GA-PSO-BP prediction of carbon emission and factor analysis

Ziyuan Wang, Xiyu Fang *, Wanran Guo

School of Mathematical Sciences, Chengdu University of Technology, Chengdu, China, 610059

* Corresponding Author Email: 13438720313@163.com

Abstract. In response to the escalating challenge of global climate change, this study presents a robust forecasting framework for carbon emissions based on a hybrid GA-PSO-BP neural network model. Leveraging high-dimensional multi-sector emission data from Sichuan Province, China, Principal Component Analysis (PCA) was employed to effectively reduce data dimensionality and eliminate noise, thus enhancing model stability. The BP neural network, optimized through the integration of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), was trained to capture the complex, nonlinear relationships inherent in carbon emission trends. The results reveal that the manufacturing sector remains the dominant contributor to overall emissions, while the wholesale and retail industry also exhibits significant emission levels, underscoring the need for targeted mitigation strategies in the service sector. Moreover, time series forecasting indicates that carbon emissions are projected to increase until approximately 2025, after which a marked decline is anticipated—a critical turning point for carbon peaking and neutrality policies. Overall, the proposed method not only delivers high prediction accuracy with low error rates but also provides actionable insights for policymakers and industry stakeholders to implement effective carbon reduction measures.

Keywords: Carbon Emissions, BP Neural Network, GA-PSO.

1. Introduction

Climate change remains one of the most pressing issues of the twenty-first century, as it poses a formidable challenge to global sustainability. In recent years, carbon emissions have drawn significant attention due to their central role in exacerbating global warming [1-2]. Moreover, policy interventions such as the Paris Agreement and national initiatives underscore the urgency of adopting effective mitigation strategies to limit temperature rise well below 2°C [3]. Against this backdrop, the accurate forecasting of carbon emissions becomes paramount, as it enables policymakers and industry stakeholders to optimize pathways toward carbon neutrality [4].

Contemporary research has emphasized the potential of artificial intelligence and data-driven methods to capture the complex and often nonlinear dynamics underlying carbon emissions. For example, neural network approaches, including recurrent neural networks (RNN) and long short-term memory (LSTM), have demonstrated superior performance in modeling temporal dependencies and projecting future trends [4-5]. However, these models often require extensive parameter tuning and are susceptible to overfitting, thereby motivating the application of metaheuristic optimization algorithms—such as particle swarm optimization (PSO), butterfly optimization algorithm (BOA), and ant-lion optimizer (ALO)—to refine model accuracy [6].

An equally critical research direction involves the selection and interpretation of influencing factors, since emission trajectories are shaped by a myriad of drivers—economic growth, energy consumption, population dynamics, and technological advancements [7]. Traditional statistical approaches like multiple linear regression and gray relational analysis (GRA) offer interpretable insights into factor importance but may struggle with high-dimensional datasets. Consequently, many studies now deploy dimensionality reduction methods such as kernel principal component analysis (KPCA) and random forest–based feature extraction to handle large-scale, heterogeneous data.

Despite notable progress in modeling accuracy, a number of research gaps persist. First, the heterogeneity of emission sources and regional differences demand more tailored analytical approaches. Second, integrating uncertainty analysis into carbon prediction models remains challenging, especially under rapidly changing policy or socioeconomic conditions. Lastly, as data availability expands, the continuous refinement of hybrid, ensemble, and deep learning models will be essential for capturing complex patterns in emerging data streams [7-8].

Building upon these insights, the present study aims to develop and validate an advanced carbon emission forecasting framework that systematically incorporates time-series modeling, metaheuristic parameter optimization, and rigorous factor selection. Through this approach, it seeks to contribute a robust decision-support tool for policymakers and industry practitioners to align with low-carbon and sustainable development goals.

2. Fundamental Functions of the BP Neural Network

2.1. Dimensionality Reduction Method

In this study, due to the high dimensionality of the dataset, directly using the original data for modeling would not only increase computational complexity but may also introduce noise and redundant information, thereby compromising the model's stability and prediction accuracy. To address this, Principal Component Analysis (PCA) is employed to reduce the dimensionality of the input features. This approach allows for the extraction of the most relevant information while eliminating unnecessary noise.

PCA is a widely used linear dimensionality reduction technique that transforms the original dataset into a new coordinate system through orthogonal transformation. In this new system, principal components are ranked by the amount of variance they explain in the data. Typically, the number of retained components is determined based on the cumulative variance contribution rate. This method effectively reduces dimensionality while preserving the primary structure of the data, providing a more compact and efficient input for subsequent neural network modeling and forecasting.

2.2. Overview of the BP Neural Network

The Back Propagation (BP) neural network has demonstrated significant advantages in processing time series data. Its multi-layer architecture and strong nonlinear mapping capability enable it to capture complex patterns and dynamic changes inherent in time series. Whether dealing with long-term trends, cyclical fluctuations, or other latent nonlinear relationships, the BP neural network can effectively model and predict them.Figure 1 shows the structure of bp neural network.

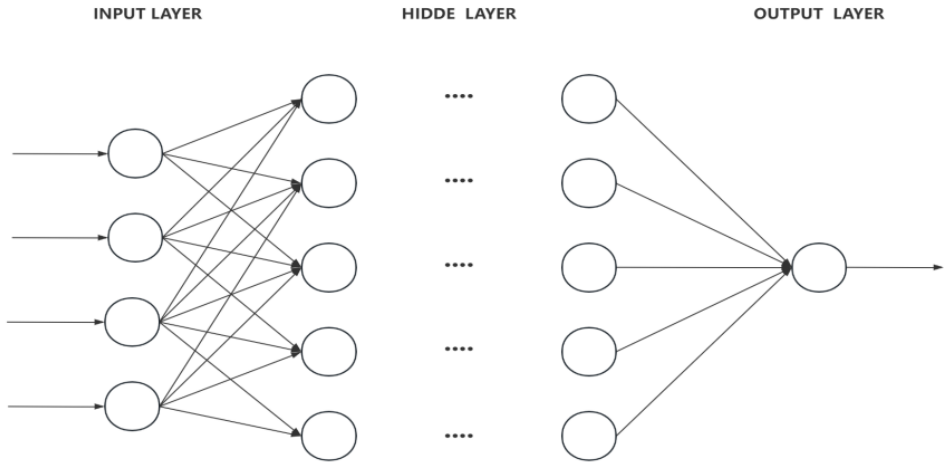

Figure 1. Structure of the BP Neural Network

In addition, through iterative optimization using the backpropagation algorithm, the BP network is capable of self-adaptive parameter adjustment, thereby continuously reducing prediction errors and improving accuracy. This adaptability and optimization capability make it particularly suitable for large-scale, multivariate time series analysis. It has been widely applied in fields such as economics, energy, and climate forecasting, providing robust data support for informed decision-making.

2.3. Neural network structure optimization method

The GA-PSO hybrid algorithm combines the advantages of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to efficiently search the hyperparameter space of the neural network. In this method, each candidate solution is treated as a particle, where the position vector represents a combination of hyperparameters (such as the number of hidden neurons, the regularization parameter α, and the learning rate), and the velocity vector indicates the direction and magnitude of movement within the search space.

In the PSO portion of GA-PSO, each candidate solution is treated as a particle, its position vector x_i represents the current hyperparameter combination, while the velocity vector v_i represents the movement direction and step size of the particle in the solution space. The updating of particles follows the following mathematical expression:

$$\begin{gathered}\boldsymbol{v}_i(t+1)=w\cdot\boldsymbol{v}_i(t)+c_1\cdot r_1\cdot(\mathbf{pbest}_i-\boldsymbol{x}_i(t))+c_2\cdot r_2\cdot(\mathbf{gbest}-\boldsymbol{x}_i(t))\\ \boldsymbol{x}_i(t+1)=\boldsymbol{x}_{\boldsymbol{i}}(t)+\boldsymbol{v}_i(t+1)\end{gathered}\tag{1}$$

Where w is the inertia weight, c_1 and c_2 is the individual and global learning factor respectively, r_1 and r_2 is the random number uniformly distributed at [0,1], which is the historical optimal position of the particle, and $\mathbf{gbest}$ is the global optimal position in the whole population. This mechanism enables particles to balance local exploration and global search, rapidly converge to the optimal solution region, and effectively search for better solutions in the hyperparameter space.

In the GA part, in order to enhance the diversity of the population and escape the local optimal, the algorithm introduces crossover and mutation operations. When two candidate solutions p_1 and p_2 meet the crossing condition, a new candidate solution is generated using the following crossing operation:

$$x_{mutated}=x+\Delta x,\quad \Delta x\backsim N(0,\sigma^2)\tag{2}$$

The standard deviation σ is usually set to σ=0.1×(upper bound−lower bound) of the parameter value range. After each crossover and variation, the RMSE evaluation index f(x) of the newly generated candidate solution will be calculated through cross-validation and used to update the corresponding individual optimal $\mathbf{pbest}$ and $\mathbf{gbest}$ global optimal. After multi-generation iteration, GA-PSO hybrid algorithm can gradually approximate the optimal combination of hyperparameters, which lays a solid foundation for the construction of high-performance BP neural networks.

3. Results

3.1. Data Description

The dataset used in this study is sourced from the China Emission Accounts and Datasets (CEADs). A corresponding reference will be included in the reference section according to the citation requirements of the CEADs website [9–13].

The data primarily focuses on carbon emissions in Sichuan Province, China, with emissions measured in terms of the equivalent coal combustion amount corresponding to energy-related emissions. The dataset encompasses the following indicators across various sectors: total emissions, agriculture and water conservancy, coal mining, oil and gas extraction, ferrous mining, non-ferrous metal mining, non-metallic mining, other mining, food processing, grain production, beverages, tobacco, textiles, garments, leather and fur, wood and bamboo products, furniture, paper, printing, cultural and sports products, petroleum refining, chemicals, pharmaceuticals, chemical fibers, rubber products, plastic products, non-metallic mineral products, ferrous metal smelting, non-ferrous metals, metal products, general machinery, special-purpose equipment, transportation equipment, electrical machinery and equipment, electronics, instruments, other manufacturing industries, waste and scrap, power and steam generation, natural gas production and supply, tap water production and supply, construction, transportation and telecommunications, wholesale and retail, other services, and urban and rural households.

Furthermore, using the equivalent coal combustion amount as a measure for carbon emissions is a rational and widely accepted approach. Firstly, this method allows for the standardization of emission indicators from different energy sources by converting various energy consumption figures into a common "coal-equivalent" metric. This conversion facilitates cross-sectoral and cross-energy comparisons, thereby providing a unified basis for analyzing emission data. Secondly, this measurement technique has been validated in practice and is extensively utilized, offering a reliable reflection of the actual emissions across diverse industries. Lastly, adopting the equivalent coal combustion approach simplifies the processing of complex energy statistics, which enhances both the operational feasibility of the data analysis and the accuracy of subsequent model predictions.

3.2. Optimization result

The training process after each round of 50 iterations produces the results shown below.

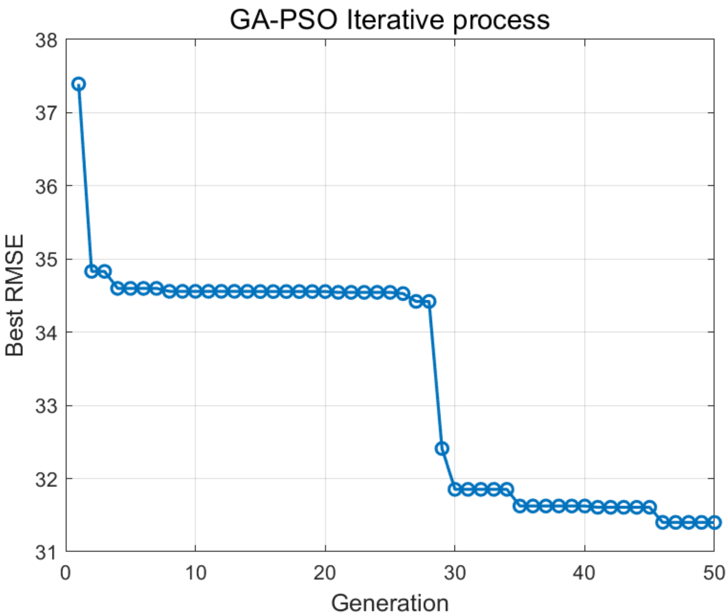

Figure 2. Training Process

As illustrated in Figure 2, the GA-PSO–optimized BP neural network exhibits a pronounced multi-phase convergence behavior. Quantitatively, the root-mean-square error (RMSE) decreases from approximately 37.4 at generation 0 to 35.3 by generation 1—a reduction exceeding 5.6%. During generations 1–29, the algorithm enters a stable exploitation phase, maintaining the RMSE around 35.3 to fine-tune the solution. At generation 30, a second rapid descent occurs, with the RMSE plummeting to about 31.8, followed by incremental improvements that yield a final RMSE of 31.3—an overall enhancement of more than 16%. This staged steep decline underscores the hybrid GA-PSO algorithm's ability to balance global search and local refinement, effectively escaping local minima and swiftly converging toward the global optimum.

3.3. Importance Ranking of Indicators

The importance ranking derived from the BP neural network is shown below:

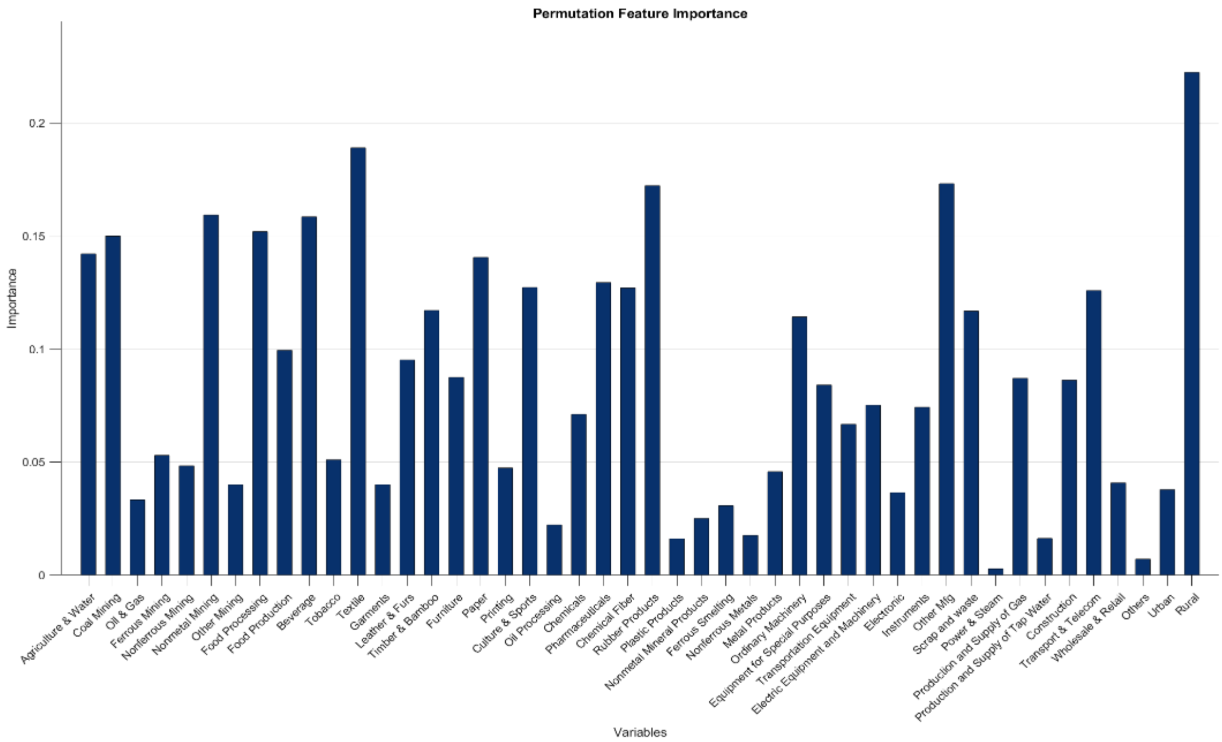

Figure 3. Importance Ranking of Indicators

As illustrated in the figure, carbon emissions from the manufacturing sector are the highest, indicating its dominant role in overall emissions. This is followed by the tertiary industry, where the “Wholesale & Retail” sector stands out with particularly high emission values—significantly exceeding those of other sub-industries within the service sector. This suggests that, aside from manufacturing, the wholesale and retail industry exerts substantial influence on carbon emissions and should be given due attention in the formulation of carbon reduction policies.

3.4. Time Series Forecasting

The application of the BP neural network in carbon emission forecasting demonstrates high accuracy and robustness. The model effectively captures complex nonlinear relationships within the data. Through deep learning on historical carbon emission records and cross-validation, the network exhibits strong fitting capabilities. Its low error rate and stable performance confirm the BP neural network's reliability in predicting future emission trends. This provides solid data support for policymakers in designing emission reduction strategies and adjusting the energy structure.

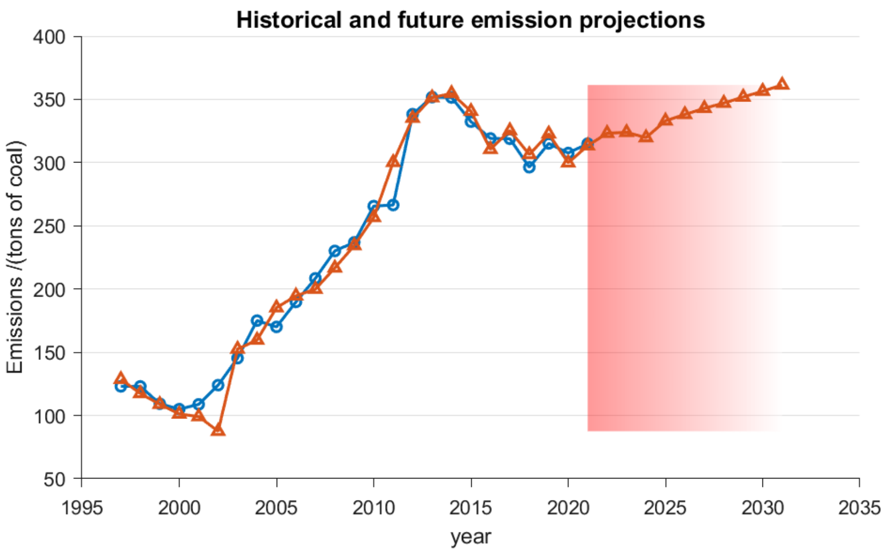

Figure 4. Forecasting Process

According to the model's prediction results, carbon emissions are expected to continue rising until around 2025, at which point a significant turning point is observed, followed by a downward trend. This inflection reflects the combined effect of multiple factors, such as national carbon reduction policies, the promotion of clean energy, and the optimization of industrial structures. The predicted peak around 2025 indicates that the growth rate of emissions will be effectively curbed, laying a solid foundation for achieving carbon peaking and ultimately carbon neutrality.

4. Conclusion

This study delivers an in-depth empirical examination of carbon emission patterns within the tertiary industry, identifying the wholesale and retail sector as a markedly higher emitter relative to other service sub-sectors. By employing advanced data-driven techniques coupled with metaheuristic optimization algorithms, the research addresses the previously unclear dynamics of sector-specific emissions and rigorously evaluates targeted mitigation measures—such as green supply chain implementation, the transformation of logistics and storage operations, and the adoption of energy-efficiency technologies. These findings furnish policymakers and enterprise stakeholders with precise, actionable guidance for intervention design, thereby advancing the low-carbon transition of the service economy.

An enhanced forecasting framework, integrating a BP neural network optimized via metaheuristic algorithms, projects a carbon-emission peak around 2025 followed by a sustained decline. The incorporation of scenario simulations enables quantitative evaluation of how varying policy intensities, technological progress, and economic growth trajectories influence future emission pathways. As a robust decision-support tool, this model equips regional and national authorities with the evidence base needed to formulate carbon neutrality strategies that balance mitigation targets with socio-economic considerations, ensuring a managed and effective transition to a low-carbon economy.

References

[1] Gao M.Y., Yang H., Xiao Q., Goh M. A novel fractional grey Riccati model for carbon emission prediction [J]. Journal of Cleaner Production, 2021, 282: 124471.

[2] Han Y.M., Cao L., Geng Z., Ping W., Zuo X., Fan J., Wan J., Lu G. Novel economy and carbon emissions prediction model of different countries or regions in the world for energy optimization using improved residual neural network [J]. Science of the Total Environment, 2023, 860: 160410.

[3] Meinshausen M., Lewis J., McGlade C., Gütschow J., Nicholls Z., Burdon R., Cozzi L., Hackmann B. Realization of Paris Agreement pledges may limit warming just below 2°C [J]. Nature, 2022, 604 (7905): 304 – 309.

[4] Murshed M., Khan U., Khan A.M., Ozturk I. Can energy productivity gains harness the carbon dioxide-inhibiting agenda of the Next 11 countries? Implications for achieving sustainable development [J]. Sustainable Development, 2022, 31 (1): 307 – 320.

[5] Ameyaw B., Yao L., Annan A., Korang J.A. West Africa’s CO_2 emissions: investigating the economic indicators, forecasting, and proposing pathways to reduce carbon emission levels [J]. Environmental Science and Pollution Research, 2020, 27: 13276 – 13300.

[6] Dai S., Niu D., Han Y. Forecasting of energy-related CO_2 emissions in China based on GM (1, 1) and least squares support vector machine optimized by modified shuffled frog leaping algorithm for sustainability [J]. Sustainability, 2018, 10 (4): 958.

[7] Cui X.W., Wu R., Zhao T. Forecasting of carbon emission in China based on gradient boosting decision tree optimized by modified whale optimization algorithm [J]. Sustainability, 2021, 13 (21): 12302.

[8] Li Y. Forecasting Chinese carbon emissions based on a novel time series prediction method [J]. Energy Science & Engineering, 2020, 8 (7): 2274 – 2285.

[9] Xu J., Guan Y., Oldfield J., Guan D., Shan Y. China carbon emission accounts 2020 – 2021 [J]. Applied Energy, 2024, 360: 122837.

[10] Guan Y., Shan Y., Huang Q., Chen H., Wang D., Hubacek K. Assessment to China's recent emission pattern shifts [J]. Earth's Future, 2021, 9 (2): e2021EF002241.

[11] Shan Y., Huang Q., Guan D., Hubacek K. China CO_2 emission accounts 2016 – 2017 [J]. Scientific Data, 2020, 7 (1): 54.

[12] Shan Y., Guan D., Zheng H., Ou J., Li Y., Meng J., Mi Z., Liu Z., Zhang Q. China CO_2 emission accounts 1997 – 2015 [J]. Scientific Data, 2018, 5: 170201.

[13] Shan Y., Liu J., Liu Z., Xu X., Shao S., Wang P., Guan D. New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors [J]. Applied Energy, 2016, 184: 742 – 750.