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# A Game-Theoretic Optimization Research for Sustainable Tourism Taxation under Overtourism

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**Abstract:** Overtourism has emerged as a major challenge for sustainable tourism, threatening both environmental integrity and local economic balance. This study focuses on Juneau, Alaska, proposing a taxation-based framework to mitigate the negative impacts of excessive tourism. We develop a Three-Party Game Model (TTE-Game) involving the tourism industry, tourists, and the environment. Each stakeholder's profit function and constraints are constructed, and the Nash equilibrium is derived using Newton’s method and dynamic system simulation. To evaluate policy impacts holistically, we apply the Analytic Hierarchy Process (AHP) to integrate stakeholder states into a unified revenue function. Through grid search and spline interpolation, the optimal environmental tax policy is identified: a 0.3 tax rate on the tourism industry and a $30 daily fee per tourist, achieving a favorable balance between economic and ecological outcomes. The model is further extended to simulate tourist redistribution between two destinations—Sanya (over-touristed) and Monkey Island (underdeveloped). Both apply the TTE-Game framework, and surplus tax revenue is used for publicity and subsidies. Using dynamic programming and optimal substructure principles, we determine a strategy that maximizes total revenue. Results suggest a 25% tax rate ($5.23 per tourist) in Sanya and 20% ($2.48) in Monkey Island. This research highlights how game theory and adaptive taxation can support decision-making in sustainable tourism planning, offering practical insights for managing resource allocation and environmental conservation.

## 1. Introduction

In recent years, overtourism has emerged as a critical threat to both ecological sustainability and local quality of life in many globally renowned destinations. Juneau, Alaska—once admired for its pristine natural landscapes—is now suffering from environmental degradation and resource overuse caused by the massive influx of tourists. The rapid retreat of the Mendenhall Glacier and increased carbon footprints from tourism-related activities serve as alarming indicators that immediate, sustainable strategies are urgently required [1].

Sustainable tourism aims to balance economic growth with environmental preservation and social responsibility. One promising approach is the implementation of environmental taxation policies that regulate tourism behavior while generating revenue for ecological restoration [2]. However, effective taxation must consider the dynamic interests and interactions among key stakeholders—namely, the tourism industry, tourists, and the environment.

To this end, we propose a novel Three-Party Game Model (TTE-Game) that integrates game-theoretic analysis with learning-based optimization techniques. By modeling stakeholders’ payoffs and constraints, we derive the Nash equilibrium under different taxation schemes using Newton’s method and dynamic simulation [3]. Furthermore, by applying the Analytic Hierarchy Process (AHP) and spline interpolation, we identify optimal environmental tax strategies that maintain a stable and favorable balance between economic gain and environmental protection.

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## 2. Methodology

### 2.1. Three-Party Game Model

Game theory analyzes strategic interactions among rational decision-makers or players, aiming to maximize individual payoffs. It involves defining players, strategies, and payoffs, with key models like the Nash equilibrium, where no player can improve by changing their strategy [4]. Evolutionary game theory examines how strategies evolve. Game theory is crucial in addressing competition, cooperation, and conflict, providing a foundation for understanding market dynamics, designing incentives, and predicting outcomes, so it seems to be a useful framework for analyzing decision-making in sustainable tourism development [5].

#### 2.1.1. Defining Payoffs

Player1: Natural Environment

To quantify the payoff of the natural environment, we propose the Environmental Degradation Index ($D$). This index is expressed as a percentage, representing the extent of environmental degradation. For example, an untouched natural environment is assigned a value of 100%. When D is 30%, it indicates that the quality of the current natural environment has deteriorated to 70% of its original ecological quality.

Player2: Tourists

To quantify tourists' payoff, we propose the concept of tourist surplus value ($W_C$), which represents the additional value tourists receive from their visit beyond the expected price they paid. This surplus value serves as an indicator of tourist satisfaction.

Considering the factor of tourism taxes, the price that tourists are expected to pay is given by:

$$Price = P + \beta \cdot TG \tag{1}$$

Where $P$ represents the ticket price, and $TG$ denotes the actual tourism tax levied. To account for the varying price sensitivity across different tourist groups, we introduce the parameter $\beta$, which acts as a price sensitivity factor, taking values in the range [0,2] and following a normal distribution.

The actual value tourists gain from visiting a tourist site is represented as:

$$Value = \alpha(1 - D) \tag{2}$$

Where (1−D) reflects the current environmental quality and $\alpha$ denotes the expected tourism experience value. Similar to price sensitivity, $\alpha$ varies across tourists and follows a normal distribution within the range $[P, P + b]$, representing the minimum and maximum expected experience values in the tourist group. The lower bound of $\alpha$ is always greater than or equal to $P$, as tourists will only choose to visit if their expected experience value exceeds or matches the price they are willing to pay.

Thus, the tourist surplus value $W_C$ can be expressed as:

$$W_C = Value - Price = \alpha(1 - D) - P - \beta \cdot TG \tag{3}$$

Player3: Tourism Industry

To quantify the tourism industry's payoff, we directly use the daily profit ($O_B$), which is calculated as revenue minus costs.

The daily revenue of the tourism industry is given by:

$$Income = N_T \cdot P \tag{4}$$

Where $P$ represents the ticket price and $N_T$ represents the daily number of tourists.

The daily costs include both the direct costs of operating the tourist site and taxes levied by the government. These are expressed as:

$$Cost = N_T \cdot (\delta + T_B) \tag{5}$$

$$T_B = P \cdot \gamma \tag{6}$$

Where $\delta$ is the cost per tourist for providing services, $N_T$ is the number of tourists per day, and $T_B$ is the income tax (Income multiplied by the tax rate $\gamma$) imposed by the government per tourist.

Thus, the profit $O_B$ of the tourism industry can be expressed as Income – Cost, which simplifies to:

$$O_B = N_T \cdot (P - \delta - T_B) \tag{7}$$

This formula represents the tourism industry's net profit after accounting for the revenue generated from tourists and the associated costs, including operational expenses and taxes.

### 2.1.2. Defining Strategies

In the course of the game, each party will adopt specific strategies, which will form a balancing network (constraints) with mutual interactions, leading to an iterative process. Based on the actual conditions of the tourism industry and ecological development, we propose the following modeling:

For the natural environment, it is unable to make decisions autonomously. In the game, its decision-making power should be represented by the government (relevant environmental agencies), reflected in the tourism tax on tourists and the income tax on enterprises. The impact of this strategy on environmental quality lies in the fact that the government's additional tax revenue will partly be used to restore the environment and may also limit the number of tourists, thereby reducing the environmental burden. For tourists, their decision-making power lies in adjusting the number of tourists based on the satisfaction of their tourism experience, which in turn affects the environment and the revenue of the tourism industry. For the tourism industry, the decision-making power is centered on maximizing profit by adjusting ticket prices, which influences both the number of tourists and tax revenue. Through their respective benefit-driven strategies, the three parties form a constraint network, as shown in the Figure 1:


Figure 1 Constraint Network.

### 2.1.3. Deriving the Iterative Process

At the first stage of deriving the iterative process, we need to introduce several equations to quantify the constraints in the above network.

Environment (government or relevant departments)-led:

Those relationships dominated by the environment (government or relevant sector) are mainly related to taxation and the resilience of the environment itself.

In 1995, D. J. Thampapillai (1995) proposed that the cost of completely repairing environmental damage should be exponentially related to the degree of environmental damage. The more damage the environment itself has accumulated, the more difficult it is to restore the environment, and the cost of repairing unit damage will increase sharply [6]. This view is further extended to the funds required to restore environmental damage partially, and is given by the following relationship:

$$g(D, D') = \int_{D'}^{D} q \cdot (e^D - e^{D'})dD \tag{8}$$

Where $q$ represents the cost required to restore 1% of the environmental degradation, $D$ is the current Environmental Degradation Index, and $D'$ is the restored Environmental Degradation Index. This equation represents the funds required to reduce the environmental degradation from $D$ to $D'$.

The environment itself also has a certain degree of self-recovery. In 2014, V. G. Aschonitis, G. Castaldelli (2014) and others reviewed a number of binary nonlinear models that describe the relative changes in ecological, biological and environmental parameters. Among them, the generalized model inspired by the equation describing the metabolic activity of phytoplankton can be used to measure the ability of ecological self-recovery [7].

$$f(t) = b \cdot exp\left(-a \cdot \left|t - t_{opt}\right|^{n}\right) \quad for\ a > 0\ and\ n > 0 \tag{9}$$

For n=1, the curve follows the patterns of Laplace distribution, while n reduction below 1 provides symmetrical sphenoid curves.

Tourist-led:

The relationship dominated by tourists is mainly related to the value of $W_c$.

When $W_c$ is less than 0, according to the previous definition, the cost is higher than the tourist's expected value of the tour. In this case, the tourist will not choose to tour. In reality, each tourist may have a different response to the expected value of the local scenery or to the additional environmental tax. Therefore, let the parameter $\alpha$ present a normal distribution of $(P, P + P_0)$ in a specific tourist group, and the parameter $\beta$ present a normal distribution of (0, 2) in the group to characterize the responses of different people in the tourist group.

$$W_C = \alpha(1 - D) - P - \beta \cdot TG$$

$$Where\ \alpha \sim N(P, P_0^2), \beta \sim N(0, 2^2) \tag{10}$$

The number of tourists $N_T$, is determined by the tourist surplus value $W_c$. The relationship is given by:

$$N_T = \sum_{i=1}^{nmax} I(W_{c_i}) \tag{11}$$

Where $nmax$ is the potential maximum number of tourists, and $I$ is a function of $W_C$ (tourist surplus value), expressed as:

$$I(W_c) = \begin{cases} 1, & W_c \geq 0 \\ 0, & W_c < 0 \end{cases} \tag{12}$$

In other words, $N_T$ can be expressed in another form, which is the maximum number of tourists multiplied by the probability of $W_c \geq 0$:

$$N_T = nmax \cdot \left(1 - \Phi\left(\frac{\mu_W}{\sigma_W}\right)\right) \tag{13}$$

Where $\mu_W$ represents the mean of $W_c$ and $\sigma_W$ represents the standard deviation of $W_c$.

Tourism industry-led:

The relationship, which is dominated by tourism, is mainly influenced by ticket prices $P$.

The goal of the tourism industry is to maximize profits, so they should also follow this when setting ticket prices. According to the tourism profit $O_B$ determined previously, the following expression can be obtained:

$$P^* = argmaxO_B(P) \tag{14}$$

Tourists and the tourism industry represent a clear Nash equilibrium game, where each party independently makes its optimal decision under the mutual constraints imposed by the other. Since $P$ will directly affect the tourist surplus value $W_c$ during the change process, and will indirectly affect the environmental quality by affecting the tourism tax, and ultimately have a huge impact on the number of tourists, which is the key parameter of the actual tourism profit. The common way to solve the Nash equilibrium point is to solve it through a series of differential equations, but the solution process is often very complicated. Newton's method uses first-order derivatives and second-order derivatives to iteratively update to solve the optimal value of the objective function. It is suitable for solving complex parameter optimization problems:

$$P_{new} = P - \frac{O_B'(P)}{O_B''(P)} \tag{15}$$

After selecting an initial $P$ value, the optimal $P^*$can be obtained by continuously calculating and iterating the above formula until convergence.

### 2.2. Extended Application for Balancing Scenic Spot Resources

During the model construction, a popular scenic spot and a less popular one are taken into account, both conforming to the previously developed game theory model. The objective is to maximize the total value of the revenue functions of the two scenic spots.

To further explore the allocation of scenic spot resources, the model also adheres to the following rules.

The total number of visitors to the n scenic spots will not exceed a certain limit:

$$\sum_{i=1}^{n} N_{Ti} \leq n_{max} \tag{16}$$

When the function values of the tourist for both scenic spots are less than zero, the tourist will not choose to travel. Otherwise, the tourist will travel to the scenic spot with a higher corresponding function.

$$choose = \begin{cases} 0, & w_{c1} < 0 \; and \; w_{c2} < 0 \\ 1, & w_{c1} > w_{c2} \; and \; \exists w_{c1} > 0 \\ 2, & w_{c2} > w_{c1} \; and \; \exists w_{c1} > 0 \end{cases} \tag{17}$$

For unpopular scenic spots, the excess tax revenue can be used for publicity and marketing to increase tourists' expected value of the scenic spot ($D_{B_1}$), or directly subsidize tourists' spending ($D_{B_2}$). Among them, the increase in tourists' expected value will not decline.

$$T_L = T_t - g(D, 0) - F_d$$
$$D_{B_1}: T_{L_{n-1}} = \gamma_1 \Delta k_{n-1}, \text{ where } \alpha_n \sim N(k_n \cdot P, \sigma^2),\ k_n = k_{n-1} + \Delta k_{n-1}$$
$$D_{B_2}: T_{L_{n-1}} = \gamma_2 P', \text{ where } w_c = \alpha(1 - D) - P - T_C + P' \tag{18}$$

## 3. Results

When the government faces conflicts of interest among the environment, tourism, and tourists, it should formulate policies to carefully and reasonably balance the interests of the three parties. In this process, the evaluation indicators for the pros and cons of policies should be composed of indicators related to the three parties.

By utilizing the Analytic Hierarchy Process (AHP) to assess the aforementioned potential factors, the relative weights of the corresponding revenue function can be determined systematically and rigorously. The results are in Figure 2 and Table 1.

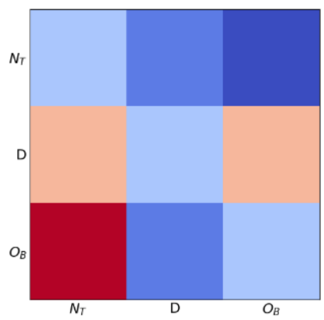


Figure 2 Judgment Matrix Heat Map.

Table 1 Weight for each factor.

| | Stands For | Weight |
|---|---|---|
| $N_T$ | Number of tourists | 0.225 |
| $D$ | Environmental damage index | -0.421 |
| $O_B$ | Tourism profit | 0.355 |

As a result, the revenue equation is:

$$S = \sum_{i=1}^{3} \epsilon_i \cdot S_i \tag{19}$$

Grid search is a method for exploring the global optimal solution of parameters. For key parameters of tax policies, such as tourist tax and corporate tax, a set of candidate values is set. The system operation results under each parameter combination are simulated by traversing the candidate values, and the value of the final benefit function is obtained. In order to further improve the precision and optimization effect of the parameters, the spline difference method is used to model the continuity of the final result so that a smooth functional relationship can be constructed between discrete grid points, helping to locate the potential optimal solution between grid points.

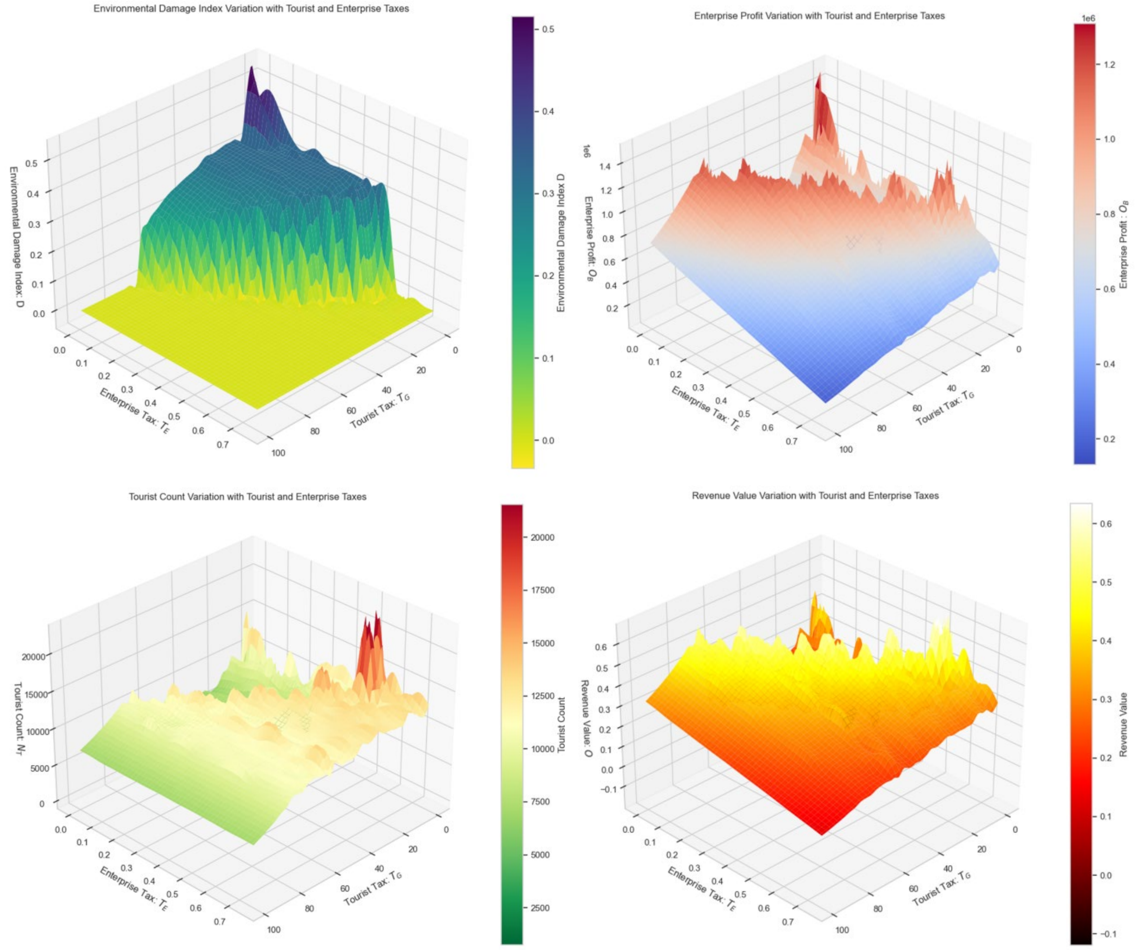


Figure 3 Visualization of the impact of different tax policies on the number of tourists, tourism profits, environmental damage, and revenue functions.

As shown in Figure 3, the optimal tax policy is: An environmental tax of about 30% is levied on a tourism industry's revenue, and an environmental tax of about \$30 is levied on tourists for a person-time.

To identify the most significant factors, we employed sensitivity indices for analysis.

$$Sensitivity\ indices = \Delta\ Objective\ Function\ Value \tag{20}$$

Through calculation, we derived the Figure 4, which clearly illustrates that the price level factor has the most substantial impact on the model. This suggests that for regions with varying price levels, the model should employ reasonable estimation methods to accurately determine the parameter$P$, thereby enhancing the model's accuracy. The parameters $N$, $D_0$, and $q$ have similar effects on the model, each contributing approximately 20% of the impact of the price level factor, indicating that these factors are of lesser importance. The parameter $\delta$ has the least effect on the model and can almost be disregarded.

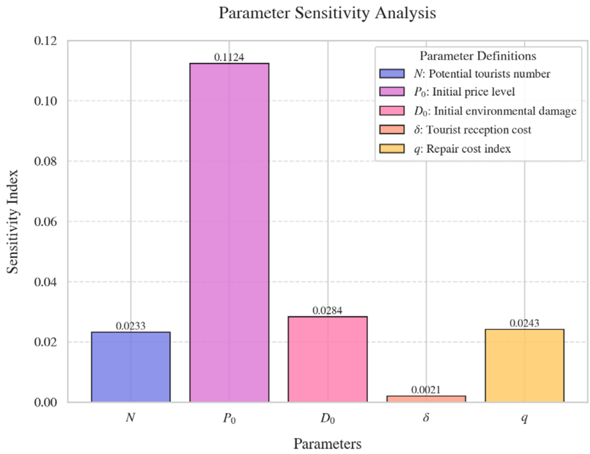


Figure 4 Parameter Importance Ranking.

To simplify the model, we regard government decision-making as a multi-stage decision. In the first stage, the government departments of popular scenic spots make tax policy decisions, and in the second stage, the government departments of unpopular scenic spots make tax expenditure decisions [8]. In the third stage, the government departments of unpopular scenic spots make tax policy decisions.

In the first stage of decision-making, a grid search method is used to traverse all possible decision sets [A1, A2, ..., An] and output the corresponding state, which is the state set after the first decision. Then, each state in the state set is input into the subsequent decision-making system. In the second stage, the decision set is [B1, B2, B3], which respectively represents the use for publicity and marketing, direct subsidies for tourists' expenses, and no decision. In the third stage, the decision set is [C1, C2, C3], which respectively represents increasing tourist taxes, increasing corporate taxes, and not increasing taxes. After completing the decision-making in each stage, the final result is output. The multi-stage dynamic programming policy decision is in Figure 5.

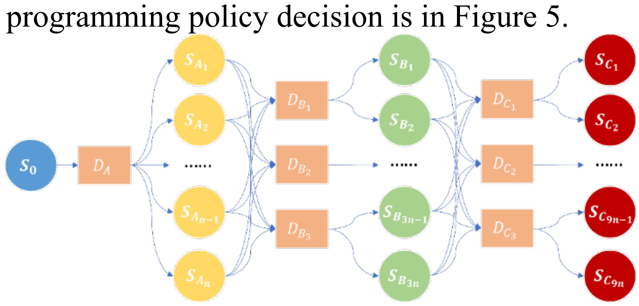


Figure 5 Multi-Stage Dynamic Programming Policy Decision Diagram.

It is impossible to traverse all states in the process of solving. The optimal substructure is a core property in dealing with dynamic programming problems, that is, the optimal solution to a problem can be constructed from the optimal solutions to its subproblems. This model conforms to the properties of the optimal substructure.

The model uses Sanya, a popular tourist scenic spot in China, and Monkey Island, an undeveloped island, as an example of an unpopular tourist attraction. The upper limit of the initial expected value of tourists to this unpopular tourist attraction is set to 1.1 times the ticket price, and the distribution is a normal distribution with a mean of 0.8 times the ticket price. The degree of environmental damage is zero, no tax is levied on tourists, and the tax rate on enterprises is 0.1.

The final simulation results show that Sanya's best tax decision is to lower the corporate tax rate to 25% and the environmental tax for tourists to visit for a day to 5.23$. The island chooses to invest funds in publicity and promotion to increase tourists' expectations of the attractions. At the end of the iteration, the best demand decision for the island is to have a corporate tax rate of 20% and an environmental tax of 2.48$ for a day to visit.

## 4. Conclusions and Future Work

In this study, we proposed a game-theoretic and learning-based optimization framework to address the challenges of overtourism through environmental taxation. Centered on the TTE-Game model involving the tourism industry, tourists, and the environment, our approach integrates Nash equilibrium analysis with learning-driven optimization techniques, such as Newton's method, dynamic system simulation, and AHP-guided revenue function construction. The optimal taxation policy derived—imposing a 0.3 rate on the tourism industry and a $30 daily tourist fee—demonstrates a balanced and sustainable configuration that aligns the interests of all stakeholders.

We further extended the model to a dual-destination setting, applying dynamic programming to simulate resource reallocation between a saturated site and an emerging attraction. This not only alleviates the pressure on overburdened destinations but also supports the strategic development of niche tourism markets. The effectiveness and adaptability of the proposed framework highlight its potential in supporting policy-making for sustainable tourism development.

Future work will focus on the following directions:

- Integration of Real-World Data: Incorporating empirical tourist behavior data, environmental indicators, and seasonal dynamics will improve the realism and predictive accuracy of the model.
- Advanced Learning Algorithms: Combining the Newton method with global optimization techniques (e.g., reinforcement learning, genetic algorithms) can enhance convergence and overcome local optima issues.
- Spatial and Temporal Modeling: Introducing spatio-temporal dynamics and high-resolution environmental impact simulation will provide more granular policy guidance.
- Risk and Uncertainty Management: Developing robust mechanisms to handle demand shocks, natural disasters, and policy uncertainty will further strengthen the system’s resilience.

Through continuous model refinement and data-driven learning, we aim to contribute more intelligent and adaptive solutions to the complex problem of overtourism in the future.

## References

[1] Jha T, Zick Y. A learning framework for distribution-based game-theoretic solution concepts[J]. ACM Transactions on Economics and Computation, 2023, 11(1-2): 1-23.

[2] Rahmati Y, Talebpour A. Learning-based game theoretical framework for modeling pedestrian motion[J]. Physical Review E, 2018, 98(3): 032312.

[3] Cheong K H, Zhao J. Adaptive strategy optimization in game-theoretic paradigm using reinforcement learning[J]. Physical Review Research, 2024, 6(3): L032009.

[4] Zhang X, Fan L, Wang S, et al. A game-theoretic framework for privacy-preserving federated learning[J]. ACM Transactions on Intelligent Systems and Technology, 2024, 15(3): 1-35.

[5] Yuan M, Shan J, Mi K. Deep reinforcement learning based game-theoretic decision-making for autonomous vehicles[J]. IEEE Robotics and Automation Letters, 2021, 7(2): 818-825.

[6] Thampapillai D J. Environmental macroeconomics: towards filling an empty box[J]. The Indian Economic Journal, 1995, 42(4): 43-58.

[7] Aschonitis V G, Castaldelli G, Bartoli M, et al. A review and synthesis of bivariate non-linear models to describe the relative variation of ecological, biological and environmental parameters[J]. Environmental Modeling & Assessment, 2015, 20: 169-182.

[8] Nepal R, Nepal S K. Managing overtourism through economic taxation: Policy lessons from five countries[J]. Tourism Geographies, 2021, 23(5-6): 1094-1115.