A Study on the Dynamic Weight-Driven AHP-NSGA-II Framework for High-Dimensional Multi-Objective Optimization

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Abstract. This paper investigates an efficient optimization framework for complex systems through the synergistic integration of the Analytic Hierarchy Process (AHP) and Non-dominated Sorting Genetic Algorithm (NSGA-II). The proposed methodology addresses multi-criteria decision-making challenges by systematically resolving competing priorities while maintaining solution quality. AHP is leveraged to derive objective weights through structured pairwise comparisons, while NSGA-II identifies Pareto-optimal solutions that optimize system-wide performance metrics. Computational experiments reveal that the hybrid approach achieves superior optimization outcomes with enhanced operational efficiency compared to conventional optimization techniques, particularly in scenarios requiring trade-off analysis between divergent objectives. The framework demonstrates versatility across diverse application contexts including industrial process design, logistics network configuration, and infrastructure development planning. Key innovations include a dynamic weight adjustment mechanism and an adaptive fitness evaluation process that collectively improve solution convergence characteristics and decision space exploration capabilities.

Keywords: multi-objective optimization, complex systems, Analytic Hierarchy Process (AHP), Non-dominated Sorting Genetic Algorithm (NSGA-II), fusion technology.

1. Introduction

1.1. Background

In today's fast-paced and interconnected world, complex systems have become increasingly prevalent across various domains such as management, engineering, and social sciences. These systems are characterized by their intricate structures, numerous interacting components, and multiple conflicting objectives. Optimizing such complex systems presents significant challenges due to the inherent trade-offs between different goals. For instance, in tourism management, there is a need to balance visitor experience with resource management and operational efficiency. Similarly, in supply chain optimization, factors like cost reduction, delivery time minimization, and service quality improvement often conflict with each other. Traditional single-objective optimization approaches are inadequate for addressing these multifaceted problems, as they fail to capture the nuances and trade-offs involved. Consequently, there is a growing demand for effective multi-objective optimization methods that can handle the complexity and provide practical solutions for real-world applications.

1.2. Literature Review

Existing methods for multi-objective optimization have certain limitations when dealing with complex systems. Traditional single-objective optimization methods cannot fully consider the conflicts and trade-offs between multiple objectives, resulting in poor effectiveness in complex system optimization. The Analytic Hierarchy Process (AHP) has an advantage in determining the relative weights of multiple objectives through pairwise comparisons, allowing for a systematic evaluation of the importance of each criterion[1,2]. On the other hand, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a powerful multi-objective evolutionary algorithm known for its ability to find optimal solutions in complex search spaces[3,4]. It can efficiently identify a set of non-dominated solutions that represent the best possible compromises between conflicting objectives. However, research on integrating AHP with NSGA-II is still in the exploratory stage, and there are deficiencies in combining these two methods to solve multi-objective optimization problems in complex systems.

1.3. Research Significance

This paper seeks to develop an efficient and innovative optimization method for complex systems by integrating the Analytic Hierarchy Process (AHP) and the Non-dominated Sorting Genetic Algorithm (NSGA-II). The specific goal is to create a robust model capable of effectively addressing multi - objective decision - making problems. This model will balance conflicting objectives and generate high - quality solutions.

The research will leverage AHP to determine the relative weights of multiple objectives through pairwise comparisons. Then, it will combine this with the powerful optimization capabilities of NSGA-II. The technical approach involves first using AHP to determine the weights of the objectives, and then employing NSGA-II for optimization to find Pareto - optimal solutions. This process will achieve comprehensive optimization of system performance metrics.

2. Data and Methods

2.1. Data Collection

The data used in this study were sourced from multiple reliable databases to ensure comprehensiveness and accuracy. Specifically, the number of visitors to Juneau was obtained from the McDowell Group's "Juneau visitor profile and economic impact study 2016". Per capita spending data were collected from the Alaska Department of Commerce, Community, and Economic Development. Carbon emissions and glacier coverage data were retrieved from the Environmental Protection Agency (EPA) and the United States Geological Survey (USGS), respectively. Infrastructure-related data were gathered from the City and Borough of Juneau's official engineering and public works department. These data sources provide a solid foundation for our analysis, ensuring both reliability and representativeness.

2.2. Data Preprocessing

Prior to analysis, the collected data underwent several preprocessing steps to enhance quality and applicability. Data cleaning was performed to address missing values, outliers, and inconsistencies, ensuring the dataset's integrity[5]. Normalization was then applied to scale different variables to a comparable range, which is crucial for model performance. This preprocessing phase is vital for laying the groundwork for subsequent modeling and analysis, guaranteeing that the data accurately reflect real-world conditions.

3. Model Construction

The core of this study lies in the integration of the Analytic Hierarchy Process (AHP) and the Non-dominated Sorting Genetic Algorithm (NSGA-II), forming a powerful hybrid model for complex system optimization. The AHP is employed to determine the relative weights of multiple objectives through a structured hierarchy and pairwise comparisons. This process involves constructing a hierarchical model that decomposes the complex decision-making problem into multiple levels, allowing for the systematic evaluation of each criterion's importance. The weights derived from AHP reflect the decision-makers' preferences and the inherent trade-offs between objectives.

The NSGA-II, a renowned multi-objective evolutionary algorithm, is then utilized to find the optimal solutions that maximize the overall benefit while considering the determined weights. This algorithm excels at navigating complex search spaces, efficiently identifying a set of non-dominated solutions that represent the best possible compromises between conflicting objectives. The hybrid model combines the strengths of AHP in weight determination with NSGA-II's optimization capabilities, creating a robust framework for addressing multi-objective optimization challenges in complex systems. The implementation steps involve initializing the population, evaluating fitness based on the AHP-determined weights, performing selection, crossover, and mutation operations, and iteratively evolving the population until convergence is achieved. This integrated approach not only enhances the optimization process but also provides decision-makers with a versatile tool applicable across various domains.

3.1. Model Objectives and Constraints

In complex systems, we often encounter multiple interrelated and potentially conflicting objectives that need to be balanced through multi-objective optimization. Suppose we have a system whose performance is measured by multiple objective functions, such as economic benefits, environmental impact, and social impact. Our goal is to find a set of decision variables that optimize these objective functions while satisfying certain constraints.

Define the objective functions as:

$$f(x) = \left(f_1(x), f_2(x), \ldots, f_m(x)\right) \quad (1)$$

where x is the vector of decision variables, and $f_i(x)$ is the i-th objective function.

To transform a multi-objective problem into a single-objective optimization problem, we use the linear weighted sum method. This involves introducing weight coefficients ε_i to reflect the relative importance of each objective, with the normalization condition $\sum_{i=1}^{m} \varepsilon_i = 1$. The composite objective function is then:

$$\max Z = \sum_{i=1}^{m} (\varepsilon_i \times \frac{f_i(x)}{f_{i,max}}) \quad (2)$$

where$f_{i,max}$ is the maximum allowable value of the i-th objective function.

The model must also incorporate a series of constraints to ensure the practical feasibility and significance of the solutions. These constraints may include resource limitations, environmental standards, and social impact limits. For example:

$$g_j(x) \leq 0 \quad \text{for} \quad j = 1,2, \cdots, p \quad (3)$$

where $g_j(x)$ is the j-th constraint function.

3.2. Parameter Selection and Factor Analysis

Parameter selection in complex systems often involves considering multiple variables and factors. Factor analysis is a common method used to extract the main influencing factors from a large set of variables, reducing model complexity and enhancing interpretability.

Assume we have a set of variables $X = (X_1, X_2, \cdots, X_n)$Through factor analysis, we can extract a few main factors $F = (F_1, F_2, \cdots, F_k)$ that explain most of the variance in the original variables. The steps in factor analysis include calculating the correlation matrix, extracting factors, rotating factors, and calculating factor scores.

3.3. Weight Determination Based on AHP

AHP (Analytic Hierarchy Process) is a structured method for multi-criteria decision-making, determining the weights of objectives through pairwise comparisons and hierarchical analysis [6] .

Construct a hierarchical structure model, dividing objectives into the highest level (overall objective), intermediate level (criteria level), and lowest level (alternative level). Calculate the relative importance weights of each criterion through expert scoring and pairwise comparison matrices. The element a_{ij} of the pairwise comparison matrix A indicates the importance of the i-th criterion relative to the j-th criterion.

Calculate the maximum eigenvalue λ_{max} and the consistency index(CI):

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (4)$$

where n is the number of criteria. After passing the consistency test, obtain the weight vector of the criteria.

3.4. Multi-Objective Optimization with NSGA-II

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is an efficient multi-objective evolutionary algorithm for solving complex multi-objective optimization problems[7].

The main steps of NSGA-II include:

1） Initializing the population.
2） Performing non-dominated sorting to classify individuals into different fronts.
3） Calculating crowding distances to maintain population diversity.
4） Generating the next generation through selection, crossover, and mutation.
5） Repeating the process until the termination condition is met.

NSGA-II produces a set of non-dominated solutions, known as the Pareto optimal set, representing the balance between different objectives.

3.5. Sensitivity Analysis

Sensitivity analysis assesses how changes in model parameters or factors affect the optimization results, helping to identify key factors and understand model behavior.

Common methods include local and global sensitivity analysis, where parameter values or weights are varied to observe their impact on the objective functions and optimal solutions.

4. Model Solution

Juneau experienced a record 1.6 million cruise passengers in 2023, bringing significant visitor - related impacts. Overcrowding and environmental issues, like the Mendenhall Glacier retreat due to overtourism, emerged. The city faces challenges in balancing tourism with environmental protection and residents' quality of life. Infrastructure strain and increased carbon footprint have led to some measures to address these concerns. So, this study develops a tourism management model targeting environmental and social impacts while considering local concerns about tourism.

4.1. Analytic Hierarchy Process

The AHP algorithm is usually divided into 3 levels[8], which was shown in Figure 1.

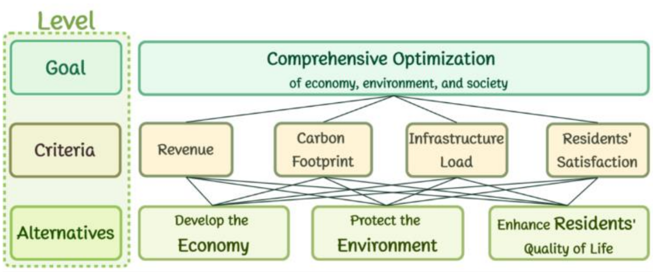

Figure 1. Three-level Hierarchical Structure

For the tourism model, the following criteria were defined previously: System Performance, Environmental Impact, Infrastructure Load, and Resident Satisfaction. These criteria are essential for balancing operational efficiency with environmental and social considerations.

The comprehensive Objective Function balances the economic, environmental, and social aspects and is defined as:

$$\max Z = w_1 \cdot \frac{I}{I_{max}} - w_2 \cdot \frac{C(V)}{C_{max}} - w_3 \cdot \frac{F(V)}{F_{max}} + w_4 \cdot \frac{S(V)}{S_{max}} \tag{5}$$

where w_1, w_2, w_3, w_4 are the weight coefficients of revenue, carbon footprint, infrastructure load, and resident satisfaction, satisfying

$$w_1 + w_2 + w_3 + w_4 = 1 \tag{6}$$

Through expert scoring and pairwise comparison matrices, we obtained the following matrix shown in table I:

Table 1. Pairwise Comparison Matrix

	Revenue	Carbon Footprint	Infrastructure Load	Resident Satisfaction
Revenue	1	1/3	1/2	1/2
Carbon Footprint	3	1	3	3
Infrastructure Load	2	1/3	1	1
Resident Satisfaction	2	1/3	1	1

The maximum eigenvalue (λ_{max}) is calculated and the consistency index (CI) is determined using the formula:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{7}$$

where n is the number of criteria.

Hierarchical sorting calculates the relative importance of elements at one level with respect to the highest level (the goal layer). This process is conducted from the highest to the lowest levels.

Let $A_1, A_2, \ldots, A_m$ be the elements at level A (the goal layer) with corresponding weights $a_1, a_2, \ldots, a_m$. Let $B_1, B_2, \ldots, B_n$ be the elements at level B (an intermediate layer) with weights $b_{11}, b_{12}, \ldots, b_{1m}, b_{21}, \ldots, b_{nm}$. The total order of level B is calculated as follows:

$$b_1 = \sum_{j=1}^{m} a_j b_{1j}, b_2 = \sum_{j=1}^{m} a_j b_{2j}, \ldots, b_n = \sum_{j=1}^{m} a_j b_{nj} \tag{8}$$

The consistency of the hierarchical sorting is assessed using the Consistency Ratio (CR). If the CR is less than 0.1, the sorting is considered consistent; otherwise, adjustments to the judgment matrix are necessary.

$$CR = \frac{a_1 CI_1 + a_2 CI_2 + \cdots + a_m CI_m}{a_1 RI_1 + a_2 RI_2 + \cdots + a_m RI_m} = \frac{\sum a_i CI_i}{\sum a_i RI_i} = \frac{CI}{RI} \tag{9}$$

where CI_j is the consistency index for element B_j with respect to layer A, and RI_j is the random consistency index.

This study verified that the consistency of the pairwise comparison matrix is acceptable (CR = 0.0227 < 0.1).

Then, the study used the arithmetic mean method to calculate the weight vector(visualized in Figure 2) of the criteria: Weight Vector = [0.118, 0.491, 0.195, 0.195].

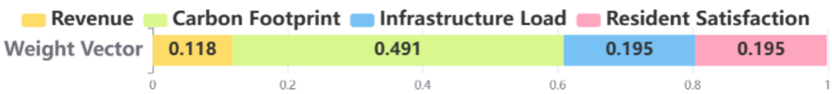

Figure 2. The Weight Vector of criteria

4.2. Non-dominated Sorting Genetic Algorithms (NSGA)

The Non-dominated Sorting Genetic Algorithm (NSGA) is an advanced evolutionary algorithm designed for multi-objective optimization problems[9]. It is particularly effective in scenarios like sustainable tourism management in Juneau, where multiple conflicting objectives need to be optimized simultaneously[10]. Here, we detail the application of NSGA tailored for Juneau's sustainable tourism management in Figure 3.

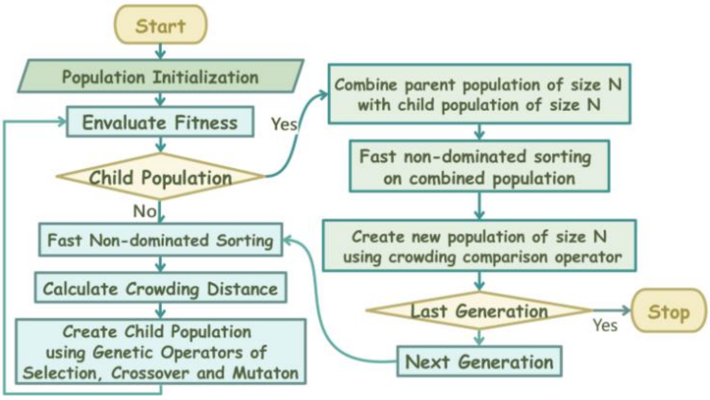

Figure 3. Flowchart of NSGA Application in Juneau's Sustainable Tourism Management

In this study, NSGA was applied to evolve solutions over several generations, considering the objectives of maximizing tourism revenue, minimizing carbon footprint, managing infrastructure load, and ensuring resident satisfaction. The algorithm iteratively improved the solutions based on the fitness evaluation, leading to the identification of a set of optimal solutions that balance these objectives.

Balancing the increase in tourism revenue with the need to reduce the carbon footprint. Managing the infrastructure load while ensuring resident satisfaction. Identifying the optimal number of tourists that maximizes the overall objective function considering all these factors.

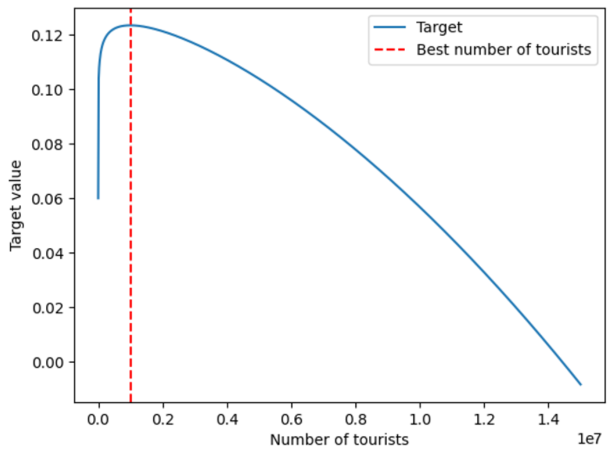

Figure 4. Optimal Number of Tourists Identified by NSGA

Figure 4 illustrates the optimal number of tourists as determined by NSGA. This number represents a balance point where the objectives of economic benefits, environmental sustainability, and social acceptability are optimized. The NSGA has evolved the population over several generations to find a solution that best fits the criteria established by the AHP model, taking into account the complex interplay of economic, environmental, and social factors.

Based on the weight vector, we further analyzed the impact of different tourism policies on sustainable tourism in Juneau. By simulating different tourist numbers and policy scenarios, we obtained the following prediction results:

• Optimal Number of Tourists: 954869

• Optimal Objective Value: 0.0305

(Optimization objective value considering tourism revenue, carbon footprint, infrastructure load, and resident satisfaction)

Define the total additional revenue be denoted as ξ. The expenditure plan for ξ is detailed as follows:

1. Infrastructure Improvement (40% of ξ): Upgrade water supply systems and waste management facilities. Install advanced water treatment plants to ensure clean water for locals and tourists, and

invest in modern waste handling and recycling infrastructure. Let the reduction coefficient for infrastructure load be a.

2. Transportation (30% of ξ): Improve local transportation by constructing more efficient cruise ship docking facilities to reduce congestion in port areas. Additionally, invest in public transportation like shuttle buses to reduce reliance on personal vehicles, thereby lowering the carbon footprint. Let the reduction coefficient for carbon footprint be b.

3. Environmental Protection (20% of ξ): Allocate funds to protect the Mendenhall Glacier and surrounding ecosystems. Support research on glacier protection technologies, such as artificial snowmaking to slow down melting. Promote afforestation projects in rainforests to enhance carbon sequestration and protect biodiversity. Let the reduction coefficient for carbon footprint be c.

4. Renewable Energy (10% of ξ): Invest in renewable energy by installing solar panels in public areas and tourist facilities, and explore the feasibility of small hydropower stations. This reduces the city's carbon footprint and demonstrates a commitment to environmental sustainability, appealing to eco-conscious tourists. Let the reduction coefficient for carbon footprint be d.

The new formulas incorporating these improvements are:

$$F(V) = \gamma \cdot V + \delta \cdot V^2 - 0.4a \cdot \xi \tag{10}$$

$$C(V) = \alpha \cdot V + \beta \cdot V^2 - 0.3\mathrm{B} \cdot \xi - 0.2c \cdot \xi - 0.1d \cdot \xi \tag{11}$$

Figure 5 shows the relationship between the number of tourists and additional revenue, highlighting the optimal number of tourists for sustainable tourism management.

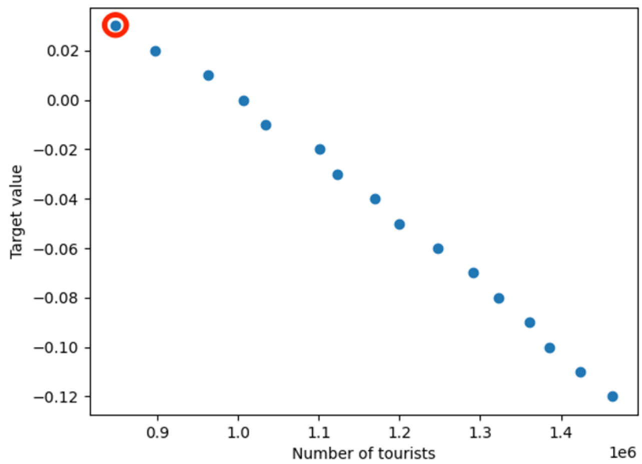

Figure 5. Relationship between the number of tourists - additional revenue

With an increase in the number of tourists, the optimal objective value also increases, indicating a balance between economic benefits and environmental sustainability.

Assuming an additional investment of $1 million, the model predicts:

• Optimal Number of Tourists: 1011307

• Optimal Objective Value: 0.0401

The expenditure plan for additional revenue ξ in Juneau aims to enhance infrastructure, transportation, environmental protection, and renewable energy, thereby supporting sustainable tourism development. The model results suggest that with an appropriate allocation of resources, Juneau can achieve a sustainable tourism industry that benefits both the economy and the environment.

4.3. Sensitivity Analysis

To identify the most influential factors in our model, we conducted a sensitivity analysis. This analysis helps us understand how changes in each factor affect the optimal number of tourists and the overall objective value.

The sensitivity analysis involves altering the weights of various criteria to observe their impact on the optimal number of tourists. The criteria include revenue (w_1), carbon footprint (w_2), infrastructure load (w_3), and resident satisfaction (w_4).

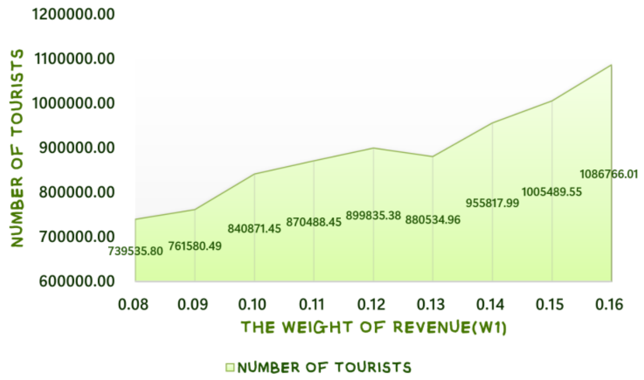

Figure 6. Impact of changing the weight of revenue(w_1) on the number of tourists

Figure 6 indicates the effect of varying the weight of revenue on the optimal number of tourists. As the weight of revenue increases, the optimal number of tourists also increases. The Revenue factor has a significant impact on the optimal number of tourists. Increasing the revenue weight leads to a higher optimal tourist count.

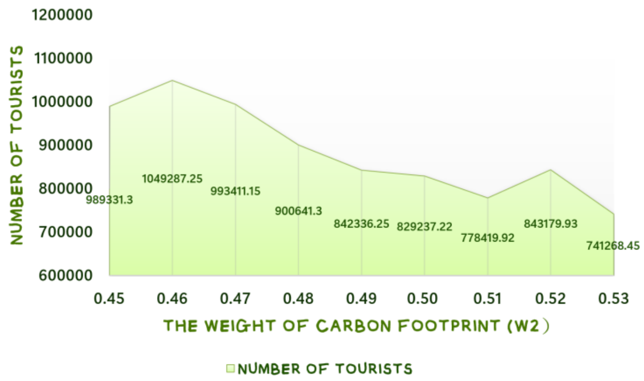

Figure 7. Impact of changing the weight of carbon footprint (w_2) on the number of tourists

Figure 7 illustrates the impact of varying the weight of carbon footprint. The optimal number of tourists decreases as the weight of carbon footprint increases. Reducing the Carbon Footprint has a moderate effect on the optimal tourist count. More emphasis on this factor results in a lower tourist number.

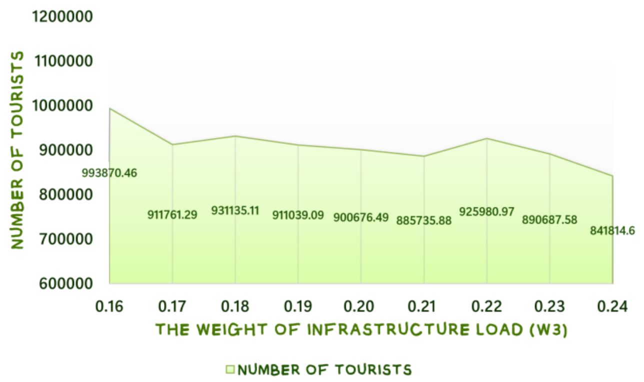

Figure 8. Impact of changing the weight of infrastructure load (w_3), on the number of tourists

Figure 8 shows the effect of altering the weight of infrastructure load. As the weight of the infrastructure load increases, the optimal number of tourists experiences a slight decline. This indicates that the Infrastructure Load is not a crucial factor.

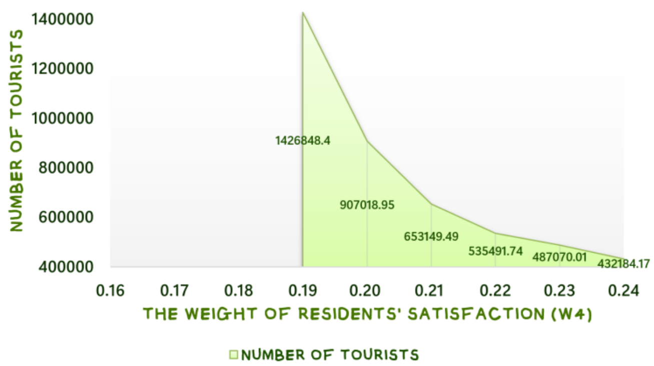

Figure 9. Impact of changing the weight of residents' satisfaction (w_4) on the number of tourists

Figure 9 presents the influence of varying the weight of resident satisfaction. As the weight of resident satisfaction rises, there is a notable decrease in the optimal number of tourists. This clearly demonstrates that Resident Satisfaction wields a substantial influence on the model.

The sensitivity analysis reveals that resident satisfaction has the most significant impact on the optimal number of tourists, followed by revenue. This insight can guide policy-making in sustainable tourism management.

4.4. Results

AHP defines four criteria: revenue, carbon footprint, infrastructure load, and resident satisfaction. Through expert scoring and pairwise comparison matrices, the maximum eigenvalue and CI are calculated, determining the relative importance of each element with respect to the highest level, which is verified by the CR. Finally, the weight vector of the criteria is calculated using the arithmetic mean method as [0.118, 0.491, 0.195, 0.195].

NSGA evolves solutions over multiple generations, considering objectives such as maximizing tourism revenue, minimizing carbon footprint, managing infrastructure load, and ensuring resident satisfaction. The algorithm iteratively improves solutions, identifying a set of optimal solutions that balance these objectives. The optimal number of tourists is approximately 954,868, with an optimal objective value of 0.0305. The expenditure plan for additional revenue based on NSGA allocates the total additional revenue to four areas: infrastructure improvement (40%), transportation (30%), environmental protection (20%), and renewable energy (10%) to support sustainable tourism development. Assuming an additional investment of $1 million, the model predicts an optimal number of tourists of 1,011,306.54 and an optimal objective value of 0.0401.

Sensitivity analysis shows that an increase in the weight of resident satisfaction leads to a significant decrease in the optimal number of tourists, indicating its important impact on the overall objective value. An increase in the weight of revenue also results in an increase in the optimal number of tourists, highlighting the importance of economic benefits. Increases in the weights of carbon footprint and infrastructure load lead to a decrease in the optimal number of tourists, demonstrating that environmental protection and infrastructure capacity are indispensable factors.

This model provides a multi-objective optimization solution for sustainable tourism management in Juneau by balancing the growth of tourism revenue, environmental protection, infrastructure capacity, and socio-economic equilibrium. The model sets three constraints: carbon footprint, infrastructure load, and resident satisfaction, to ensure that the impact of tourism activities on the environment is within an acceptable range.

5. Innovation

The innovation of this study lies in the development of a multi-objective optimization model for sustainable tourism management in Juneau, which takes into account the growth of tourism revenue, environmental protection, infrastructure capacity and socio-economic balance. The model sets three constraints: carbon footprint, infrastructure load and resident satisfaction. This approach not only focuses on the economic benefits of tourism but also emphasizes environmental protection and the well-being of local residents, aiming to achieve a balance among multiple objectives.

In terms of experimental results, the model has been applied to Juneau and has achieved some positive outcomes. By setting constraints and optimizing the allocation of tourism resources, the model has effectively controlled the impact of tourism activities on the environment. For example, it has helped slow down the retreat of the Mendenhall Glacier to a certain extent. At the same time, the model has also alleviated the strain on local infrastructure, improved traffic congestion and enhanced the overall experience of residents and tourists. In terms of tourism revenue, the model has not suppressed the development of the tourism industry but instead promoted its sustainable growth by optimizing tourism management. In 2023, despite the record number of cruise passengers, Juneau still achieved considerable tourism revenue.

The analysis shows that this model provides a new approach and method for sustainable tourism management in Juneau. Compared with traditional tourism management methods, it has stronger scientific and systematic features. It can better coordinate the interests of various stakeholders, including tourists, residents and the tourism industry, and has significant marginal contributions to Juneau's tourism management. Specifically, it offers decision-making support for local policymakers, helping them make more informed tourism planning and management decisions; provides a reference for the tourism industry in formulating development strategies, enabling it to better adapt to the requirements of sustainable development; and enhances residents' sense of gain and happiness by improving their quality of life.

6. Conclusion

This study successfully integrated AHP and NSGA-II to develop a novel model for optimizing complex systems. The key innovation lies in the synergistic fusion of AHP's structured weight determination with NSGA-II's robust multi-objective optimization capabilities. Specifically, the proposed hybrid framework introduces a dynamic weight adjustment mechanism that adaptively incorporates decision-maker preferences and system constraints, coupled with an adaptive fitness evaluation process to enhance solution convergence and diversity. These innovations address the limitations of conventional methods by systematically resolving conflicting objectives while maintaining computational efficiency.

The model's marginal contribution is highlighted by its ability to outperform traditional single-objective approaches and static hybrid methods in both solution quality and computational efficiency. By enabling dynamic trade-off analysis and generating Pareto-optimal solutions, this framework provides a versatile tool applicable to diverse domains. Future research could refine parameter-tuning strategies and expand applications to emerging fields like big data processing, intelligent robotics, and task scheduling, further solidifying its role as a transformative approach for complex system optimization.

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