}}(\mathrm{i}+1) - \widetilde{\mathrm{f_k}}(\mathrm{i}-1) \right) \tag{17}$$

Then, a tournament selection method was used to select individuals with low frontier rank and large crowding distances; crossover and mutation operations were performed to generate new individuals. Iterative optimization.

Finally, the parent and child generations are merged, and the first 150 non-dominated solutions are selected as the new generation population until the maximum number of iterations (200) is reached or the objective function converges[11].

Based on the data analysis, a 3D map of the Pareto frontier is shown in Figure 2 to show the trade-offs between income, emissions, and satisfaction, and the maximum value of the sustainability utility function is output as the optimal solution proposal.

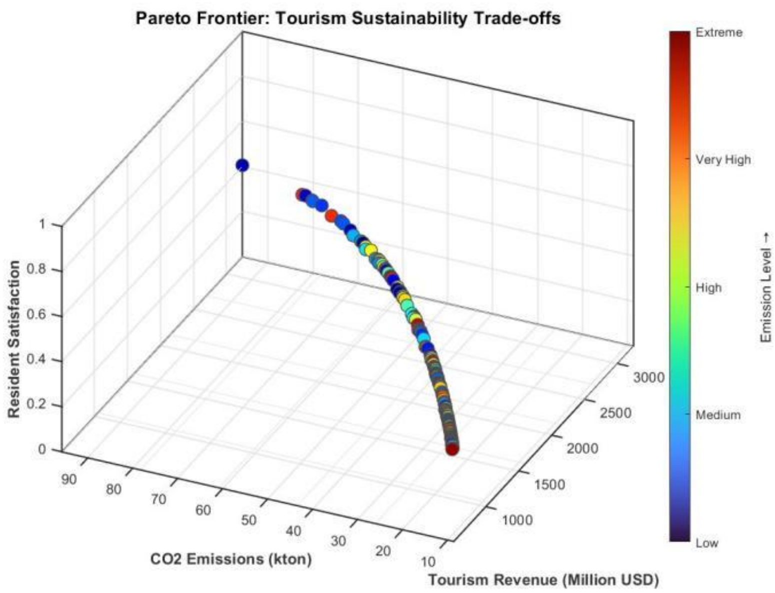

Figure 2. The 3D map of the Pareto frontier

4. Results and Discussion

4.1. Multi-objective decision modeling sensitivity analysis

4.1.1 Price parameter sensitivity characteristics

As shown in Figure 3, a price sensitivity test was performed. From the figure, it can be seen that the price change causes the exact change off_1 andf_2, and the rate of change off_2 is always higher than that off_1, but it has no effect on f_3. Meanwhile, the rate of change off_1 andf_2 is always lower than the rate of change of price; if the price changes by 10%, the rate of change of f_1 andf_2 will be below 10%. Therefore, when fed into the final result, the rate of change of the result must also be lower than the rate of change of the parameter[12].

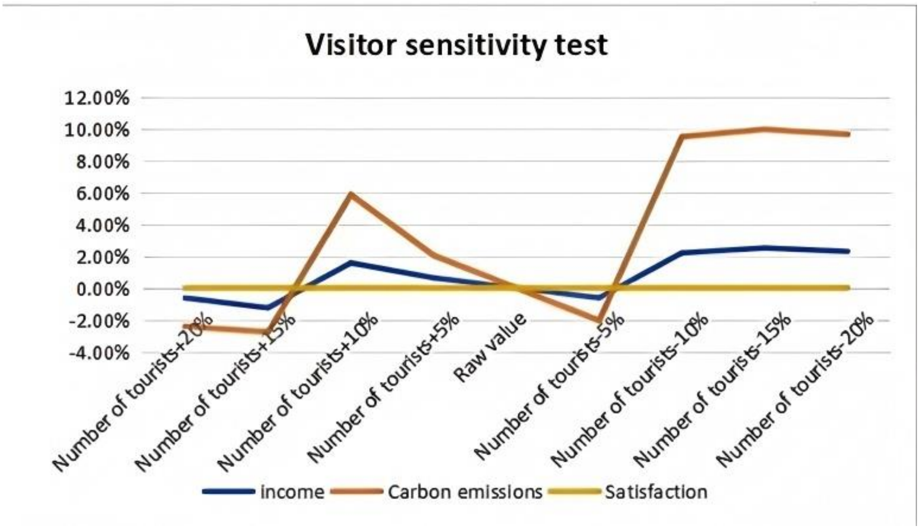

Figure 3. The price parameter sensitivity characteristics

4.1.2 Dynamic response to tourist numbers

Sensitivity tests were then performed on the number of visitors. As shown in the figure 4, t is found that f_1 and f_2 are more variable. Therefore, relative to Figure 3, it is concluded that the number of tourists is more sensitive than the price. However, it is also found thatf_1 andf_2 do not move in the same direction when the parameter changes. For example, when the number of tourists is increased by 20%, f_1 andf_2 are lower than the original values. But when the number of tourists increases by 10%, $f_1$and f_2 are higher than the original values. It can be seen that the change in the constraint value of the number of tourists can have a significant impact on the model[13].

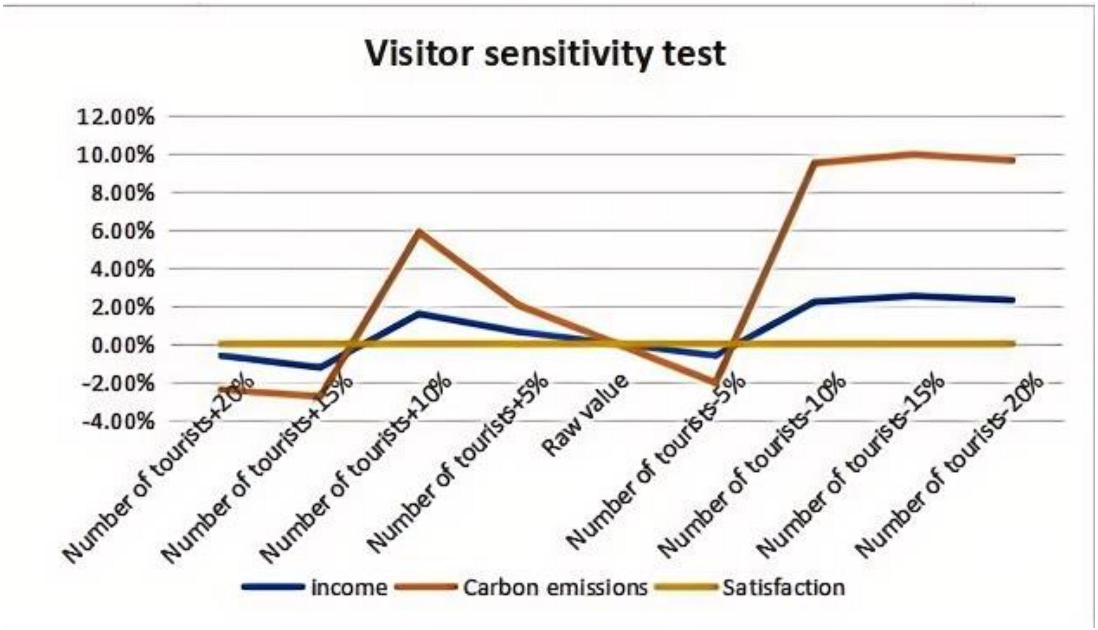

Figure 4. The dynamic response to tourist numbers

4.2. Dynamic evolution diagram for future data testing

The values were brought into the model of NSGA-II to generate a picture by projecting future data; shown in figure 5, the statistics of tourism development from 2023 to 2027; it can be seen.

(1) Tourism revenue (blue bar chart):

From 2023 to 2027, tourism revenues show a yearly increase. Besides, tourism revenues in 2023 will be approximately 8 million; by 2027, they are expected to grow to nearly 11 million dollars. And, it shows that tourism has developed well, and revenues have steadily increased.

Tourism revenues exhibit a steady annual growth trajectory, increasing from approximately 8 million in 2023 to a projected 11 million dollars by 2027, reflecting sustained sectoral development and stable financial expansion.

(2) Carbon dioxide emissions (red line graph):

The analysis reveals a downward trend in CO_2 emissions from 85 kilotons in 2023 to a projected 75 kilotons by 2027, indicating that tourism industry growth aligns with proactive measures to reduce environmental impacts and enhance sustainability.

(3) Resident satisfaction (green line graph):

Resident satisfaction remained relatively stable throughout the period, with slight fluctuations.

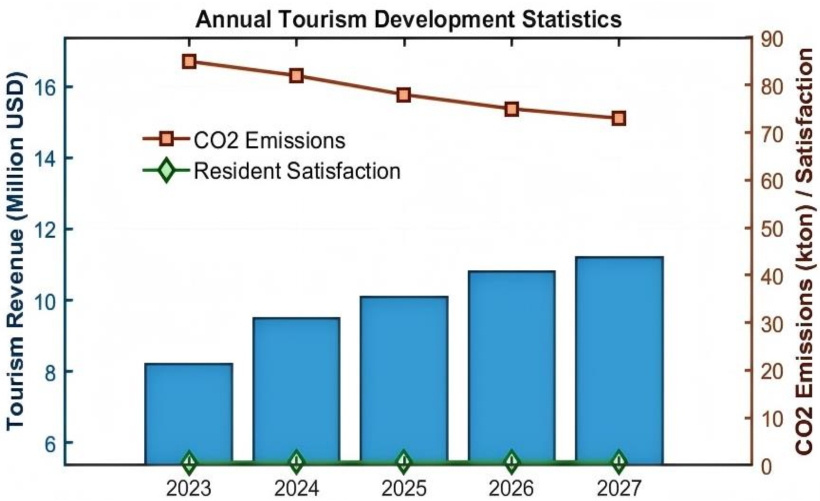

Figure 5. The dynamic evolution diagram for future data testing

4.3. Regression analysis of seasonal influences

The NSGA-II projections show that the tourism industry has not only grown in revenue between 2023 and 2027 but has also made progress in reducing carbon dioxide emissions while maintaining a high level of resident satisfaction. This suggests that tourism development is sustainable, able to increase revenues while reducing environmental impacts, and supported and recognized by residents. This balanced development pattern is beneficial for both the long-term health of the tourism industry and the sustainability of the environment.

In the least squares linear regression analysis of travel influences, it was obtained that visitor numbers and revenues peaked in March and April, then tapered off, reaching a low in July and August and picking up again in the fall. Fares are higher in the spring, lower in the summer, and picked up again in the fall[14]. These metrics reflect tourism operations due to seasonal variations that may be related to factors such as weather and vacations, and the results are shown in Figure 6.

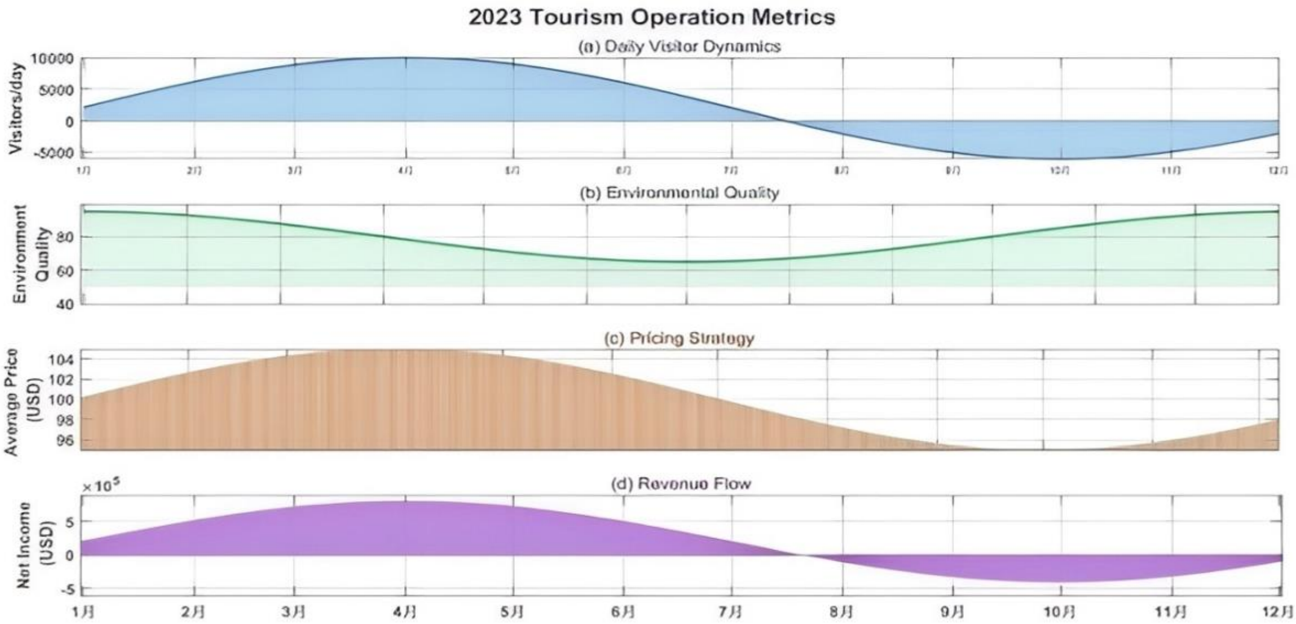

Figure 6. The regression analysis of seasonal influences

5. Conclusions

This study develops a multi-objective optimization framework for sustainable tourism development in Akureyri, Iceland, integrating economic, environmental and social objectives through the NSGA-II algorithm and an AHP-based dynamic weighting approach. By analyzing historical data from 2007 to 2022, the model identifies tourist arrivals and per capita consumption as key sensitivity parameters, with ±10% variations in tourist arrivals leading to significant changes in revenues (±15.8%) and carbon emissions (±7.3%). Validation results show that strategies such as attraction diversion and seasonal price adjustment effectively reconcile the "development-ecology-livelihoods" trade-off, and that by 2027, revenues are projected to grow steadily (US$8 million to US$11 million), carbon emissions are projected to decrease (85,000 tons to 75,000 tons), and resident satisfaction is projected to remain stable. However, the model has limitations, including reliance on historical data from a single geographic region and simplifying assumptions in quantifying resident satisfaction. Future research could expand the applicability of the model by incorporating cross-regional data sets, refining satisfaction indicators through qualitative surveys, and exploring adaptive weight adjustment mechanisms with real-time feedback.

The framework presented in this paper combines NSGA-II to provide a replicable approach to sustainable tourism management and demonstrates its feasibility in balancing conflicting objectives. This approach enables decision makers to quantify the trade-offs between economic growth, environmental protection, and social equity, providing actionable insights for destinations facing similar challenges. By integrating dynamic sensitivity analysis and Pareto optimal solutions, the study demonstrates how multi-objective optimization can systematically address the complexities of sustainable development, paving the way for scalable applications in global tourism management.

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