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A HYBRID GA-PSO AND COUPLING COORDINATION FRAMEWORK FOR MULTI-OBJECTIVE OPTIMIZATION IN SUSTAINABLE TOURISM SYSTEMS

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Abstract: Rapid tourism growth has boosted local economies but also posed environmental and social challenges, highlighting the need for sustainable management. This study presents a hybrid optimization framework that integrates Genetic Algorithm with Particle Swarm Optimization (GA-PSO) with a Coupling Coordination Degree (CCD) mechanism to balance social, economic, and environmental subsystems. The model targets maximization of employment, tourism revenue, and glacier stability under statistical and coordination constraints. Regression analysis and the entropy weight–TOPSIS method were applied to quantify subsystem interactions. Results show that GA-PSO outperforms single GA and PSO, achieving an optimal coordination degree of 0.6254. Employment, tourism revenue (USD 147 million), and environmental sustainability all showed notable improvements. This research extends the use of hybrid evolutionary algorithms in sustainable tourism and provides quantitative support for policymakers seeking to balance economic growth, social well-being, and ecological resilience.
Keywords: Sustainable tourism; Multi-objective optimization; GA-PSO; Coupling coordination degree

1 INTRODUCTION

Juneau, Alaska, with a population of about 30,000, has faced mounting challenges in tourism carrying capacity due to the rapid growth of cruise tourism in recent years. On the busiest day in 2023, the city hosted seven cruise ships and more than 20,000 visitors. While this influx significantly bolstered the local tourism economy, it also generated negative externalities, including environmental pollution, traffic congestion, and pressure on local resources. These impacts have intensified community concerns over the sustainable management of tourism.

Research on tourism-related carbon emissions and resource regulation has developed along several lines. Previous studies developed an impact assessment model for cruise ship pollution and estimated the direct costs, demonstrating that environmental costs far outweighed the associated economic benefits[1,2]. However, these studies did not propose an effective dynamic coordination mechanism. Previous studies employed a coupling coordination degree model to examine the relationship between urban development and ecological civilization construction, but the analyses were limited to static evaluations and failed to provide dynamic cross-system optimization strategies[3,4]. Literature integrated the entropy weight-TOPSIS method with coupling coordination to assess the synergetic development of the economy, ecology, and tourism, revealing an overall upward trend but highlighting persistent regional disparities[5,6]. While these studies illuminated interrelationships across multiple dimensions, they did not account for more complex factors such as carbon emissions or social feedback mechanisms. Literature applied structural equation modeling to demonstrate that tourism participation significantly enhances residents' psychological and political empowerment, thereby reinforcing support for sustainable tourism[7]. Nonetheless, this work was largely confined to a social perspective and lacked integration with other dimensions. In contrast, studies proposed a variety of optimization algorithms—including GM-PSO, multi-objective optimization, PSO-based visitor distribution, and improved NSGA-II—that effectively improved efficiency and coordination in areas such as HPC workflow scheduling, tourism project funding allocation, balancing visitor experience with profitability, and managing the environmental carrying capacity of urban tourism[8-11]. Despite these advances, the methods remain restricted to single-dimensional optimization and have yet to realize comprehensive trade-offs across the socio-economic-environmental nexus.

Despite these advances, notable gaps remain in the field of sustainable tourism. First, research on multi-objective coordinated optimization tailored to complex tourism systems is still limited. Second, the systemic coupling among social feedback, environmental carrying capacity, and economic benefits has not been sufficiently examined, which constrains integrated coordination and policy-level decision-making.

To address these gaps, this study develops a three-subsystem multi-objective model that integrates the GA-PSO optimization algorithm with the Coupling Coordination Degree (CCD) mechanism. Focusing on the tourism context of Juneau, the model seeks to realize system optimization and dynamic scheduling across social, economic, and environmental subsystems, thereby providing both theoretical support and quantitative evidence for sustainable development.

2 METHOD

In the sustainable tourism development of Juneau, multiple factors such as visitor numbers, carbon emissions, and rainfall interact and jointly shape the coordinated development of social, economic, and environmental subsystems. To design more effective sustainability strategies, this study applies a multi-objective optimization approach, drawing on the Triple Bottom Line (TBL) framework and the United Nations 2030 Agenda for Sustainable Development. The objectives are classified into social, economic, and environmental dimensions, enabling a comprehensive assessment of interactions among subsystems and their impacts on economic growth, social well-being, and environmental protection. The ultimate aim is to maximize overall urban benefits while promoting coordinated development across the three subsystems.

2.1 Establishment of Multi-System Coordination Model Optimized by GA-PSO

2.1.1 Establishment of objective function

Against the backdrop of advancing global sustainable development goals, tourism in Juneau has become a key driver of local economic and social growth, exerting notable impacts across social, economic, and environmental dimensions. On the social side, tourism contributes to job creation, income growth, and overall economic expansion, thereby enhancing social well-being. However, the surge in visitor numbers has also intensified traffic congestion and placed pressure on public infrastructure. Optimizing the social subsystem therefore requires a balance between positive and negative effects. Economically, the core value of tourism lies in generating revenue. This process relies on increases in tourist arrivals, higher per capita spending, and synergistic growth within related industries such as hotel taxation, producing chain effects. Environmentally, large tourist inflows heighten ecological stress, particularly threatening glacier ecosystems. Rising carbon emissions and accelerated glacier melting may trigger irreversible environmental changes. Thus, achieving sustainable tourism development hinges on reconciling tourism growth with the protection of natural resources.

To comprehensively assess the multifaceted impacts of tourism on social, economic, and environmental dimensions, this study defines three optimization objectives: maximizing the annual average employment rate, maximizing tourism revenue, and maximizing the mean elevation of glaciers. Accordingly, multiple regression models are constructed to examine the influence of tourism activities on each dimension, which in turn serve as the basis for formulating the objective functions.

At the social dimension, to quantify the effects of tourism development on local residents' well-being, this study establishes an Ordinary Least Squares (OLS) model, with the annual average employment rate as the dependent variable and visitor numbers and residents' social satisfaction as independent variables:

$$f_1(m, m_1) = \alpha_0 + \alpha_1 m + \alpha_2 m_1 \tag{1}$$

At the social dimension, the annual average employment rate in Juneau is defined as the dependent variable $f_1(m, m_1)$, where m denotes annual tourist arrivals and m_1 represents social satisfaction.

At the economic dimension, tourism revenue is used as the core indicator of economic benefits. A log-linear regression model is constructed to analyze the relationships among tourist arrivals, average per capita tourist expenditure, hotel tax revenue, and tourism revenue:

$$f_2(m, n_1, n_2) = \beta_0 + \beta_1 \cdot \log m + \beta_2 \cdot \log n_1 + \beta_3 \cdot \log n_2 \tag{2}$$

where $f_2(m, n_1, n_2)$ denotes tourism revenue, m is the number of tourists, n_1 indicates per capita expenditure, and n_2 refers to hotel tax revenue.

At the environmental level, in order to explore the potential impacts of tourism activities on glacier ecosystems, the mean glacier elevation is taken as the dependent variable. A ridge regression model is constructed to capture the statistical relationships among tourist arrivals, annual precipitation, carbon emissions, and mean annual temperature:

$$f_3(m, L_1, T_1, E_1) = \gamma_0 + \gamma_1 \cdot L_1 + \gamma_2 \cdot m + \gamma_3 \cdot E_1 + \gamma_4 \cdot T_1 \tag{3}$$

where $f_3(m, L_1, T_1, E_1)$ represents mean glacier elevation, m is the number of tourists, L_1 denotes carbon emissions, T_1 is mean annual temperature, and E_1 represents precipitation. The model achieves a coefficient of determination $R^2 = 0.865$, indicating a good fit.

Through these regression models, the impacts of tourism on the economic, social, and environmental subsystems can be effectively interpreted. On this basis, the optimization objectives for sustainable tourism development are defined as maximizing employment, tourism revenue, and glacier elevation. The multi-objective optimization function is therefore expressed as:

$$\max S = \max f_1(m, m_1) + \max f_2(m, n_1, n_2) + \max f_3(m, L_1, T_1, E_1) \tag{4}$$

2.1.2 Determination of constraint conditions

To ensure the feasibility and adaptability of the model in promoting sustainable development in Juneau, two constraints are introduced. The first is a statistical constraint, aimed at securing the robustness and reliability of the estimated relationships. Specifically, each decision variable is restricted to the 95% confidence interval implied by the ordinary least squares (OLS) regression results:

$$x_i^L \le x_i \le x_i^U, i = 1,2, \ldots, n. \tag{5}$$

Here, x_i^L and x_i^U denote the lower and upper bounds of variable x_i, obtained from the 95% confidence interval of the OLS regression. This interval reflects parameter uncertainty, accounts for model uncertainty, and ensures that variables remain within empirically grounded and statistically supported ranges.

The second is a coupling coordination constraint, introduced to address the interdependencies among the three subsystems in the multi-objective optimization process. To quantify and regulate their coordination, the coupling coordination degree (CCD) is employed as a constraint indicator:

$$D \geq D_0 \tag{6}$$

In this expression, D denotes the coupling coordination degree, and D_0 is a preset minimum threshold that guarantees a sufficient level of coordinated development across the social, economic, and environmental subsystems. This constraint ensures that no single subsystem is excessively prioritized at the expense of overall system performance.

2.1.3 Comprehensive evaluation by entropy Weight-TOPSIS method

To objectively evaluate the composite score of each subsystem, this study adopts the entropy-weight method to determine the weights of indicators. By calculating the information entropy of each indicator, the method reflects the uncertainty and variability of indicators, and thereby derives their weights. The specific steps are as follows:

1. Construct the probability matrix by dividing each standardized value by the column sum:

$$p_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{n} Z_{ij}} \tag{7}$$

where Z_{ij} is the standardized data, and p_{ij} is the probability of sample i under indicator j.

2. Compute the entropy of each indicator:

$$E_j = -k \sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right), \tag{8}$$

$$k = \frac{1}{\ln(n)}, \tag{9}$$

where k is the normalization constant, p_{ij} are the elements of the standardized matrix, and n is the number of samples.

3. Calculate the information utility value of each indicator:

$$d_j = 1 - E_j \tag{10}$$

4. Determine the weight of each indicator based on its information utility:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, \tag{11}$$

where d_j is the information utility value, \$m\$ is the number of indicators, and w_j is the weight of indicator j. The results of indicator weights are shown in Table 1.

Table 1 Weights of Each Indicator

Target Level	Targets	Causality	Weights
Society	Employment Rate	+	25.16%
	Satisfaction	+	33.15%
	Tourist Arrivals	+	41.69%
Economy	Hotel tax	+	26.5%
	Tourist Revenue	+	12.51%
	Per Capita Expenditure	+	50.17%
	Tourists arrivals	–	10.83%
Environment	Glacier Average Elevation	+	28.52%
	Annual Precipitation	+	13.94%
	Tourists Arrivals	–	20.56%
	Annual Average Temperature	–	24.23%
	Carbon Emissions	–	12.75%

5. Then TOPSIS is used to comprehensively score each subsystem, and the positive and negative ideal solutions are obtained:

$$A^{+} = \left\{max\left(v_{ij}\right)\right\}, A^{-} = \left\{min\left(v_{ij}\right)\right\} \tag{12}$$

Where v_{ij} is the element of the weighted normalized matrix.

6. Calculate the distance between the evaluation object and the positive and negative ideal solution:

$$D_i^{+} = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - A_j^{+}\right)^2}, D_i^{-} = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - A_j^{-}\right)^2} \tag{13}$$

7. Calculate the comprehensive score of each subsystem:

$$C_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{14}$$

2.1.4 Determination of the coupling coordination degree

Firstly, based on the comprehensive scores S_1,, S_2, and S_3 of each subsystem obtained by the entropy weight method, the coupling degree between the three is calculated:

$$C = \frac{S_1 \cdot S_2 \cdot S_3}{(S_1 + S_2 + S_3)^3} \tag{15}$$

Secondly, construct the coordination index:

$$T = \epsilon_1 S_1 + \epsilon_2 S_2 + \epsilon_3 S_3 \tag{16}$$

where ϵ_1,ϵ_2,ϵ_3 are the weights of each subsystem. This study assumes that the three weights are equal, that is :

$$\epsilon_1 = \epsilon_2 = \epsilon_3 = \frac{1}{3} \tag{17}$$

Finally, the coupling coordination degree is obtained:

$$D = \sqrt{C \cdot T} \tag{18}$$

In order to ensure the balanced development between the various dimensions, we introduce the following constraints in the optimization model:

$$D \geq \mathrm{D}_0 \tag{19}$$

among them, D_0 represents the minimum acceptable level of coordination, which in this study is set at $D_0 = 0.6$. The threshold setting and the grading criteria for the coupling coordination degree are based on previous study and further adjusted according to the characteristics of the sample used here[12]. In order to facilitate comparison and interpretation, the coupling coordination degree D is categorized into six levels, as shown in Table 2.

Table 2 Classification of Coupling Coordination Degree

Degree of Coordination	Development Type	Degree of Coordination	Development Type
$0 \leq D \leq 0.2$	Severe Imbalance	$0.5 < D \leq 0.6$	Primary Coordination
$0.2 < D \leq 0.4$	Moderate Imbalance	$0.6 < D \leq 0.8$	Secondary Coordination
$0.4 < D \leq 0.5$	Slight Imbalance	$0.8 < D \leq 1.0$	Excellent Coordination

3 MODEL OPTIMIZATION AND SOLUTION

3.1 Genetic Algorithm-Particle Swarm Optimization (GA-PSO)

3.1.1 Genetic algorithm

The genetic algorithm is a global optimization technique that mimics the evolutionary processes observed in nature. Its fundamental operations include selection, crossover, and mutation. The key steps are as follows.

1. Selection: Individuals with higher fitness are selected for reproduction based on the fitness function $f(x)$. The fitness function is defined as:

$$P(x) = \frac{f(x)}{\sum_{i=1}^{N} f(x_i)} \tag{20}$$

where, $P(x)$ represents the selection probability, which is based on the individual's fitness, and N denotes the population size.

2. Crossover: New individuals are generated through the crossover operation, with the crossover formula given as follows:

$$x_{\mathbf{new}} = \alpha x_1 + (1 - \alpha) x_2 \tag{21}$$

where, α denotes the crossover weight, while x_1 and x_2 represent the two parent individuals.

3. Mutation: With a certain probability, individuals undergo mutation, defined by the following formula:

$$x_{new} = x_{old} + \delta \tag{22}$$

where, δ denotes the mutation amplitude.

3.1.2 Particle swarm optimization

The particle swarm optimization algorithm is an optimization method rooted in swarm intelligence, inspired by the foraging behavior of bird flocks. By facilitating information exchange among particles, the algorithm enhances the convergence speed of solutions. Its fundamental steps are as follows:

1. Particle velocity update:

$$v_i = w \cdot v_i + c_1 \cdot r_1 \cdot (pbest_i - x_i) + c_2 \cdot r_2 \cdot (gbest - x_i) \tag{23}$$

2. Particle position update:

$$x_i = x_i + v_i \tag{24}$$

where, v_i denotes the velocity of particle, x_i represents its position, $pbest_i$ refers to the individual best solution, and $gbest$ indicates the global best solution. The parameter w is the inertia weight, while c_1 and c_2 are acceleration coefficients.

The GA-PSO algorithm integrates the global search capability of the genetic algorithm with the information-sharing mechanism of particle swarm optimization, thereby balancing global and local exploration, accelerating convergence, and enhancing optimization performance. The research process is illustrated in Figure 1.

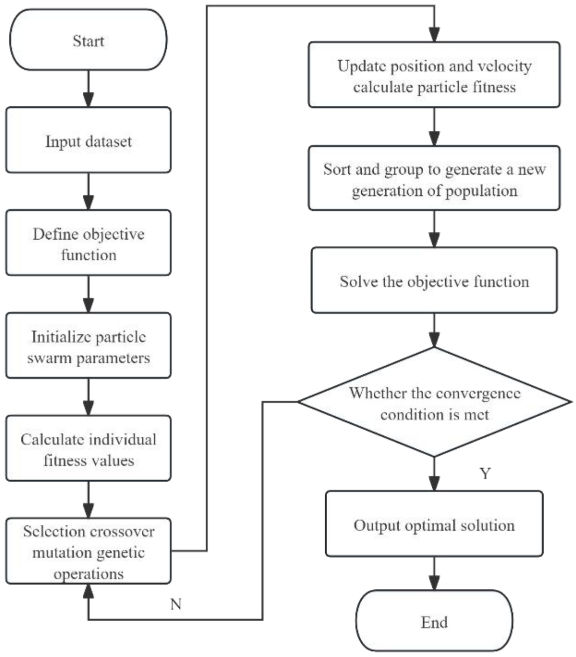

Figure 1 Flow Chart of GA-PSO Algorithm

3.2 Tourism Optimization Strategy based on the GA-PSO Algorithm

After completing the fitting of the social, economic, and environmental subsystems, this study derives the corresponding fitting equations for each dimension.

Social dimension:

$$f_1(m, m_1) = 0.5063 - 2.82 \times 10^{-8} \cdot m - 0.0002 \cdot m_1 \tag{25}$$

Economic dimension:

$$f_2(m, n_1, n_2) = 16.7610 + 7.5152 \times 10^{-2} \cdot log\, m - 1.9589 \times 10^{-3} \cdot log\, n_1 + 2.8657 \times 10^{-7} \cdot log\, n_2 \tag{26}$$

Environmental dimension:

$$f_3(m, L_1, T_1, E_1) = 1400.0 + (-0.0055) \cdot L_1 + 0.0032 \cdot m + 0.02 \cdot E_1 + 1.5 \cdot T_1 \tag{27}$$

Building on this foundation, a multi-objective optimization function was developed to support the sustainable development of tourism in Juneau City, as presented below:

$$max\, S = max\, f_1\,(m, m_1) + max\, f_2\,(m, n_1, n_2) + max\, f_3\,(m, L_1, T_1, E_1) \tag{28}$$

$$s.t. \begin{cases} x_i^L \leq x_i \leq x_i^U, i = 1,2, \ldots, n \\ D \geq D_0 \end{cases} \tag{29}$$

Due to the nonlinear nature of the objective function, the complexity of the constraints, and the conflicting characteristics among the objectives, this study employs a hybrid optimization approach that integrates genetic algorithm with particle swarm optimization (GA-PSO). The performance of this hybrid method is compared with that of the individual genetic algorithm and particle swarm optimization algorithms. The corresponding convergence trajectories are presented in Figure 2.

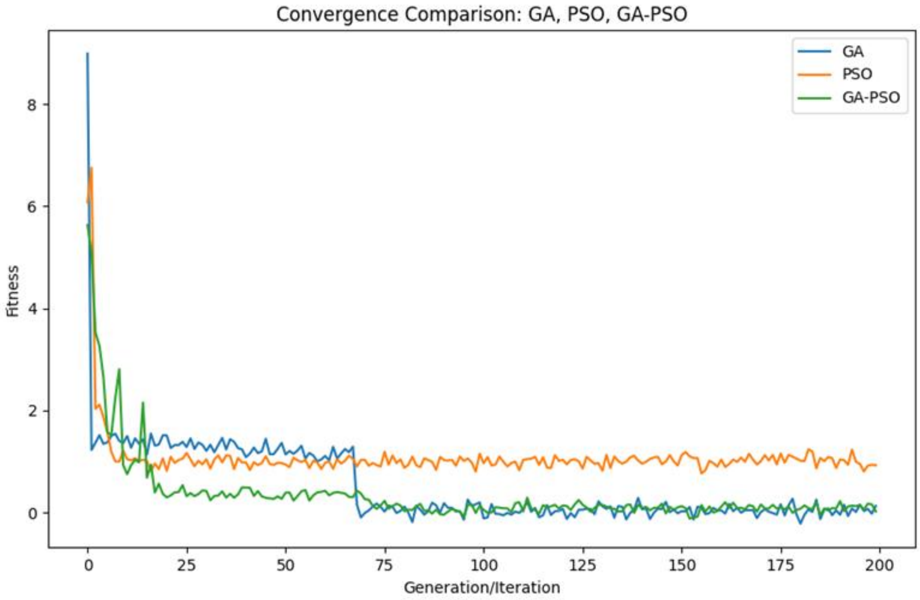

Figure 2 Experimental Comparison Chart of Algorithm Optimization Effect

As illustrated by the convergence curve in Figure 2, the three algorithms show distinct differences in their optimization processes. GA initially converges slowly, with significant fluctuations in the early iterations. Although it gradually reduces the fitness value, its overall stability is limited. PSO, on the other hand, shows faster convergence in the early stages but stabilizes after approximately 30 iterations, with the fitness value remaining at a relatively high level. This suggests that PSO tends to become trapped in a local optimum in later iterations, limiting further improvement. In contrast, the GA-PSO hybrid demonstrates a similar fast descent in the initial phase. However, by leveraging the crossover and mutation mechanisms of the genetic algorithm, it maintains strong global search capabilities during the middle and later stages, effectively avoiding premature convergence. As a result, GA-PSO achieves a superior solution with fewer iterations, demonstrating greater convergence accuracy and stability in the later stages.
After applying the GA-PSO algorithm, each decision variable converged to its optimal solution, as presented in Table 3.

Table 3 Solution Results of Decision Variables

Decision Dimension	Decision Variable	Optimal Solution
Society	Employment Rate	0.5663
	Social Satisfaction	34.45%
	Number of Tourists	2,371,370
Economy	Total Tourism Revenue	147,024,940 USD
	Per Capita Consumption	62.58 USD
	Hotel Tax	4,290,392 USD
Environment	Air Quality Index	84.64
	Annual average elevation	1,456.78 m
	Precipitation	62.38 mm
	Carbon Emissions	35,860 tons
	Average Annual Temperature	44.91° F

The results show that this solution achieves an optimal balance across the social, economic, and environmental dimensions, with a coordination equilibrium of 0.6254. Notably, both the employment rate and tourism revenue are high, while environmental indicators fall within acceptable ranges. This suggests that the GA-PSO algorithm effectively balances economic development, social benefits, and ecological protection. Based on these findings, we offer the following recommendations.
Economic Aspects: Juneau City should focus on developing the high-end tourism market by offering premium eco-tourism, cultural experiences, and customized travel services. This approach will help increase visitor spending, as well as boost hotel tax revenues and other related taxes.
Environmental Aspects: The city should enforce strict carbon emission controls while leveraging climate advantages, such as temperature, to promote low-carbon tourism initiatives. It is also important to develop green transportation options, encourage the use of renewable energy, and implement effective management of tourism-related carbon emissions.

Social Aspects: To improve overall urban livability, Juneau City should enhance infrastructure, optimize transportation networks, and improve public service facilities. Strengthening feedback mechanisms to address the needs of both tourists and residents will also be essential.

The GA-PSO hybrid algorithm effectively addresses the complex optimization challenges in tourism systems, which involve multiple objectives and constraints. Its global optimization capabilities and efficient constraint handling offer Juneau City a viable pathway toward sustainable development across tourism, the economy, society, and the environment.

4 CONCLUSION

In conclusion, this study proposes a GA-PSO-based multi-objective optimization framework that integrates social, economic, and environmental dimensions, offering a coordinated pathway for sustainable tourism development in Juneau City. The findings demonstrate that the hybrid approach achieves superior balance among employment, revenue, coordination, and ecological thresholds compared with single algorithms, thereby providing both theoretical insights into multi-system coupling and practical guidance for policy formulation.

Nevertheless, the model has limitations in terms of parameter generalizability and the exclusion of dynamic feedback mechanisms. Future research should expand the application of hybrid optimization to diverse tourism contexts, incorporate carbon emissions and social feedback into the framework, and explore real-time adaptive algorithms to enhance robustness and scalability.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Carić H. Challenges and prospects of valuation–cruise ship pollution case. Journal of cleaner production. 2016, 111: 487-498.

[2] Klein R A. Responsible cruise tourism: Issues of cruise tourism and sustainability. Journal of Hospitality and Tourism Management. 2011, 18(1): 107-116.

[3] Hu X, Dong C, Wang Y. Coupled and coordinated analysis of urban green development and ecological civilization construction in the Yangtze River Delta region. Sustainability. 2023, 15(7): 5955.

[4] Yin Z, Tang Y, Liu H, et al. Coupling coordination relationship between tourism economy-social welfare-ecological environment: Empirical analysis of Western Area, China. Ecological Indicators. 2023, 155: 110938.

[5] Tang C, Zeng R, Han Y. Coupling coordination evaluation of economic development, ecological environment, and the tourism industry in ski resorts. Journal of Cleaner Production. 2023, 426: 139076.

[6] Luo Z, Xu A, Gao S. Research on the coupling coordination relationship between tourism carrying capacity and the high-speed railway network: a case study in China. IEEE Access. 2023, 11: 20426-20444.

[7] Gautam V, Bhalla S. Exploring the relationships among tourism involvement, residents' empowerment, quality of life and their support for sustainable tourism development. Journal of Cleaner Production. 2024, 434: 139770.

[8] Hafsi H, Gharsellaoui H, Bouamama S. Genetically-modified multi-objective particle swarm optimization approach for high-performance computing workflow scheduling. Applied soft computing. 2022, 122: 108791.

[9] Arbolino R, Boffardi R, De Simone L, et al. Multi-objective optimization technique: A novel approach in tourism sustainability planning. Journal of Environmental Management. 2021, 285: 112016.

[10] Su F, Duan C, Wang R. Optimization model and algorithm design for rural leisure tourism passenger flow scheduling. Ieee Access. 2020, 8: 125295-125305.

[11] Tan Q. Research on sustainable carrying capacity of urban tourism environment based on multi objective optimization algorithm. Results in Engineering. 2023, 19: 101344.

[12] Shi T. Coupling coordination degree and spatial network effect of ecological protection and high-quality economic development in the Yellow River Basin. German Economic Review. 2020, 3: 25-34.