

Research on Carbon Emission Prediction Model for Building Structure Construction Based on ARIMA-BPNN

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Abstract. In this study, a hybrid prediction model based on the fusion of ARIMA and BP neural network is proposed to accurately predict the carbon emissions during the construction phase. The model adopts a ‘decomposition-integration’ strategy, extracting the linear features in the time series by ARIMA model and capturing the nonlinear patterns of the residuals by BP neural network. The empirical analysis is based on the 12-month carbon emission data of a construction project, and the results show that the hybrid model has a root mean square error (RMSE) of 0.0115 on the test set, and 92.18% of the predictions are within 1% of the relative error, which is significantly better than the single prediction model.

Keywords: carbon emission prediction, building construction, ARIMA, BP neural network, hybrid model

1. Introduction

As the problem of global climate change becomes increasingly serious, “carbon peaking and carbon neutrality” has become a common goal for countries around the world. Studies have shown that China, as the world's largest carbon emitter, the achievement of its carbon peaking and carbon neutrality targets is crucial to global climate governance, and under the scenario of low economic growth and low carbon energy consumption, China can reach the peak in 2026 and achieve carbon neutrality in 2056 [1], whereas there are significant differences in the carbon emissions of various provinces, and most of which can reach the peak in 2030, but the achievement of carbon neutrality in 2060 needs to rely on carbon capture and storage technologies [2]. Systematic literature analysis indicates that the hotspots of carbon peaking and carbon neutrality research focus on low carbon transformation of key industries and management science, which provide theoretical support and policy recommendations for China to achieve carbon neutrality [3]. Urbanisation has a significant impact on the timing of peak carbon emissions from buildings, with the rural residential sector expected to be the first to peak in 2027, while the overall building sector will peak in 2037 [4]. In addition, new energy sources (e.g. solar, wind, hydrogen) and artificial carbon conversion technologies are the core pathways to carbon neutrality, with China's carbon emissions expected to peak in 2030 and decline significantly by 2060 [5]. The urban residential building sector has significant carbon reduction potential, with low carbon awareness, electrification rates and the proportion of clean energy sources being key factors driving its early peaking [6]. Energy system transition modelling suggests that China's carbon emissions will peak between 2025-2030, with a 60% share of renewable energy by 2050, and lead to significant air quality improvements [7]. These studies provide a scientific basis and practical path for the global achievement of carbon neutrality targets.

The construction phase of a building results in large and significantly fluctuating carbon emissions due to the extensive use of machinery and equipment, the consumption of fossil energy and the transport of building materials, among other activities. Accelerated urbanisation in China has led to a rapid expansion of building scale, with building construction energy consumption accounting for 9% of the country's total energy consumption from 2000 to 2016, and with urban residential and public buildings being the main sources of carbon emissions, with building scale, structural type, and material production efficiency being the main driving factors [8]. The global construction industry emitted 5.7 billion tonnes of CO₂ in 2009, accounting for 23% of total global emissions, of which 94% were indirect emissions, mainly from hard coal, natural gas and non-energy use, while direct emissions originated from fossil fuels such as petrol and diesel, with emerging economies contributing nearly 60% of the emissions [9]. 2020 China's energy consumption for building construction amounts to 520 million tonnes of standard coal, with an implied carbon emission of 15 billion tonnes of CO₂, which is slowly declining but still accounts for a significant proportion of total carbon emissions from the construction sector, highlighting the important impact of the construction phase on achieving peak carbon and carbon neutral targets [10]. In addition, carbon emitting activities in the life cycle of construction waste (e.g., transport, landfill, etc.) further indicate the complexity and volatility of carbon emissions during the construction phase [11]. Smart city construction indirectly reduces carbon emissions from building construction through technological progress, industrial structure upgrading and energy structure optimisation, but its effect has a lag, usually appearing in the third year of policy implementation [12]. Digital infrastructure construction promotes low-carbon development by optimising the construction process, which is especially effective in cities with high and low carbon endowments, but its non-linear characteristics may lead to an increase in carbon emissions in cities with low endowments [13]. The analysis of carbon emissions in the whole life cycle of buildings shows that the construction phase accounts for 20-50% of the total emissions, and the average ratio of annual carbon emissions in the construction phase to those in the operation phase is 0.62, which further confirms the importance of carbon emissions in the construction phase [14].

Accurate prediction of carbon emissions during the construction phase of a building is of great significance to achieve carbon emission control over the whole life cycle of the building. Studies on future land use changes and carbon emissions in the Yellow River Basin using FLUS and ARIMA models have shown that carbon emissions from construction land use have a linear growth trend, and that optimal prediction is crucial for regional carbon emission reduction [15]. In addition, research on the application of life cycle assessment (LCA)-based tools in the building design phase showed that lowering the threshold of LCA data application can help architects control carbon emissions in the construction phase more effectively [16]. A study for an 11-storey frame building in Shenzhen, China, showed that prefabricated component assembly can significantly reduce carbon emissions through the optimisation of QFD-SEM and NSGA-II models [17]. The application of Random Forest and ARIMA-LSTM models in the study of carbon emissions in the eastern, central and western regions of China shows that the method can predict the trend of regional carbon emissions more accurately, which provides a scientific basis for the prediction of carbon emissions during the construction stage [18]. The application of ARIMA model in the study of future carbon emissions in South Africa shows that the prediction results are in line with the trend of future carbon emissions in South Africa [19]. The ARIMA model showed high efficiency in the prediction of energy consumption and carbon emission of an automotive parts manufacturing company in South Africa, which can provide a scientific basis for energy saving and emission reduction of the company [20]. In addition, a study combining empirical modal decomposition (EMD), autoregressive integral sliding average model (ARIMA) and truncated singular value decomposition (TSVD) techniques on multi-country and multi-industry carbon emission data showed that the method can significantly improve the accuracy

and efficiency of daily carbon emission prediction [21]. Further studies have shown that the application of ARIMA model to the forecasting of future electricity consumption in Ghana indicates that electricity consumption will continue to grow up to 2030 and it is recommended that future demand be met through energy restructuring and the application of renewable energy technologies [22]. These studies provide important theoretical and methodological support for the prediction and control of carbon emissions in the construction phase of buildings.

In recent years, deep learning methods have shown significant superiority in time series forecasting, especially when dealing with complex data and high-precision forecasting tasks. It has been shown that forecasting high-frequency financial time series using a hybrid model combining ARIMA and LSTM can significantly improve forecasting accuracy and reduce computational complexity [23]. In addition, by combining ARIMA with deep learning models (e.g., LSTM and GRU) to predict electricity peaks, it was found that the prediction performance of the ARIMA-LSTM hybrid model outperformed that of a single model [24]. Further research shows that the average error rate of LSTM model in time series forecasting is 84%-87% lower than that of ARIMA model, which verifies the significant advantage of deep learning in high-precision forecasting [25]. These research results provide more efficient and accurate tools for carbon emission prediction, thus promoting the realisation of carbon emission control in the whole life cycle of buildings.

Based on this, this study innovatively proposes a hybrid prediction model combining ARIMA and BP neural network, aiming to give full play to the complementary advantages of ARIMA model in linear trend capture and BP neural network in nonlinear pattern recognition, and to significantly improve the accuracy and reliability of the prediction of carbon emissions from building construction. The ARIMA model is able to effectively capture the linear trend in the time series, while the BP neural network is good at dealing with non-linear relationships. By making full use of the advantages of the two methods, the accuracy and reliability of carbon emission prediction in building construction are improved.

2. Theoretical foundation

2.1. Analysis of construction carbon emissions

Carbon emissions during the construction phase come mainly from energy consumption and construction activities, which can be summarized as fossil fuel combustion, machinery and equipment operation, and material transport. In this study, the carbon emission factor method is used to systematically account for the construction carbon emissions, which are classified into two categories: direct emissions and indirect emissions. Direct emissions mainly come from the fossil fuel combustion process at the construction site, including the diesel consumption of various types of construction machinery and equipment (e.g., excavators, cranes, etc.) and the carbon emissions generated by the use of fuel in temporary facilities (e.g., generators, boilers, etc.). Indirect emissions are mainly related to power consumption and material transport, in which carbon emissions from electricity consumption in construction take into account the energy conversion losses in the power production process, while carbon emissions from material transport include fuel consumption of transport vehicles and energy consumption in the logistics process. This classification method comprehensively reflects the carbon emission characteristics of the construction process and provides a scientific accounting basis for the subsequent carbon emission prediction and control.

2.2. Forecasting methods

2.2.1. ARIMA model

The ARIMA(p,d,q) model, as a classic method in the field of time series analysis, has a core architecture precisely defined by three key parameters: p represents the autoregressive order, reflecting the linear dependence between the current observations and the historical values; d denotes the difference order, which is used to transform the non-stationary series into a stationary series through the difference operation; and q is the moving average order, which is used to capture the stochastic fluctuations in the time series. The model is constructed by firstly The model construction process firstly achieves smoothness by performing d-order difference processing on the original series, and then combines the p-order autoregressive term and q-order moving average term to portray the linear characteristics of the series. In the parameter identification stage, the initial determination of the parameter ranges is mainly based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, and the Akaike Information Criterion (AIC) is used for model preference to ensure that the selected model achieves an optimal balance between goodness-of-fit and complexity. This systematic modelling approach can effectively extract the linear features in the time series and lay the foundation for subsequent hybrid modelling.

2.2.2. BP neural network model

In this study, a systematic grid search approach is used to refine the optimal design of the network structure of a multilayer perceptron (MLP). The study sets up three hidden layer configuration schemes: (100,50), (150,75) and (200,100), which represent network structures of different complexity. To prevent model overfitting, the early stopping method is introduced as a regularisation strategy, and the validation set proportion is set to 15% (validation_fraction=0.15), and the training is automatically terminated when the loss function of the validation set does not decrease for 30 consecutive epochs. This design effectively controls the complexity of the model and improves the generalisation performance while ensuring the model learning ability.

2.3. Feature engineering

2.3.1. Temporal feature construction

In this study, temporal features were first constructed and extracted from the raw data. Specifically, based on the date data, key time dimension features such as month, day of the week and season were systematically extracted. Among them, month features reflect the cyclical pattern of change in construction activities, week features are used to capture the difference between working days and rest days, and season features reflect the potential impact of climatic conditions on construction carbon emissions. In addition, considering the special characteristics of construction activities on weekends, this study specially constructs weekend feature markers to distinguish the differences in carbon emission patterns between weekdays and weekends, which provides important time dimension information to support the accurate prediction of the subsequent model.

2.3.2. Sliding window feature

Secondly, this study constructed a multi-scale time window to capture the dynamic change characteristics of carbon emission influencing factors. Based on the theory of time series analysis, four representative time window scales of 3 days, 7 days, 14 days and 30 days were selected to statistically analyse the three key characteristic indicators, namely, fuel consumption of machinery and equipment, electricity consumption at construction sites and the distance of transporting building

materials, respectively. Specifically, the mean, standard deviation, maximum and minimum values of each indicator were calculated in each time window, so as to comprehensively portray the dynamic change pattern of construction activities. In addition, in order to further quantify the trend of each indicator, this study also calculates the rate of change feature, i.e., the magnitude of change between adjacent time points within the window period, which can effectively reflect the sudden change characteristics of construction activities and provide an important feature support for the subsequent model to capture the short-term fluctuations and long-term trends of carbon emissions. Through the construction of multi-scale time windows, this study achieves the refined feature extraction of the influencing factors of construction carbon emissions.

2.3.3. Interactive features

In order to further explore the correlation between features, this study constructed an interactive feature indicator system. The synergistic relationship between energy consumption and logistics and transport was effectively quantified by calculating the ratios of fuel consumption (L) of mechanical equipment to electricity consumption (kW·h) at the construction site (fuel-electricity ratio), the ratio of fuel consumption (L) to the distance of building materials transported (km) (fuel-distance ratio), and the ratio of electricity consumption (kW·h) at the construction site to the distance of transported (km) (electricity consumption-distance ratio). The ratio of energy consumption to transport distance (km). These interaction indicators not only reflect the efficiency characteristics of energy use in the construction process, but also provide multi-dimensional characteristic interaction information for carbon emission prediction.

2.3.4. Energy equivalent characteristics

In addition, this study constructed an energy equivalent characteristic system to achieve a unified quantitative analysis of energy consumption. The total energy consumption is calculated by the formula:

$$E_{\text{total}} = F \cdot c_f + P \cdot c_p \quad (1)$$

Where F represents the fuel consumption of machinery and equipment (L), c_f is the calorific value of fuel (MJ/L), P represents the electricity consumption at the construction site (kW·h), and c_p is the energy equivalent coefficient of electricity (MJ/(kW·h)). Based on the total energy consumption, the energy intensity (EI) indicator was further calculated with the formula:

$$EI = \frac{E_{\text{total}}}{D} \quad (2)$$

where D denotes the transport distance of building materials (km). This feature system achieves the unified quantification of different types of energy consumption and provides standardised energy consumption feature indicators for carbon emission prediction.

3. Hybrid model building

3.1. Framework design

In this study, a hybrid forecasting model based on the ‘decomposition-integration’ strategy is proposed. The model firstly extracts the linear components of the time series using the ARIMA model, and then uses the residual series of the ARIMA model as the input of the BP neural network to capture the nonlinear features of the data. Ultimately, the prediction results of the two models are integrated by a weighted fusion method to fully exploit the synergistic advantages of the linear and nonlinear

models. In the data preprocessing stage, standardised processing is used to eliminate the influence of magnitude, and the method of adding features is applied to deal with the missing values, while a reasonable time window division is carried out based on the characteristics of the time series, so as to provide high-quality data bases for model training. This staged processing strategy effectively improves the prediction accuracy and generalisation ability of the model.

3.2. Model integration

In this study, the direct superposition method is used to construct the hybrid prediction model, and the final prediction value is obtained by linearly superimposing the prediction results of the ARIMA model with the prediction results of the BP neural network on the residuals. The method can be expressed as:

$$\hat{y} = \hat{y}_{ARIMA} + \hat{y}_{BP} \quad (3)$$

Where $\hat{y}$ is the final predicted value, $\hat{y}_{ARIMA}$ is the prediction result of the ARIMA model, and $\hat{y}_{BP}$ is the prediction result of the BP neural network on the residuals.

4. Engineering examples and analysis of results

4.1. Project overview

The study collects complete carbon emission data during the construction period from 1 January to 31 December 2022, which mainly contains core indicators such as fuel consumption of construction machinery and equipment, electricity consumption of temporary facilities, and mileage of construction materials transported. In the data preprocessing stage, this paper fills in the missing data reasonably to ensure the data quality. In order to evaluate the model performance, the data set is divided into a training set and a test set in the ratio of 8:2, in which the first 80% of the data (about 292 days) is used for model training and parameter optimisation, and the remaining 20% of the data (about 73 days) is used for model performance testing, which not only ensures the adequacy of the training data, but also ensures the reliability of the test results.

4.2. Analysis of projected results

4.2.1. Overall predicted effect

The results show that the hybrid model proposed in this study has excellent prediction performance. Specifically, the root mean square error (RMSE) of the model is 0.0115 and the mean absolute error (MAE) is 0.0051, both of which are at a low level, indicating that the deviation between the model's predicted and actual values is small. Meanwhile, the coefficient of determination (R^2) of the model reaches 0.9990, indicating that the model is able to explain nearly 100 per cent of the variance of the target variable and has a high goodness of fit. These evaluation indexes comprehensively indicate that the model performs well in both prediction accuracy and stability, and can provide reliable technical support for construction carbon emission prediction. As shown in Figure 1, the scatter distributions of measured and predicted values show an obvious linear trend, and the data points are closely surrounding the fitted straight line, indicating that the predicted results of the model have a high degree of consistency with the actual situation, which further verifies the accuracy of the prediction.

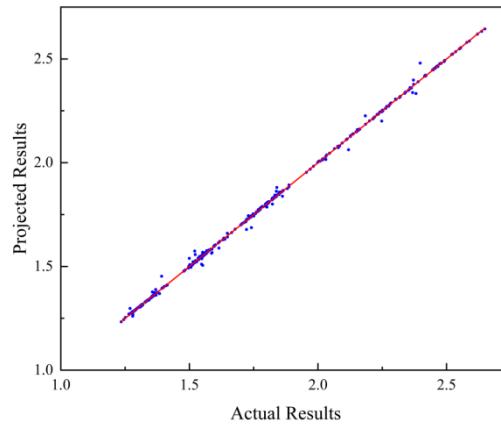


Figure 1. Predicted-measured scatterplot

Some of the predictions are shown in Table 1:

Table 1. Comparison of predicted-measured results (2022/12/05-2022/12/31)

Date	Measured carbon emissions (t)	Projected carbon emissions (t)	Relative error (%)
2022-12-15	2.49183	2.49241	0.02328
2022-12-16	2.52020	2.52141	0.04801
2022-12-17	2.47330	2.47652	0.13019
2022-12-18	2.47920	2.47889	0.01250
2022-12-19	2.45717	2.45688	0.01180
2022-12-20	2.46489	2.46643	0.06248
2022-12-21	2.46636	2.46366	0.10947
2022-12-22	2.49095	2.48769	0.13087
2022-12-23	2.52365	2.52364	0.00040
2022-12-24	2.53539	2.53491	0.01893
2022-12-25	2.55035	2.54903	0.05176
2022-12-26	2.55552	2.55414	0.05400
2022-12-27	2.57896	2.57939	0.01667
2022-12-28	2.58877	2.58652	0.08691
2022-12-29	2.62058	2.61984	0.02824
2022-12-30	2.63672	2.63316	0.13502
2022-12-31	2.64917	2.64483	0.16382

4.2.2. Characteristics of the error distribution

In terms of the characterisation of the error distribution, the hybrid prediction model constructed in this study shows good prediction accuracy and stability. Specifically, the average relative error of the model is 0.2989%, a metric that indicates that the overall prediction bias of the model is small and has high prediction accuracy. The standard deviation of the relative error is 0.5842%, reflecting a low degree of dispersion of the prediction error and a good stability of the prediction results. The maximum relative error of the model is 4.3610%, and this extreme value may occur at special times when construction activities fluctuate dramatically, such as extreme weather or peak construction periods. Overall, the error distribution characteristics indicate that the model can provide accurate and reliable prediction results in most cases, which provides effective technical support for real-time

monitoring and management of construction carbon emissions. The relative error distribution of the prediction model is shown in Figure 2.

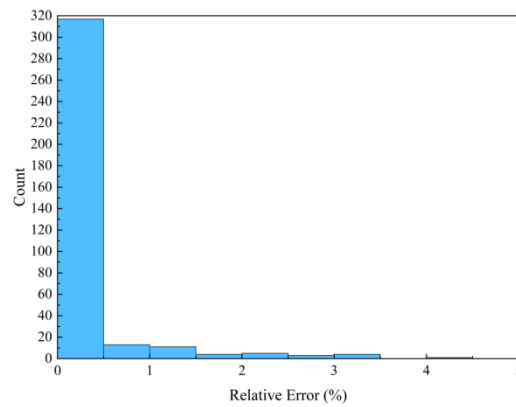


Figure 2. Histogram of error distribution

4.2.3. Assessment of prediction accuracy

In the assessment of the model's prediction accuracy, the results show that 92.18 per cent of the prediction samples have their relative errors controlled within ± 1 per cent, and 100 per cent of the prediction samples have their relative errors within ± 5 per cent. This distribution feature indicates that the model has high prediction accuracy and stability, with more than 90% of the prediction results having an error within 1%, showing that the model is able to provide highly accurate prediction values in most cases. Meanwhile, the error of all data prediction results is controlled within 5%, which further confirms the reliability of the model in practical application and provides a strong support for accurate prediction and management of construction carbon emissions.

4.3. Model evaluation

In terms of prediction accuracy, the hybrid model outperforms the single model in all three evaluation metrics, which are compared in Table 2:

Table 2. Comparison of timing predictions

Model type	RMSE	MAE	MAPE
ARIMA model	0.016	0.012	0.70%
BP model	0.372	0.306	17.52%
Hybrid model	0.011	0.005	0.30%

The results show that the hybrid model proposed in this study achieves a significant improvement in forecasting performance compared to the single model. Compared with the ARIMA single model, the root mean square error (RMSE) of the hybrid model was reduced by 31.25%, the mean absolute error (MAE) was reduced by 58.33%, and the mean absolute percentage error (MAPE) was reduced by 57.14%; and compared with the BP neural network single model, the root mean square error (RMSE) of the hybrid model was reduced by 97.04%, the mean absolute error (MAE) decreased by 98.37%, and the mean absolute percentage error (MAPE) decreased by 98.29%. The substantial improvement in these indicators fully demonstrates the effectiveness of the hybrid strategy. In terms of stability, the relative error standard deviation of the hybrid model is only 0.58%, and the relative error of 100% of the prediction results is controlled within 5%, which is significantly better than that of the single model, showing strong anti-interference ability and generalisation performance, and

providing reliable technical support for the practical engineering applications. The prediction results of ARIMA, BP and hybrid models are shown in Figure 3, Figure 4 and Figure 5 respectively.

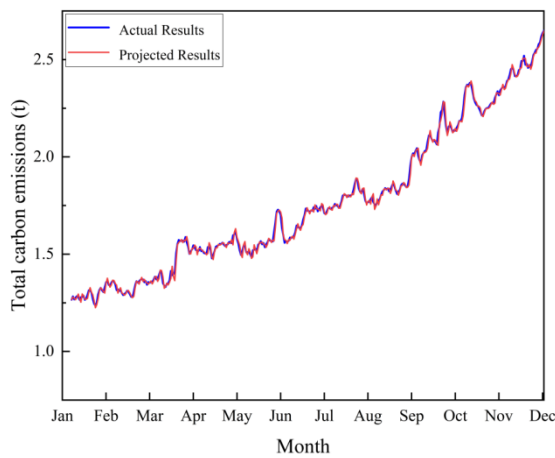


Figure 3. Prediction results of ARIMA model

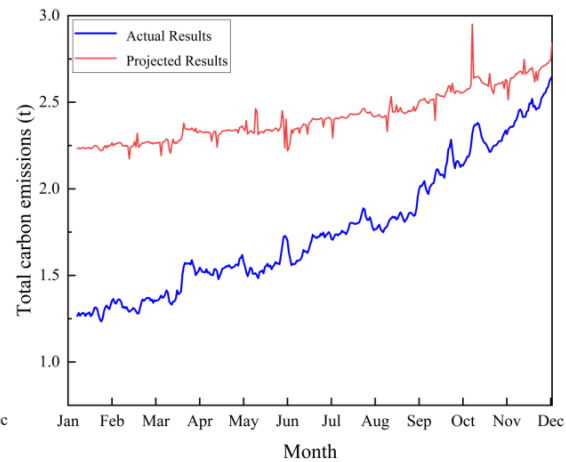


Figure 4. Prediction results of BP model

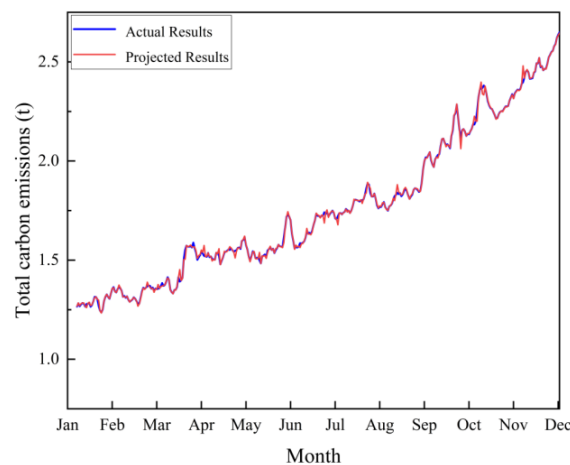


Figure 5. Prediction results of hybrid model

The applicability analysis shows that the hybrid model proposed in this study is able to effectively handle the complex characteristics of building construction carbon emission data through the synergy of ARIMA and BP neural networks. The ARIMA model is good at capturing linear trends in the data, while the BP neural network focuses on dealing with the nonlinear residual components, and this division of labour mechanism makes the model particularly suitable for carbon emission with obvious periodicity and trends in the data prediction.

5. Conclusion

In this study, the ARIMA-BP hybrid model was used to predict the carbon emissions of building construction units and the following main conclusions were drawn:

- The ARIMA-BP hybrid model demonstrates significant performance advantages in the prediction of carbon emissions from building construction. Compared with the optimal results of a single model, the prediction accuracy of this hybrid model is significantly improved: the RMSE is reduced by 31.25%, the MAE is reduced by 58.33%, and the MAPE is reduced by 57.14%. These

improvements fully demonstrate the superiority of the hybrid model in capturing the linear and nonlinear features of carbon emission time series.

- The feature engineering system constructed in this study significantly improves the model performance through multi-dimensional feature extraction. Among them, the sliding window feature effectively captures the time dependence of carbon emissions, and the energy equivalent feature realises the unified quantification of heterogeneous energy sources, which provides key feature support for accurate model prediction.
- The prediction model proposed in this study shows excellent prediction performance in different time scales, with 92.18% of the prediction results having relative errors controlled within 1%, and this stable prediction ability across time scales fully proves the practicability and reliability of the model, which provides effective technical support for the dynamic monitoring and management of construction carbon emissions.
- The hybrid prediction method proposed in this study innovatively combines the advantages of ARIMA model and BP neural network to provide a scientific and reliable technical solution for the prediction of carbon emissions from building construction. The method can not only accurately predict the trend of carbon emission, but also effectively identify the key influencing factors, providing data support and decision-making basis for the development of carbon emission reduction strategies and optimisation of construction plans in engineering projects. In actual project application, the method can be integrated into the carbon emission monitoring system to achieve dynamic prediction and early warning of carbon emissions, helping the construction industry to achieve the goal of “carbon peaking and carbon neutrality”.

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