Mathematical Modeling and Algorithm Application
ISSN: 3006-0842 | Vol. 6, No. 2, 2025

Research on Sustainable Development of Tourism Industry in Juneau Based on Nonlinear Optimization

Tianshu Wang[1, *], Jiajun Li[2], Wenshuo Zhang[3] and Xiaxia Cui[4]

[1]School of Emergency Management, Xihua University, Chengdu, China

[2]School of Chemical Engineering, Shenyang University of Chemical Technology, Shenyang, China

[3]School of Mechanical and Power Engineering, Shenyang University of Chemical Technology, Shenyang, China

[4]School of Economics and Management, Shenyang University of Chemical Technology, Shenyang, China

[*] **Corresponding author**: Tianshu Wang

Abstract: This study constructs a comprehensive mathematical model to assess the current state of tourism development in Juneau and propose sustainable optimization strategies. The model integrates key factors such as visitor numbers, carbon emissions, infrastructure pressure, and resident satisfaction. Aiming to maximize economic benefits and minimize environmental and social costs, it incorporates a feedback mechanism to characterize the dynamic redistribution of tourism revenue across infrastructure, environmental protection, and community welfare investments. Sensitivity analysis verifies the robustness of the model. The model is further extended to overtourism cities such as Xi'an. Using the analytic hierarchy process (AHP) to identify core influencing factors, a strategy for attracting less popular attractions based on dynamic pricing, facility improvements, and transportation optimization is proposed. Finally, multi-objective coordinated optimization is achieved by adjusting weights and pricing parameters. Prediction results indicate that this strategy can increase tourism revenue by approximately 20% while reducing carbon emissions by approximately 15%, providing a quantifiable and scalable decision-making framework for addressing overtourism and achieving sustainable urban tourism development.

Keywords: Nonlinear optimization, feedback mechanism, sensitivity analysis, Analytic Hierarchy Process, dynamic pricing strategy

1. INTRODUCTION

With the rapid development of the global tourism industry, sustainable tourism has become a core issue in balancing economic growth, ecological protection, and social harmony. Tourism in Juneau, Alaska, is key to increasing local economic revenue and enhancing its reputation. However, it faces tensions between development and sustainability, such as overtourism, ecological pressures, inadequate infrastructure, and imperfect income distribution mechanisms. Many destinations around the world face similar challenges. While existing research has proposed sustainable tourism concepts and strategies, there is a lack of personalized and systematic sustainable tourism models for natural ecotourism cities like Juneau, and no comprehensive framework for practical implementation. Therefore, developing a sustainable tourism model tailored to Juneau and constructing an optimized framework can not only alleviate these challenges and ensure the long-term sustainability of the tourism industry, but also provide a reference for similar destinations around the world, with important theoretical and practical significance.

In recent years, data-driven modeling methods have been widely used in urban system analysis, especially in the fields of housing price prediction and urban governance, showing great potential. Studies by Xu Dandan [1], Cui Huiying [2], Zhou Liangjin et al. [3] have shown that models such as multivariate linear regression, BP neural network and random forest have excellent performance in capturing complex nonlinear relationships, providing effective tools for predicting urban economic variables. Li Jing [4] further pointed out that big data statistical analysis is being deeply integrated into urban planning, supporting scientific decision-making and optimal resource allocation. In terms of urban sustainable development, Hu Zhichao et al. [5] constructed an urban resilience assessment system, emphasizing the dynamic response to environmental and social pressures through feedback mechanisms, reflecting the key role of system modeling in improving urban adaptability. However, existing research mostly focuses on a single field, and there is still a lack of quantitative models for the coordinated optimization of economic benefits, environmental impacts and residents' welfare in the tourism industry. Drawing on the above modeling methods, this paper constructs a dynamic mathematical model that integrates tourist numbers, carbon emissions, infrastructure pressure, and resident satisfaction. It introduces a feedback mechanism to characterize the long-term effects of policy regulation, and identifies key influencing factors through sensitivity analysis. It proposes an optimization strategy based on dynamic pricing and attracting non-popular attractions, providing a quantifiable and scalable decision-making support framework for the sustainable development of urban tourism.

2. STUDY DESIGN

2.1. Sustainable tourism model

The construction of the objective function involves the integration of key variables representing economic benefits, environmental impact, and social well-being. By defining these variables and establishing appropriate relationships among them, the objective function is formulated to maximize economic gains while minimizing environmental degradation and maintaining high levels of resident satisfaction. This balanced approach ensures that the model aligns with the principles of sustainable development and provides a robust framework for decision-making in tourism management.

The daily standard function $Q_{objective}(V, P_1, P_2, P_3)$ is delineated into four distinct components, as outlined below:

2.1.1. Economic income

$$I(V) = V * R + k * V \tag{1}$$

R represents the per capita consumption, which quantifies the average expenditure of each tourist. This parameter is crucial for assessing the economic impact of tourism on the local economy; k denotes the ratio coefficient of additional income relative to the number of tourists. This coefficient facilitates the evaluation of how incremental tourist numbers translate into increased revenue, thereby enabling a more nuanced understanding of the economic benefits derived from tourism activities.

2.1.2. Carbon emission

$$C_{(v, I_{env})} = \alpha * V + \beta * V^{1.5} - k_2 * I_{env} \tag{2}$$

α, β: Emission coefficients reflecting the baseline and accelerated growth of emissions due to increased tourist traffic. k_2:An emission-reduction coefficient, reflecting how effectively environmental investments can counteract additional carbon emissions. I_{env} :The total expenditure dedicated to environmental protection or emission abatement

2.1.3. Infrastructure pressure

$$(V, I_{infa}) = \gamma * V + \delta * V^{1.5} - k_1 I_{infa} \tag{3}$$

γ,δ: Infrastructure pressure coefficients, indicating how infrastructure demand escalates under both normal and high-load conditions. k_1: A coefficient denoting the effectiveness of infrastructure investment in reducing stress on existing systems (e.g., transportation, water supply, electricity). I_{infa}:The total funding dedicated to developing or upgrading infrastructure to accommodate the increased tourist flow.

2.1.4. Resident satisfaction

$$S(V, I_{comm}) = S_0 * exp(-\zeta * V) - k_3 I_{comm} \tag{4}$$

S_0: Baseline (initial) satisfaction level in the absence of tourism-induced disruptions. ζ : A sensitivity parameter dictating the exponential decay of satisfaction with respect to the tourist volume. k_3: The “cost” coefficient for community welfare investments, capturing how these expenditures impact the net satisfaction measure within the model’s formulation. I_{comm}: Funds allocated to community welfare, such as public events, cultural preservation, and social security measures.

In the framework of sustainable tourism, the feedback mechanism is defined as the systematic enhancement of infrastructure, environmental conservation, and community welfare achieved through the optimized distribution of income. This mechanism is critical for promoting the sustainable development of the tourism industry. The implementation of feedback mechanisms aims to mitigate negative impacts and amplify positive outcomes by ensuring the rational allocation of expenditure plans. By strategically directing financial resources towards key areas, the feedback system supports the resilience and long-term viability of tourism activities, thereby fostering a balanced integration of economic, environmental, and social objectives.

In building the feedback mechanism, to improve the underlying architecture, residual fitting is first used to build a new tree by modeling the residuals from the previous iteration, gradually addressing the errors of the previous tree and improving model prediction accuracy. Gradient descent optimization is then used to iteratively refine the model by minimizing the residuals. In each iteration, the model parameters are updated in the opposite direction of the loss function gradient, gradually reducing the overall error and improving performance, as shown in Figure 1 below.

The implementation of the feedback mechanism balances economic, environmental, and social factors in a multi-objective optimization manner through strategic expenditure allocation and integrated feedback loops, ensuring that the allocation of financial resources can optimize economic performance, reduce environmental impact, enhance social welfare, and contribute to the overall development of Juneau's tourism industry. Its introduction is crucial to sustainable development, and it uses adaptive management strategies to respond to challenges such as increased carbon emissions and increased infrastructure pressure, promote resident satisfaction and community welfare, and dynamically adjust expenditure allocation based on real-time feedback to build a flexible sustainable tourism framework that balances growth with environmental protection and social equity.

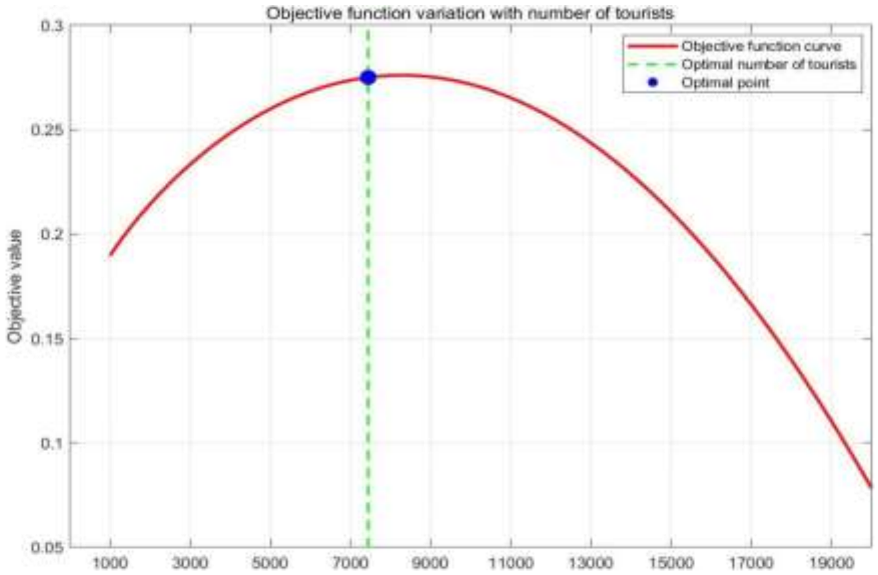

Fig. 1 Objective function

2.2. Frequency estimation without prior information

Accurately estimating signal frequency is a challenging task when the signal amplitude and phase information cannot be obtained in advance. To address this problem, a series of key methods and technical means are required.

2.2.1. Analysis of Noise Characteristics

Effective frequency estimation necessitates the ability to distinguish between signal and noise amidst interference. Noise characteristics may vary across different operational stages, such as various phases of flight. Therefore, it is imperative to design adaptive estimation algorithms that account for these variations by analyzing the statistical properties of noise, including power spectral density. This adaptive approach ensures robustness in fluctuating noise environments.

2.2.2. Frequency Estimation Methods

Two principal methods are employed for frequency estimation:

Autocorrelation Analysis: This technique leverages the periodic nature of the signal to estimate its frequency. By analyzing the autocorrelation function, the periodicity inherent in the signal can be identified, facilitating accurate frequency determination.

Fourier Transform (FFT) Spectral Analysis: The Fast Fourier Transform (FFT) is utilized for spectral analysis to decompose the signal into its constituent frequency components. Prominent frequency peaks in the resulting spectrum enable the effective extraction of frequency information, providing a clear identification of dominant frequencies within the signal.

2.2.3. Blind Source Separation and Optimization Methods

In scenarios where amplitude and phase information are unavailable, blind source separation (BSS) techniques become essential. BSS can isolate useful signal information from a mixture of signals, thereby enabling accurate frequency estimation. Additionally, optimization algorithms, such as least squares, are employed for intermittent signal reception. These algorithms fit the observed data to a model, facilitating the precise calculation of signal frequency despite interruptions or partial data.

2.2.4. Noise Adaptive Design

Designing frequency estimation algorithms requires dynamic adjustment of algorithm parameters based on real-time noise characteristics. This adaptive design is crucial for maintaining estimation accuracy, particularly in environments where received data may be discontinuous or heavily contaminated by noise. By continuously tuning the algorithm parameters in response to noise variations, the frequency estimation process remains resilient and reliable.

The core goal of this paper is to accurately estimate signal frequency without prior knowledge of amplitude and phase information. The proposed solution integrates methods such as autocorrelation analysis, FFT spectrum analysis, blind source separation, and optimization algorithms. Furthermore, it emphasizes the importance of adaptive noise processing to mitigate the adverse effects of noise on frequency estimation. This comprehensive approach ensures robust and accurate frequency estimation in challenging signal environments, as shown in Figure 2 below.

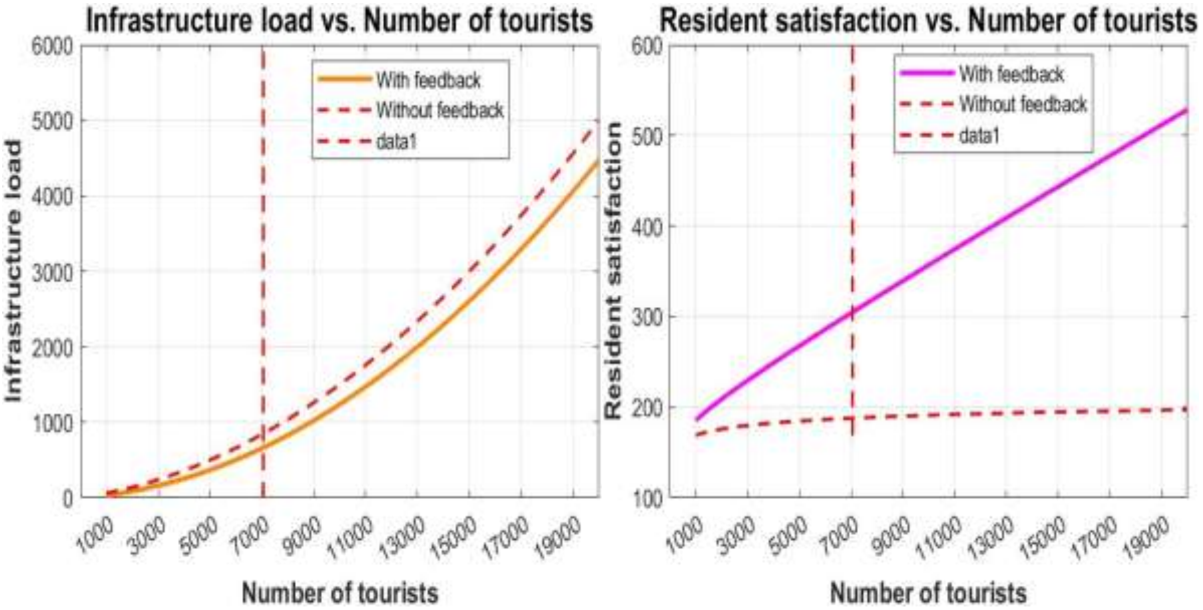

Fig. 2 Number of tourists

2.3. Frequency Estimation in Intermittent Reception Mode

Accurately estimating the signal frequency when signals are received intermittently presents significant challenges due to discontinuous data and limited information. Therefore, it is necessary to design an efficient algorithm that can reliably estimate the frequency with limited, discontinuous observation data. The proposed solution includes the following key steps: signal preprocessing to enhance available information, compensating for missing data using interpolation or extrapolation methods, extracting frequency features using time-frequency analysis or parametric modeling, and improving estimation accuracy through iterative optimization. This approach enables robust frequency estimation under low duty cycle reception conditions.

2.3.1. Analysis of Intermittent Reception Characteristics

A comprehensive analysis of intermittent reception characteristics is essential. This includes examining the availability of signal data across different time intervals and identifying patterns of signal presence and absence. To address data discontinuities, signal reconstruction techniques, such as interpolation or extrapolation methods, are employed to fill data gaps. These techniques ensure a continuous signal representation, thereby facilitating more accurate frequency estimation.

2.3.2. Autocorrelation Analysis for Periodicity Identification

Autocorrelation analysis is utilized to detect the periodicity inherent in the signal. By computing the autocorrelation function, the algorithm can identify repeating patterns and determine the fundamental frequency of the signal. This method leverages the periodic nature of the signal to enhance the precision of frequency estimation, especially in the presence of intermittent data.

2.3.3. Frequency Extraction through Spectral and Optimization Methods

Multiple frequency extraction techniques are integrated to obtain effective frequency information:

Spectral Analysis: The application of Fourier Transform (FFT) or other spectral decomposition methods allows for the identification of dominant frequency components within the signal spectrum. This facilitates the isolation of significant frequency peaks corresponding to the signal of interest.

Least Squares Optimization: Optimization algorithms, such as the least squares method, are employed to fit the reconstructed signal data to a sinusoidal model. This fitting process enhances the accuracy of frequency estimation by minimizing the residual errors between the observed and modeled signals.

Sliding Window Techniques: Sliding window methods are implemented to perform localized frequency analysis over short time segments of the signal. This approach is particularly effective in handling non-stationary signals, where frequency characteristics may vary over time.

2.3.4. Noise Suppression and Signal Enhancement

The presence of noise can significantly impact the accuracy of frequency estimation. To mitigate this, appropriate noise suppression techniques are incorporated:

Kalman Filtering: This recursive filtering method estimates the state of a dynamic system from noisy measurements, thereby enhancing the signal-to-noise ratio (SNR) and improving frequency estimation accuracy.

Wiener Filtering: Wiener filters are applied to minimize the mean square error between the estimated and true signals, effectively reducing noise and preserving essential signal features necessary for accurate frequency determination.

These noise suppression techniques ensure that the frequency estimation process remains robust against varying noise levels and maintains high precision despite the challenges posed by intermittent reception.

The core objective of Problem Three is to develop a robust algorithm capable of accurately estimating signal frequency in intermittent reception scenarios. The proposed solution integrates the analysis of intermittent reception characteristics, autocorrelation-based periodicity identification, advanced spectral and optimization methods for frequency extraction, and effective noise suppression techniques. This comprehensive approach ensures reliable frequency estimation by addressing the challenges of data discontinuity and noise interference, thereby facilitating the sustainable performance of signal processing systems in adverse reception conditions

2.4. Sensitivity Analysis

Sensitivity analysis is used to evaluate the impact of input variables on model outputs and identify key parameters in optimization decisions. The process involves systematically changing the range of input parameters (parameter variation), quantifying their impact on the output (impact measurement), observing and recording changes in model responses (model response evaluation), and calculating the sensitivity indicators of each variable (sensitivity calculation). In the preliminary analysis of the frequency estimation problem, a basic model must first be established based on known signal characteristics (such as amplitude, frequency, and phase). However, noise interference poses a major challenge, especially because it exhibits time-varying characteristics at different flight phases, which seriously affects the accuracy of frequency estimation. Therefore, it is necessary to conduct an in-depth analysis of the noise component in the signal and combine sensitivity analysis methods to evaluate its impact on the estimation performance.

In practical applications, frequency estimation methods must be highly adaptable to signal characteristics to cope with complex and changing environmental conditions. This adaptability can be achieved by combining time-domain and frequency-domain analysis techniques: in the time domain, the least-squares method is used to model and fit the signal waveform to extract its dynamic characteristics; in the frequency domain, the fast Fourier transform (FFT) is used to analyze the signal spectrum and identify the dominant frequency components. However, achieving high-precision frequency estimation faces several key challenges: first, in-depth analysis of the statistical characteristics of noise and its interference mechanisms on the signal is required; second, the appropriate time-domain or frequency-domain estimation technique should be selected based on the application scenario; and third, effective mitigation of signal interference and intermittent data reception is required to improve the robustness and accuracy of the estimation.

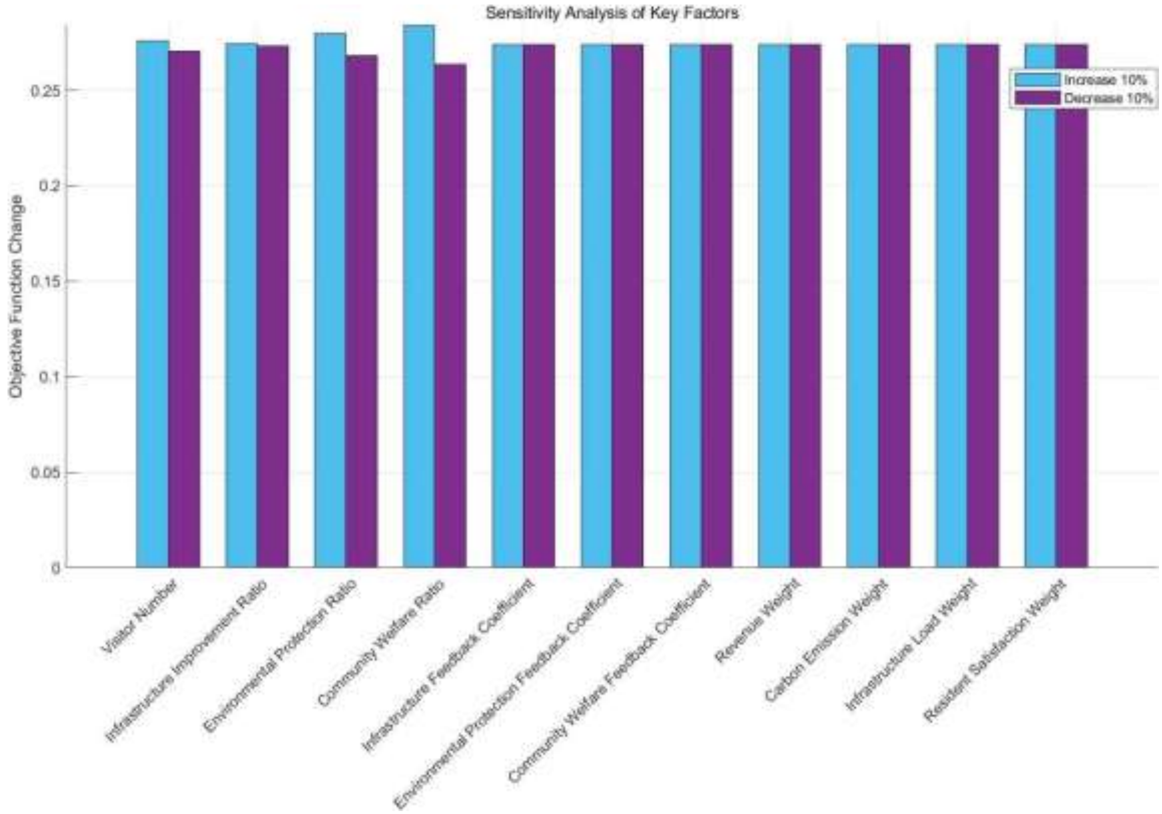

Fig. 3 The steps for Sensitivity analysis

To address the challenges posed by intermittent signal reception, more advanced processing strategies are needed. On the one hand, intelligent optimization algorithms such as particle swarm optimization (PSO) can be used to perform global searches and fine-tune frequency parameters to improve estimation accuracy. On the other hand, noise suppression techniques such as Kalman filtering can be combined to effectively filter out random interference and enhance signal intelligibility. By integrating advanced signal processing methods and optimization mechanisms, they achieve stable and reliable frequency estimation even under harsh conditions of high noise and low duty cycle. This result provides a high-quality data foundation for subsequent key parameter calculations (such as wind speed measurement), which is of great significance in engineering practice, as shown in Figure 3 below.

The stacked bar chart in Figure 4 illustrates the impact of a 10% change in each variable on the objective function. Specifically, when weight variables such as "Revenue Weight" and "Resident Satisfaction Weight" increase or decrease by 10%, the change in the objective function is relatively small, indicating that these variables have a limited impact on the results. However, variables related to actual operational and environmental pressures, such as "Number of Tourists" and "Infrastructure Pressure Weight," have a significantly greater impact on the objective function with the same magnitude of change, indicating that they are key factors affecting system performance. Furthermore, feedback coefficient and ratio variables such as "Infrastructure Feedback Coefficient" and "Environmental Protection Ratio" also exhibit high sensitivity; even small changes in them can cause significant fluctuations in the objective function. Therefore, when formulating strategies, it is important to focus on these highly sensitive variables and ensure system stability and optimal operation through refined management and regulation.

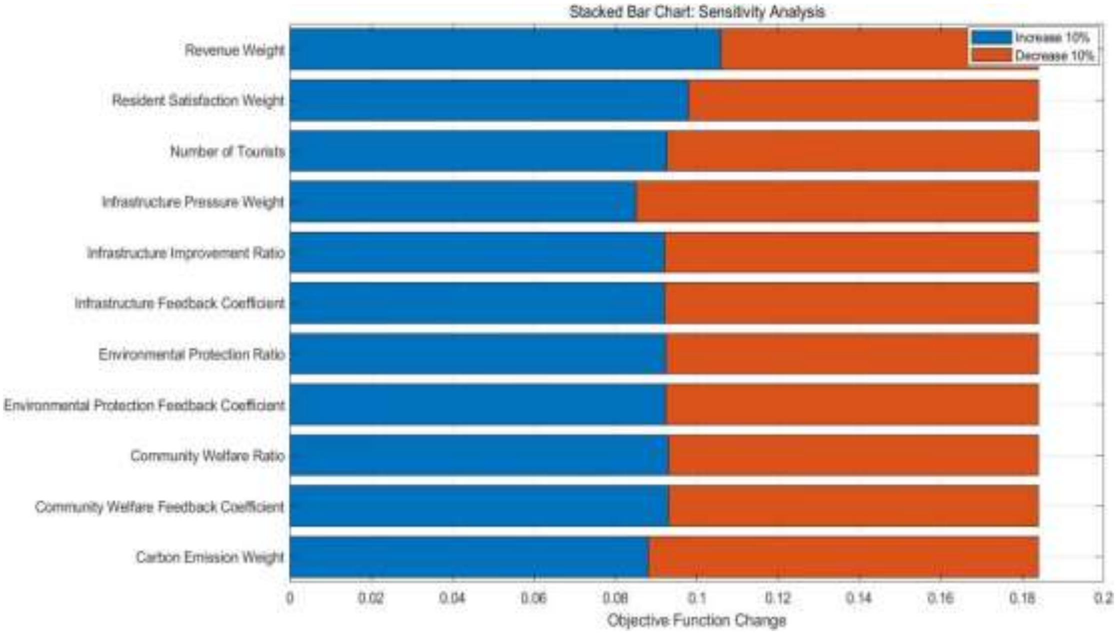

Fig. 4 Sensitivity Analysis

3. CONCLUSION

This study addresses the challenge of accurately estimating signal frequency in complex dynamic environments and proposes a comprehensive approach that integrates preprocessing, frequency domain analysis, and intelligent optimization. The approach aims to improve the accuracy and robustness of aircraft navigation systems in the presence of external interference and parameter variations. First, the original signal is processed to remove the DC component to ensure its zero-mean characteristic, thereby enhancing the accuracy of spectral analysis. A window function is then introduced to weight the signal, effectively suppressing spectral leakage caused by signal truncation. Furthermore, a frequency domain transform technique is used to extract the signal spectrum, and a preliminary frequency estimate is determined by identifying energy peaks. To further enhance estimation performance, especially under non-ideal conditions such as ambient noise and intermittent reception, a particle swarm optimization (PSO) algorithm is combined with a Kalman filter to achieve global optimization of the frequency parameters and noise suppression. Experimental results demonstrate that this approach significantly enhances the accuracy and stability of frequency estimation, providing a reliable data foundation for acquiring key state parameters in aviation navigation systems. This approach is of great significance for improving the perception capabilities and operational reliability of modern aircraft under complex operating conditions.

6. REFERENCES

[1] Xu Dandan. Comparative study on Xi'an housing price forecast based on multiple linear regression model and BP neural network [J]. Real Estate World, 2022 (08): 11-13.

[2] Cui Huiying. Research on improvement based on extreme random forest algorithm and second-hand housing price prediction [D]. Dalian Jiaotong University: 2023. DOI: 10.26990/D.cnki.gsltc.2023. 000640.

[3] Zhou Liangjin, Zhao Mingyang. Analysis of second-hand housing prices in Shenzhen based on random forest [J]. China Market, 2022 (26): 68-71 +133. DOI: 10.13939/j.cnki.zgsc.2022. 26.068.

[4] Li Jing. "Research on the Application of Big Data Statistical Analysis in Urban Planning and Construction". Journal of Hulun Buir College 32.02 (2024): 79-82.

[5] Hu Zhichao, Wang Xinhao, Zhang Jian, Huang Shengxiong. Urban resilience evaluation system and improvement strategy [J]. Macroeconomic Management, 2021 (11): 72-77. DOI: 10.19709/j.cnki.11-3199/f.2021. 11.019.