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Comparative Sensitivity Analysis of GA, PSO, and PSO-GA Algorithms for Carbon Environment Development and Sustainability

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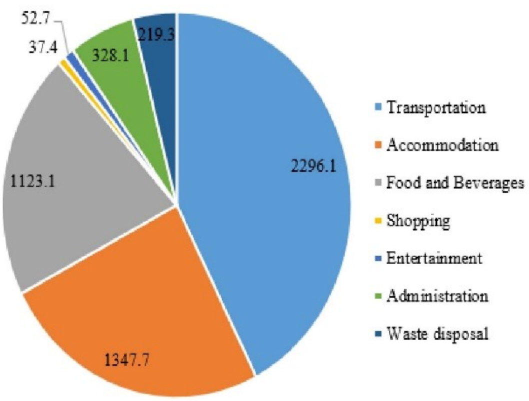
Graphical abstract



Abstract

To effectively address the CO_2 emissions in the tourism place, in this study focuses a Sanshan scenic spot for precise prediction. The main factors contributing CO_2 emission as, accommodation, transportation and catering services which intends to improve the need of carbon emission forecasting methods. To address this issue, we proposed an innovatively integrating the optimization algorithms Genetic Algorithm and Particle Swarm Optimization for accurately predicting the CO_2 emissions. Initially, this system taken input from the CO2 emissions occurred from the year of 2010 to 2020. The optimization model contains the input variables, initializing populations, evaluating fitness values, and iterating until convergence to found best prediction model. The experimental results of the proposed PSO-GA system attains 9.86 highest sensitivity showcases best performance in predicting CO_2 emissions, as evidenced by its superior Adjusted Rand Index value of 1 after 160 iterations. The predicted and measured values of CO_2 emissions using this algorithm remains significant and advanced carbon environment development at scenic spots. The PSO-GA was used to calculate the carbon emissions of three mountainous scenic spots over the next five years, and the medium and high carbon levels should change to a medium carbon development stage by 2024.

Keywords: Scenic spot, CO_2 emission, sensitivity, genetic algorithm, environment, transportation

1. Introduction

With the continuous accumulation of the greenhouse effect, global warming is becoming more serious, and the development direction of the carbon environment has attracted significant attention [Qiu *et al.* 2020; Li *et al.* 2020; Sarkar *et al.* 2018; Kim *et al.* 2019; Wang *et al.* 2021]. Tourism, known as a "smoke-free industry", has positively promoted economic development, social progress, and environmental protection [Jiang *et al.* 2020]. However, tourism infrastructure, activities, and management will inevitably cause CO_2 emissions. At present, tourism carbon emissions account for approximately 3.4% of the total global carbon emissions [Singh *et al.* 2018; Mura *et al.* 2021]. Therefore, it is imperative to correctly evaluate the development status of the carbon environment at scenic spots. During carbon emission assessment evaluation, a critical step is to effectively extract, classify, and measure the parameter values in the carbon environment. During decomposition of the target variable into independent variables, the change contribution values measured by different algorithms have specific differences, especially for complex and diverse data types [Wang *et al.* 2021; He *et al.* 2018; Gao *et al.* 2021; Hilario-Caballero *et al.* 2020]. Therefore, the integration evaluation of data information requires algorithms with high compatibility. In this context, the present study used the carbon environment development evaluation of scenic spots as the starting point to undertake algorithm optimisation research to promote the energy conservation, emission reduction, and sustainable development of the tourism industry.

Scholars have undertaken research on the effective prediction methods of carbon emissions. Acheampong *et al.* established an artificial neural network carbon emission intensity model to effectively predict the growth of carbon dioxide emission intensity [Acheampong and

Boateng 2019]. Vansia and Dhodiya [2021] used the genetic algorithm (GA), non-dominated sorting GA, and improved adaptive multi population elite Jaya algorithm to solve the problem of transportation product quantity and facility location to make product turnover with minimum transportation costs, carbon emissions, and transportation times. To reduce the carbon emission of the power sector, Melgar *et al.* [2020] proposed an environmental asset planning method, which adopted a two-stage robust hybrid planning model and considered various planning, carbon emission trading, and demand response schemes simultaneously to reduce the final total CO_2 emissions of the power sector in the region by 15%. Fang *et al.* [2017] proposed a CO_2 emission prediction method based on the improved particle swarm optimisation (PSO) algorithm, which effectively optimised the super parameters of covariance function in Gaussian process regression, and suggested policies and measures to reduce CO_2 emissions. Zhang *et al.* [2017] studied the basic theoretical framework of the structural decomposition analysis (SDA) model, analysed the structure and characteristics of different algorithms, and comprehensively evaluated the applicability and effectiveness of each algorithm. Li *et al.* [2021] conducted an in-depth analysis on the main sources of carbon emissions from the transportation industry, conducted a linear regression between the influencing factors and CO_2 emissions from the transportation industry, compared the predicted values of different algorithms with the actual values, and optimised the algorithm with the highest degree of fitting.

There are many algorithms for carbon emission measurement, and the algorithms with wide applicability and effectiveness are briefly introduced [Domingos *et al.* 2018; Bsch *et al.* 2018; Kang *et al.* 2017; Zhan *et al.* 2019]. GA is a computing model used to simulate the process of biological evolution and natural selection in Darwin's theory of genetic mechanism of biological evolution. It is a method to find the optimal solution by simulating the process of natural evolution. With the help of natural genetics, the first generation of the population evolves generation by generation according to the principle of survival of the fittest, and produces an optimal solution with more and more adaptability through cross and compilation. PSO simulates the flight foraging behavior of birds, and regards each bird in the population as a feasible solution to the optimization problem [Stephan and Georg 2019; Nilakantan *et al.* 2017; Shi *et al.* 2018; Zhao *et al.* 2021]. Each particle in the PSO algorithm has the memory function. During each iteration, the particle adjusts its path through the two optimal extremum of individual and group, and finds the optimal solution of the problem through multiple iterations. GA algorithm searches from the solution string set, with a large coverage, which is conducive to the global optimization of the problem. However, this algorithm can not fully express the constraints of the optimization problem, with a long operation time, and can not be quantitatively analyzed in terms of algorithm accuracy and feasibility. PSO algorithm has the advantages of node transfer function and no gradient information, and its calculation speed is fast [Mga *et al.* 2020; Zhang *et al.* 2020]. The two can be combined and improved accordingly to make up for each other's shortcomings [Gautam and Khanna 2018].

The study novelty encompasses the integration of optimization techniques as PSO-GA for accurate CO_2 emission prediction considering the factors to perform sensitivity analysis and comprehensive evaluation of carbon environment development. To promote the sustainable development of the tourism sector, the present study utilised the Sanshan scenic spot as the research object to undertake research on the evaluation algorithm of carbon environment development.

The main contribution of this study as follows,

- The CO_2 emission sources at scenic spots were analysed, and the CO_2 emission values of transportation, accommodation, and catering services were obtained to comprehensively compare the proportion and correlation of carbon emissions of various influencing factors and determine the main carbon sources of CO_2 emission at three mountainous scenic spots.
- The sensitivities of the GA, PSO algorithm, and PSA-GA were analysed to evaluate the CO_2 emission measurement performance of the various algorithms. In addition, the adjusted Rand coefficient was measured based on the ARI, and the convergence speed and data compatibility of each algorithm were evaluated regarding the three influencing factors of transportation, accommodation, and catering services.

Finally, by observing the fit of the CO_2 emission prediction curves and measuring the curves of the three algorithms, the optimal algorithm for carbon environment development evaluation was determined, and this algorithm was used to predict and evaluate the development of the carbon environment at the three mountainous scenic spots.

2. Materials and method

Zhenjiang Sanshan scenic spot is located in the southwest of Jiangsu Province and the South Bank of the lower reaches of the Yangtze River. It is composed of Jinshan, Jiaoshan, and Beigu mountains, covering an area of 46.3 km^2. It is a comprehensive tourist attraction integrating natural, cultural, and urban scenery, and plays an important supporting role in constructing the urban ecological environment [Romanov and Leiss 2022; Romanov and Leiss 2020; Chen *et al.* 2019; Ghobadi *et al.* 2018; Karmakar, and Das, M. 2022; Yang *et al.* 2019; Pradeep *et al.* 2024; Rajaram *et al.* 2024]. During the carbon emission calculation at the Sanshan scenic spot, the energy consumption data of transportation, accommodation, restaurants, and other places were collected through field sampling ensuring the models' predictions reflect real-world conditions. Then, based on the scale of each factor, the samples were classified to obtain the average energy consumption level under the same scale and the energy consumption was converted into standard coal for the carbon emission calculation [Singh *et al.* 2024; Rajaram and Baskar 2023; Chiranjeevi and Rajaram 2022; Liu *et al.* 2022; Banerjee *et al.* 2021; Carlson *et al.* 2024]. Gathered data converted into CO_2 emissions using standard coal equivalence. By capturing real-world data, the study ensured that the carbon emission models accurately reflect actual conditions, enhancing the reliability of the predictions and the effectiveness of the proposed optimization algorithms. In the present study, the improved PSO algorithm was used to optimise the input weight and threshold in the GA, and an optimised PSO-GA carbon emission prediction model was obtained. The PSO and GA method is chosen for the purpose of effectively optimizing the complexity and nonlinear prediction models.

The steps were as follows: (1) Sample interval and factor variable setting – the present study selected the carbon emission data from 2010 to 2020 as the target set, the carbon emission factors such as transportation, accommodation, and catering as the input variables, and carbon emission as the output; (2) Parameters such as population size, maximum number of iterations, hidden layer nodes, location, and maturity were set; (3) The population was initialised randomly and the fitness function was selected; (4) The fitness value was calculated and judged whether the maximum number of iterative steps or the optimal solution was reached; (5) The carbon emissions were predicted and the evaluation of the carbon environment development level completed.

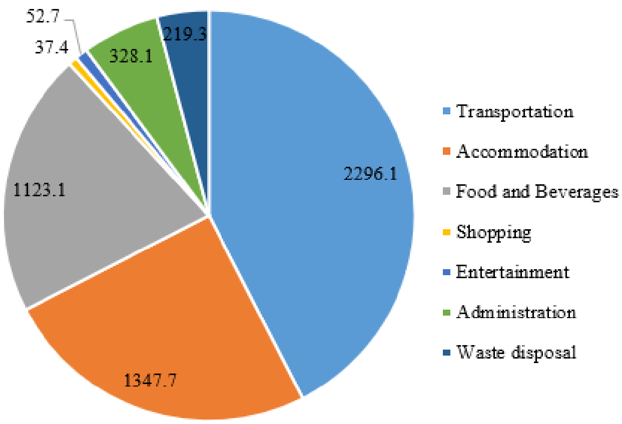


Figure 1. Carbon emission of three mountain scenic spots in 2018

Reviewing these studies revealed primary contributors to CO_2 emissions at tourist spots. The sensitivity analysis shows an effectiveness of PSO-GA in emission predictions. Additionally, the field sampling approach ensured precise, real-world data for improved accuracy. These results showcase the importance of targeted emission reduction strategies and robust predictive models.

3. Results and Discussion

3.1. Selection of influencing factors

Statistics were performed on the CO_2 emissions and their proportion in seven aspects of transportation, accommodation, food and beverages, shopping, entertainment, administration and waste disposal in the district in 2018, as shown in **Figure 1**. From the perspective of the CO_2 emission structure, the CO_2 emission related to transportation was 2296.1 t, nearly half of the total CO_2 emission, which is the factor with the highest CO_2 emission at the three mountainous scenic spots. Mainly affected by its geographical location, the Sanshan scenic spot is close to the Zhenjiang urban area and only 1.5 km away from the commercial centre. The connection between the scenic spot and the city is relatively close. The roads near the scenic spot belong to the main urban traffic lines. There are many social vehicles, with large flow, high speed, and severe tail gas pollution, resulting in significant CO_2 emissions. Therefore, transit traffic plays a leading role in the CO_2 emissions of transportation at the Sanshan scenic spot, with emissions of 1563.6 t, accounting for 68.1% of the CO_2 emission of transportation and 28.9% of the total CO_2 carbon emission of tourist attractions. Ferries and speedboats are the main means of transportation in the scenic spot, and their CO_2 carbon emissions are 376.6 t and 133.2 t, accounting for 16.4% and 5.80%, respectively, which are behind the proportion of transit traffic.

Significant CO_2 is generated in accommodation, especially when air conditioning is used intensively during summer and winter [Rajaram *et al.* 2024; Singh *et al.* 2024]. The average CO_2 generated by each person staying in the hotel for one night is as high as 32.19 kg, which greatly influences the CO_2 emission at the scenic spot. In 2018, the CO_2 emissions generated by the accommodation industry were 1347.7 t, accounting for approximately 24.9% of the total CO_2 emission of tourist attractions. The catering service industry also produces CO_2 during cooking and processing waste materials. CO_2 emissions in this sector are after transportation and accommodation, accounting for 20.8% of the total CO_2 emissions at the scenic spot. As the three mountainous scenic spots focus on natural mountains and rivers and historical monuments, the CO_2 emissions in tourism shopping, entertainment facilities, and management are lower; however, the CO_2 emissions formed cannot be ignored. The above influencing factors were verified by binary correlation analysis. The correlation degree between transportation and CO_2 emission at the scenic spot was the highest, and the correlation coefficient was 0.9987, which are the leading factor affecting CO2 emissions in the three mountainous scenic spots. The second was the accommodation and catering industry, and the correlation coefficients were 0.9926 and 0.9918, respectively. The CO_2 emissions of the tourism transportation, accommodation, and catering services were the main carbon sources at the Sanshan scenic spots. Controlling carbon emission from these three aspects is vital for energy conservation and emission reduction at scenic spots.

3.2. Algorithm sensitivity analysis

To evaluate the measurement performance of various algorithms, the sensitivities of the GA, PSO algorithm, and PSO-GA were analysed. To determine the algorithm with the highest sensitivity, most accurate results, and widest practicability, the influencing factor values of the three parameters of transportation, accommodation, and catering services were used and increased or decreased by 10% on the original data. Then, each algorithm was tested, using the measured results in 2018 as the standard, and the calculation results under the different conditions were compared. The sensitivity results of the three algorithms to each influencing factor are shown in **Table 1**. The PSO algorithm had the lowest sensitivity (8.59), followed by the GA (8.68). The PSO-GA had the highest sensitivity (9.86) and the algorithm had good sensitivity to the main factors affecting CO_2 emission, with a sensitivity value between 9.66 and 9.88.

Table 1. Sensitivity of each algorithm on influencing factors of CO_2 emissions

CO_2 emissions		Transportation	Accommodation	Catering	Shopping	Entertainment	Waste
PSO	Increase	2513.3	1467.8	1215.1	41.1	57.6	237.4
	Decrease	2108.5	1227.1	1029.1	34.2	48.9	199.4
	Sensitive value	9.46	8.91	8.19	9.94	9.18	8.28
	M	8.17	8.95	8.37	8.46	7.38	9.04
GA	Increase	2086.2	1236.3	1050.2	34.5	48.4	200.3
	Decrease	2099.5	1233.3	1029.1	34.0	47.8	199.6
	Sensitive value	9.14	8.27	6.49	7.64	8.28	8.64
	M	8.56	8.49	8.37	9.15	9.43	8.97
PSO-GA	Increase	2069.0	1216.0	1011.5	33.7	47.6	197.4
	Decrease	2070.6	1217.5	1012.4	33.7	47.6	197.5
	Sensitive value	9.89	9.77	9.94	9.82	9.83	9.96
	M	9.82	9.66	9.86	9.78	9.82	9.94

Convergence in the algorithm iteration means that a stable solution can be obtained via finite step iteration, and the change in the continuous iteration is lower than the set accuracy. The faster the speed of obtaining the stable solution, the better the convergence and data compatibility of the algorithm. The ARI was applied in the model evaluation of the given index information, that identifies the changes in input and guiding the system improvement to enhance reliability. The range of values was [-1,1]. The larger the ARI value, the better the result. The ARI parameter validates PSO-GA effectiveness for accurately forecasting carbon emissions, supporting its practical application in carbon management strategies.

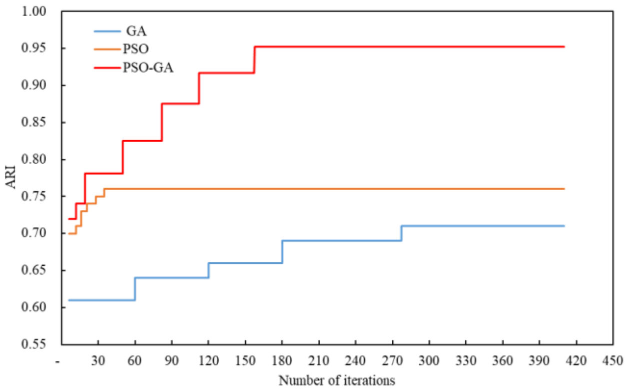


Figure 2. ARI index changes of algorithms in transportation data set

Figure 2 shows all algorithm types. The PSO algorithm, GA, and PSO-GA comparison charts of the ARI change trend for the transportation data set show that the PSO algorithm had the fastest speed, and the model entered the convergence stage after 35 iterations; however, its ARI value was low, at approximately 0.76. The GA had the slowest operation speed, converging after 280 steps, and its ARI value was the smallest, at approximately 0.7. The operation speed of the PSO-GA was between the other two algorithms, converging when n = 157, although its ARI value was the largest at 0.95, and the accuracy of the results was better than the other two algorithms. Therefore, the PSO-GA was the best at the CO_2 emission measurement.

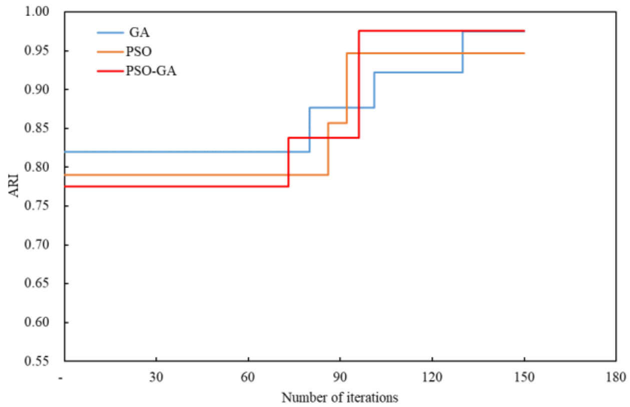


Figure 3. ARI index change of each algorithm under accommodation data set

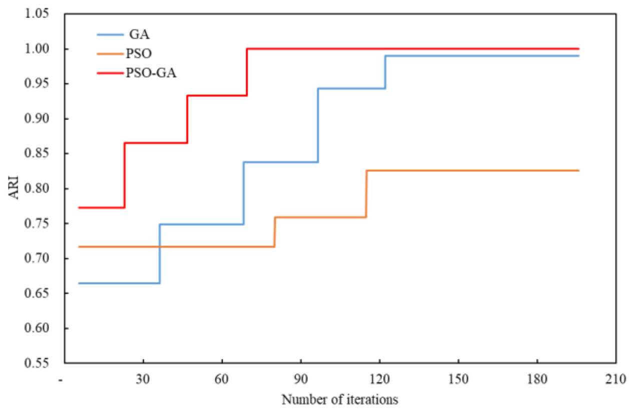


Figure 4. ARI index changes of algorithms under catering service data set

Figure 3 shows the various algorithm (PSO algorithm, GA, and PSO-GA) comparison charts of the ARI change trend for the accommodation industry data set. The PSO still had the fastest convergence speed. When the number of iteration steps was 92, the ARI curve entered the stable stage; however, the accuracy of its calculation result was low and the ARI value was the smallest. The results of the CO_2 emission measurement for the GA and PSO-GA were the same; however, the former entered the convergence stage first and the number of iterations increased by 34 steps. Therefore, the PSO-GA performed the best in the operation of CO_2 emission in the accommodation industry data set.

Figure 4 compares the ARI change trend for the PSO algorithm, GA, and PSO-GA for the catering service data set. When the number of iteration steps was lower than 70 generations, the ARI value of the PSO-GA reached the optimal (ARI = 1), whereas the ARI values of the PSO algorithm and GA converged after 110 steps, and the ARI value under the PSO-GA was slightly greater than that of the PSO algorithm (0.99); however, it was much larger than the ARI value of the GA (0.83). Therefore, after 160 iterations, the ARI value of the PSO-GA was higher than that of the PSO algorithm and GA, and the ARI value of the former showed that the measurement result was ideal, and the ARI can reach 1. Therefore, the change in the ARI for the comprehensive transportation, accommodation, and catering service data sets showed that the CO_2 measurement result under the PSO-GA model was ideal in accuracy and optimisation efficiency.

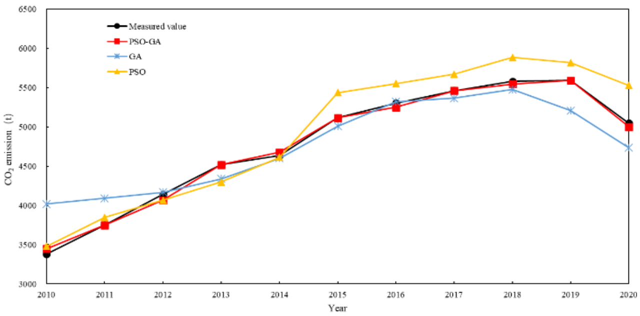


Figure 5. CO_2 emission prediction curve and measured curve of different algorithms

The PSO algorithm, GA algorithm and PSO-GA algorithm model are used to predict the CO_2 emissions of the Sanshan tourist attractions from 2010 to 2020 and compare them with the measured values. The fitting trend of the predicted curve and the measured value curve is shown in **Figure 5**. According to the analysis of the measured change trend of CO_2 emissions in the Sanshan scenic spots in recent ten years, during 2010-2016, with the rapid development of the national economy, the number of tourists is gradually increasing, and the CO_2 emissions are increasing year by year, with an average annual growth of 269.2 tons. With the promulgation of a series of ecological

Restoration policies by the government, people's awareness of environmental protection have been greatly improved. Although the number of tourists coming to the Sanshan Scenic Area has increased significantly, its CO_2 emissions have only increased slightly. The average annual growth rate in 2017-2019 is 96t, which is 64.3% lower than before. In recent years, affected by the new crown epidemic, the number of tourists has decreased significantly, and its CO_2 emissions have decreased from 5592.4t to 5047.9t. It can be seen from the fitting figures under each algorithm that the predicted CO_2 emissions by PSO-GA algorithm are highly consistent with the actual values, which can effectively predict the CO_2 emissions of the Sanshan Scenic Area. At the same time, it also proves that the PSO algorithm and GA algorithm are feasible to mix in terms of CO_2 emissions of tourist attractions.

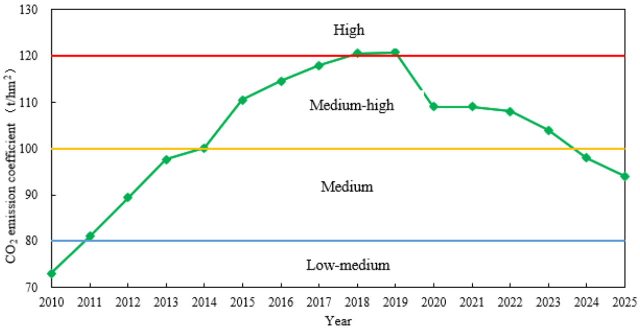


Figure 6. Level chart of carbon environment development (2021-2025 is the predicted value)

Combined with the development level of the evaluation system at the scenic spot, a carbon environment development level map of the three mountainous scenic spots was drawn (**Figure 6**). In 2010, the CO_2 emission coefficient of the three mountainous scenic spots was relatively small, 73 t/km^2, which was a low carbon development level. From 2011 to 2014, the CO_2 emission coefficient was between 80 and 100 t/km^2, and the carbon environment was in the medium carbon development stage. Over the following three years, CO_2 emissions gradually increased and the carbon environment gradually transited to medium and high carbon development levels. In 2018 and 2019, the three mountainous scenic spots were evaluated as high carbon environments with severe pollution. With improved scenic spot management level and awareness by tourists of environmental protection, the ecological environment has been effectively restored. At present, it is in the medium and high carbon stages. It is predicted that the CO_2 emission coefficient at the Sanshan scenic spot will fall below 100 t/km^2 in 2024, entering the medium carbon level development stage.

4. Conclusions

In conclusions, the proposed PSO-GA model significantly predicts the CO_2 in the tourist spot. The study attains the effective results, for CO_2 emissions related to transportation, accommodation, and catering services accounted for 42.5%, 24.9%, and 20.8% of the total CO_2 carbon emissions and their correlations were 0.9987, 0.9926, and 0.9918, respectively, and are the main influencing factors of carbon emissions at the three mountainous scenic spots. The CO_2 measurement sensitivities of the GA, PSO algorithm, and PSO-GA were analysed. The sensitivity of the PSO-GA was the highest (9.86), followed by the GA (8.68) and PSO (8.68). ARI evaluates the convergence of each algorithm in the transportation, accommodation, and catering service data sets, after 160 iterations, the ARI value of the PSO-GA was the highest, the measurement result was the most ideal, and its ARI reached 1. The CO_2 emissions predicted by the PSO-GA fitted with the actual value, and effectively predicted the CO_2 emissions at the three mountainous scenic spots. During 2010-2020, the carbon environment development level of the three mountainous scenic spots was low carbon (2010) → medium carbon (2011-2014) → medium high carbon (2015–2017) → high carbon (2018 and 2019) → medium high carbon (2020). The carbon environment development level is expected to become the medium carbon development stage by 2024.Despite advancements, the study with shortcomings of single scenic spot that might not fully contains geographical and environmental contexts. Additionally, the three common factors are employed other sources were overlooked. Future work should expand to multiple locations and included wider range of contributing factors to enhance the models generalizability. Integrating advanced data collection methods and comparative studies will also improve the robustness and applicability of the carbon emission models.

Nomenclature

GA	genetic algorithm
PSO	particle swarm optimisation
ARI	adjusted Rand index
SDA	structural decomposition analysis

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