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Dynamic Prediction of Manufacturing Energy Allocation Efficiency Based on Transformer Time-Series Model

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ABSTRACT Manufacturing is a major sector of energy consumption and carbon emissions, improving energy allocation efficiency is essential for promoting green transformation and low-carbon development. To dynamically predict manufacturing energy allocation efficiency, this study proposes an integrated framework combining efficiency measurement and Transformer-based time-series forecasting. First, an energy allocation efficiency evaluation index system is constructed from the perspectives of energy input, capital input, labor input, desirable output, and undesirable output. The SBM-DEA model with undesirable outputs is then applied to measure manufacturing energy allocation efficiency under economic and environmental constraints. Based on the measured efficiency series and related influencing factors, including industrial structure, energy structure, technological innovation, environmental regulation, and carbon intensity, a multivariate Transformer time-series model is developed to forecast future efficiency trends. Results show that manufacturing energy allocation efficiency presents an overall upward trend, but regional and sectoral heterogeneity remains significant. Compared with ARIMA, SVR, Random Forest, XGBoost, LSTM, GRU, and TCN models, the Transformer model achieves better prediction performance in terms of MAE, RMSE, MAPE, and R2. Further interpretability analysis indicates that technological innovation, energy structure, industrial structure, environmental regulation, and carbon intensity are the key factors affecting the dynamic evolution of energy allocation efficiency. This study provides a useful methodological framework for manufacturing energy efficiency prediction and offers decision-making support for energy optimization, carbon reduction, and green industrial transformation.

INDEX TERMS Transformer, Manufacturing energy allocation efficiency, SBM-DEA, Dynamic prediction.

I. INTRODUCTION

Manufacturing is one of the major sources of energy consumption and carbon emissions, and its pattern of energy use is closely associated with industrial green transformation, resource allocation optimization, and the achievement of carbon peaking and carbon neutrality goals. With the continuous adjustment of the global energy structure and the growing demand for low-carbon development, the manufacturing sector is expected not only to reduce total energy consumption but also to improve the allocation efficiency of energy across production processes, industrial sectors, and technological pathways. Energy allocation efficiency reflects the coordination among energy input, economic output, and environmental constraints, making it an important indicator for evaluating the quality of manufacturing development. However, manufacturing energy systems are highly complex and dynamic, and their efficiency changes are jointly affected by industrial structure, technological progress, energy prices, environmental regulation, and carbon emission constraints. Therefore, accurately characterizing the dynamic evolution of manufacturing energy allocation efficiency and predicting its future trend have become important issues in the fields of energy economics and intelligent manufacturing. Existing studies have mainly focused on energy efficiency evaluation, energy consumption forecasting, and the analysis of influencing factors. On the one hand, data envelopment analysis, stochastic frontier analysis, SBM-DEA models, and the Malmquist index have been widely used to measure manufacturing energy efficiency and total-factor energy efficiency, providing useful tools for identifying inefficient energy use, regional differences, and sectoral heterogeneity [1-5]. On the other hand, traditional statistical models and machine learning methods have also been applied to the prediction of energy consumption, carbon emissions, and industrial output, including ARIMA, support vector regression, random forest, LSTM, and GRU models [6-9]. However, conventional efficiency evaluation methods mostly emphasize static measurement or historical comparison and are less capable of directly capturing future trends. Meanwhile, commonly used time-series forecasting models still have limitations in modeling long-term dependencies, multivariate interactions, and nonlinear dynamic changes. Transformer-based models have shown strong representation capability in long-sequence forecasting tasks. Through the self-attention mechanism, they can capture complex relationships across different time steps and variables, providing a promising methodological foundation for the dynamic prediction of manufacturing energy allocation efficiency [10-15]. Accordingly, this paper proposes a Transformer-based prediction framework for manufacturing energy allocation efficiency. The SBM-DEA model is first used to calculate efficiency values based on energy, capital, labor, desirable output, and undesirable output indicators. Then, the efficiency results are combined with factors such as industrial structure, technological innovation, energy structure, environmental regulation, and carbon emission intensity to build a multivariate time-series dataset. On this basis, the Transformer model is applied to forecast future efficiency trends. Model performance is compared with traditional and deep learning methods, while attention and feature contribution analyses are used to reveal the main driving factors. This study provides useful support for improving energy allocation, reducing carbon emissions, and promoting green manufacturing transformation.

II. LITERATURE REVIEW

A. MANUFACTURING ENERGY EFFICIENCY EVALUATION

Manufacturing energy efficiency evaluation has become an important research topic in energy economics, industrial green transformation, and environmental management. Early studies commonly used single indicators, such as energy consumption per unit of output, energy intensity, or the elasticity of energy consumption, to measure the level of energy use. These indicators are easy to calculate and can reflect the basic relationship between energy consumption and economic output. However, manufacturing production usually involves multiple factors, including energy, capital, labor, technology, and environmental constraints. A single energy-consumption indicator is therefore insufficient to fully characterize the allocation relationship between energy input and economic output. Accordingly, an increasing number of studies have adopted a total-factor perspective by incorporating energy input, capital input, labor input, desirable output, and undesirable output into a unified evaluation framework, so as to measure manufacturing energy allocation efficiency and green development performance more comprehensively [1-5]. In terms of methods, data envelopment analysis, stochastic frontier analysis, SBM-DEA models, Super-SBM models, and the Malmquist index have been widely applied to energy efficiency measurement. DEA does not require a predetermined production function and is suitable for evaluating efficiency with multiple inputs and outputs. The SBM-DEA model further considers input redundancy and output shortfall, allowing the sources of inefficiency to be identified more precisely. When undesirable outputs such as carbon emissions, industrial exhaust gas, wastewater, or pollutant emissions are incorporated, the model can evaluate energy-use performance under environmental constraints. Existing studies have shown that manufacturing energy efficiency exhibits significant regional and sectoral heterogeneity and is closely associated with industrial structure, technological innovation, environmental regulation, energy prices, and resource endowments. Nevertheless, most existing studies remain focused on historical measurement, cross-sectional comparison, and influencing-factor analysis, while relatively limited attention has been paid to predicting the future trend of energy allocation efficiency.

B. ENERGY CONSUMPTION AND EFFICIENCY FORECASTING

With the development of intelligent manufacturing, energy management systems, manufacturing energy forecasting has become an important support for energy allocation optimization and energy-saving and carbon-reduction decisions. Existing studies mainly focus on energy consumption forecasting, electric load forecasting, carbon emission prediction, and industrial production energy-use forecasting. Traditional statistical models, such as ARIMA, grey prediction models, and exponential smoothing models, have certain advantages in small-sample and linear-trend forecasting. However, their ability to capture complex nonlinear relationships, abrupt changes, and multivariate coupling mechanisms is limited. With the improvement of data availability and computing capacity, machine learning models have been widely used in manufacturing energy forecasting, including support vector regression, random forest, gradient boosting trees, and XGBoost. These models can effectively capture nonlinear relationships among variables, but they still have limitations in modeling continuous temporal dependence and long-term dynamic evolution [6-9]. Deep learning models have been applied to energy time-series forecasting. LSTM and GRU alleviate the gradient vanishing problem of traditional recurrent neural networks through gated structures and can capture temporal dependencies in energy consumption sequences. TCN extracts multi-scale temporal features through causal convolution and dilated convolution, showing high computational efficiency in long-sequence modeling. However, the prediction of manufacturing energy allocation efficiency differs from general energy consumption forecasting. Energy allocation efficiency is not a simple energy-use value but a comprehensive efficiency indicator formed by the joint effects of energy input, economic output, and environmental constraints. It therefore presents stronger nonlinear, lagged, and structural-change characteristics. As a result, traditional statistical models or conventional recurrent neural networks may be insufficient to fully identify long-term dependencies, policy shock effects, and multivariate interaction mechanisms in the evolution of manufacturing energy allocation efficiency.

C. TRANSFORMER-BASED TIME-SERIES FORECASTING

Transformer was originally proposed for sequence modeling tasks, and its core advantage lies in the self-attention mechanism, which can directly establish dependencies among different positions in a sequence. Compared with recurrent neural networks, Transformer does not need to transmit hidden states step by step along the temporal dimension, and therefore has clear advantages in parallel computation and long-range dependency modeling. In recent years, Transformer has been widely introduced into time-series forecasting, leading to a variety of improved models for long-sequence prediction. For example, Informer reduces the computational complexity of long-sequence forecasting through sparse attention and is suitable for multivariate prediction over long temporal horizons. Autoformer incorporates series decomposition into deep forecasting models and improves long-term forecasting by separating trend and periodic components. FEDformer further enhances the representation of periodic fluctuations and long-term trends from the frequency-domain perspective [10-13]. In addition to these models, PatchTST and iTransformer provide new perspectives for multivariate time-series forecasting. PatchTST divides time series into local patches and uses them as modeling units, which preserves local temporal patterns while reducing the computational cost of attention. iTransformer adjusts the conventional temporal modeling manner of Transformer by treating variables as tokens, thereby emphasizing the interactions among variables in multivariate time series [14-15]. These developments indicate that Transformer has evolved from a general sequence modeling tool into an important methodological framework for complex time-series forecasting. For the prediction of manufacturing energy allocation efficiency, Transformer can not only capture long-term trends in efficiency sequences but also integrate external variables such as energy structure, technological innovation, environmental regulation, and carbon emission intensity to identify dynamic evolution patterns driven by multiple factors.

D. RESEARCH GAP

In summary, existing studies have provided a solid theoretical and methodological foundation for manufacturing energy efficiency evaluation and energy time-series forecasting, but several gaps remain. First, manufacturing energy efficiency studies are mainly based on static evaluation and ex-post analysis, focusing on efficiency differences across regions, sectors, or years, while insufficient attention has been paid to the prediction of future trends in energy allocation efficiency. Second, most existing energy forecasting studies take energy consumption, electric load, or carbon emissions as prediction targets, whereas dynamic prediction of energy allocation efficiency as a comprehensive efficiency indicator remains relatively limited. Third, although traditional machine learning and recurrent neural network models can handle nonlinear relationships and temporal dependencies to some extent, they still face limitations in modeling long sequences, multivariate interactions, and non-stationary changes. Fourth, some deep learning-based forecasting studies emphasize accuracy improvement but pay insufficient attention to the interpretation of the driving factors behind prediction results, which limits their practical value for manufacturing energy allocation optimization and policy-making. To address these gaps, this study combines energy allocation efficiency evaluation with Transformer-based time-series forecasting and develops an integrated framework for the dynamic prediction of manufacturing energy allocation efficiency. Unlike studies that focus solely on energy consumption forecasting, this study first measures manufacturing energy allocation efficiency from the perspective of multiple inputs, multiple outputs, and environmental constraints, and then incorporates the efficiency series and its influencing factors into a multivariate time-series prediction model. In this way, the study extends the research logic from efficiency evaluation to trend prediction and decision-oriented interpretation. Furthermore, the applicability of the Transformer model to manufacturing energy allocation efficiency prediction is examined through comparison with traditional statistical models, machine learning models, and representative deep learning models. Attention weights and feature contribution analysis are also used to identify the key driving factors. This study is expected to enrich the methodological system of dynamic energy efficiency prediction and provide useful references for energy-saving, carbon-reduction, energy structure optimization, and green transformation in the manufacturing sector.

III. METHODOLOGY

A. ENERGY ALLOCATION EFFICIENCY INDEX SYSTEM

Manufacturing energy allocation efficiency reflects the input-output transformation capacity of energy factors in the manufacturing production process. Unlike simple energy consumption intensity, energy allocation efficiency focuses not only on whether energy consumption is reduced, but also on whether energy input can generate high-quality economic output under the joint effects of capital, labor, technology, and environmental constraints. Therefore, this study constructs an evaluation index system for manufacturing energy allocation efficiency from three dimensions: inputs, desirable outputs, and undesirable outputs. The input indicators mainly include energy input, capital input, labor input, and technology input; desirable outputs reflect the economic output capacity of the manufacturing sector; and undesirable outputs are used to characterize the environmental costs generated during energy use (Table I).

In practical data processing, the above indicators can be adjusted according to data availability. If the research object is provincial manufacturing, provincial-level panel data can be used; if the research object is the manufacturing industry, data from manufacturing subsectors can be adopted. To reduce the influence of differences in measurement units on model estimation, the original data are standardized before DEA measurement and time-series prediction. For positive indicators, min-max normalization is used:

TABLE 1. Evaluation Index System of Manufacturing Energy Allocation Efficiency

Indicator type	Indicator	Symbol	Description
Input	Energy input	x_1	Total energy consumption, electricity consumption, or standard coal consumption
Input	Capital input	x_2	Fixed asset investment or capital stock of manufacturing industry
Input	Labor input	x_3	Number of manufacturing employees
Input	Technology input	x_4	R&D expenditure, patent applications, or digitalization level
Desirable output	Economic output	y_1	Industrial added value, total output value, or operating revenue
Desirable output	Profit output	y_2	Total profit or main business income
Undesirable output	Carbon emissions	b_1	CO2 emissions generated by manufacturing energy consumption
Undesirable output	Pollutant emissions	b_2	Industrial SO2, wastewater, exhaust gas, or smoke dust emissions

$$x'_{it} = \frac{x_{it} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{1}$$

For undesirable output indicators, since a smaller value indicates better environmental performance, reverse normalization can be applied in the prediction modeling stage:

$$b'_{it} = \frac{\max(b_i) - b_{it}}{\max(b_i) - \min(b_i)} \tag{2}$$

where xit denotes the original value of the i-th indicator in period t, and x'it denotes the standardized value. Through this processing, different indicators can participate in model analysis on a comparable scale, improving the stability of efficiency measurement and prediction modeling.

B. SBM-DEA MODEL WITH UNDESIRABLE OUTPUTS

To evaluate the efficiency of energy allocation in the manufacturing sector, this study employs the slack-based measure data envelopment analysis model with undesirable outputs. Although conventional DEA approaches are widely used for assessing efficiency under multiple-input and multiple-output conditions, their radial measurement structure may fail to fully reflect input excesses and output deficiencies. In contrast, the SBM model incorporates slack variables directly into the efficiency measurement process, which enables a more precise assessment of redundancies in energy, capital, and labor inputs, as well as shortages in desirable economic outputs. In addition, since energy consumption in manufacturing activities is commonly associated with carbon emissions and other environmental pollutants, undesirable outputs should be incorporated into the evaluation framework. Assume there are n decision-making units, each of which contains m input indicators, s1 desirable output indicators, and s2 undesirable output indicators. For the o-th decision-making unit, the input vector, desirable output vector, and undesirable output vector are expressed as:

$$x_o = (x_{1o}, x_{2o}, \ldots, x_{mo})^{\mathsf{T}} \tag{3}$$

$$y_o^g = (y_{1o}^g, y_{2o}^g, \ldots, y_{s_1 o}^g)^{\mathsf{T}} \tag{4}$$

$$b_o = (b_{1o}, b_{2o}, \ldots, b_{s_2 o})^{\mathsf{T}} \tag{5}$$

The SBM-DEA model with undesirable outputs is formulated as follows:

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + \sum_{q=1}^{s_2} \frac{s_q^b}{b_{qo}}\right)} \tag{6}$$

$$x_o = X\lambda + s^- \tag{7}$$

$$y_o^g = Y^g\lambda - s^g \tag{8}$$

$$b_o = B\lambda + s^b \tag{9}$$

$$\lambda \geq 0, \quad s^- \geq 0, \quad s^g \geq 0, \quad s^b \geq 0 \tag{10}$$

where ρ denotes the manufacturing energy allocation efficiency score; X, Yg, and B represent the input matrix, desirable output matrix, and undesirable output matrix, respectively; λ is the intensity vector; and s−, sg, and sb represent input redundancy, desirable output shortfall, and undesirable output redundancy, respectively. In general, when $\rho = 1$, the decision-making unit is located on the efficient frontier; when $\rho < 1$, there is a certain degree of inefficiency in energy allocation. To further distinguish differences among efficient decision-making units, the Super-SBM model can also be introduced, allowing efficiency scores greater than 1 and enabling a more detailed ranking across regions or sectors. Through the SBM-DEA model, the manufacturing energy allocation efficiency series of different regions or sectors over time can be obtained:

$$E_{it} = \mathrm{DEA}(X_{it}, Y_{it}^g, B_{it}) \tag{11}$$

where Eit denotes the energy allocation efficiency of region or sector i in year t. This efficiency series serves as the core prediction target in the subsequent Transformer-based time-series forecasting model.

C. TRANSFORMER-BASED DYNAMIC PREDICTION MODEL

After obtaining the manufacturing energy allocation efficiency series, this study further constructs a Transformer-based time-series prediction model to forecast its future trend. Compared with traditional time-series models, Transformer can directly capture dependencies among different time steps through the self-attention mechanism, making it suitable for modeling energy allocation efficiency series with long-term trends, nonlinear changes, and multivariate interactions. In this study, energy allocation efficiency and its related influencing factors are jointly constructed as a multivariate time series. For region or sector i, the input features in period t can be expressed as:

$$Z_{it} = [E_{it}, IS_{it}, ES_{it}, TI_{it}, ER_{it}, CI_{it}, EP_{it}] \tag{12}$$

where Eit denotes energy allocation efficiency, ISit denotes industrial structure, ESit denotes energy structure, TIit denotes technological innovation level, ERit denotes environmental regulation intensity, CIit denotes carbon emission intensity, and EPit denotes energy price or energy cost. Based on the sliding-window method, the model input sequence is expressed as:

$$Z_{i,t-L+1:t} = [Z_{i,t-L+1}, Z_{i,t-L+2}, \ldots, Z_{it}] \tag{13}$$

where L represents the historical time-window length. The prediction target is the energy allocation efficiency in the

$$\widehat{E}_{i,t+h} = F_\theta(Z_{i,t-L+1:t}) \tag{14}$$

where $F_\theta(\cdot)$ denotes the Transformer prediction model, θ represents the model parameters, and $\widehat{E}_{i,t+h}$ is the predicted energy allocation efficiency. The Transformer model mainly consists of an input embedding layer, a positional encoding layer, multi-head self-attention layers, feed-forward neural network layers, and an output layer. First, the original input features are transformed into high-dimensional hidden vectors through linear mapping:

$$H_0 = W_e Z + P \tag{15}$$

where We is the input embedding matrix and P is the positional encoding used to preserve temporal order information. The model then calculates the correlations among different time steps through the self-attention mechanism. For the query matrix Q, key matrix K, and value matrix V, the scaled dot-product attention is given by:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \tag{16}$$

To capture sequence dependencies from different representation subspaces, the model further adopts the multi-head attention mechanism:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \tag{17}$$

$$\text{head}_j = \text{Attention}(QW_j^Q, KW_j^K, VW_j^V) \tag{18}$$

After passing through multiple Transformer encoder layers, the model extracts long-term dependencies and multivariate interaction features from the energy allocation efficiency series. Finally, the future efficiency value is generated through a fully connected output layer:

$$\widehat{E}_{i,t+h} = W_o H_T + b_o \tag{19}$$

To improve model generalization, the mean squared error is adopted as the loss function during training, and Dropout and L2 regularization are used to reduce overfitting:

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N}(E_i - \widehat{E}_i)^2 + \lambda\|\theta\|_2^2 \tag{20}$$

To avoid temporal information leakage, the training, validation, and test sets are divided according to chronological order rather than random sampling. The training set is used for parameter learning, the validation set is used for hyperparameter tuning, and the test set is used for final performance evaluation.

TABLE 2. Baseline Models for Prediction Performance Comparison

Model type	Model	Purpose of comparison
Statistical model	ARIMA	Tests the ability of traditional linear time-series modeling
Machine learning model	SVR	Evaluates nonlinear regression performance under limited samples
Machine learning model	Random Forest	Compares ensemble-based nonlinear prediction ability
Machine learning model	XGBoost	Compares gradient boosting performance on structured variables
Deep learning model	LSTM	Tests recurrent neural network performance for temporal dependence
Deep learning model	GRU	Compares simplified gated recurrent structure
Deep learning model	TCN	Tests convolution-based long-sequence modeling ability
Proposed model	Transformer	Evaluates self-attention-based dynamic prediction performance

D. MODEL EVALUATION METRICS

To comprehensively evaluate the predictive performance of the Transformer model for manufacturing energy allocation efficiency, this study uses MAE, RMSE, MAPE, and R2 as the main evaluation metrics. MAE measures the average absolute error between predicted and observed values and directly reflects the overall prediction bias. RMSE is more sensitive to large errors and is suitable for evaluating the model's ability to fit abnormal fluctuations. MAPE represents the relative error level and facilitates comparison across different regions or sectors. R2 measures the degree to which the model explains variations in energy allocation efficiency (Table II).

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|E_i - \widehat{E}_i| \tag{21}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - \widehat{E}_i)^2} \tag{22}$$

$$\text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{E_i - \widehat{E}_i}{E_i}\right| \tag{23}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(E_i - \widehat{E}_i)^2}{\sum_{i=1}^{N}(E_i - \overline{E})^2} \tag{24}$$

E. NTERPRETABILITY ANALYSIS

To improve the interpretability of model results, this study further analyzes the key driving factors of manufacturing energy allocation efficiency changes from both temporal and variable dimensions. First, based on the attention weights in the Transformer model, the influence of different historical periods on the current prediction result can be identified. If certain years or time windows receive higher attention weights, it indicates that the energy allocation status, industrial structural changes, or policy shocks during those periods may have a stronger impact on future efficiency. The attention weight matrix is expressed as:

$$A = \text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right) \tag{25}$$

By visualizing attention weights, it is possible to observe whether the model focuses more on short-term fluctuations or long-term trends during the prediction process. Second, feature contribution analysis is introduced to identify the direction and relative importance of different influencing factors in predicting energy allocation efficiency. Specifically, permutation importance, SHAP values, or sensitivity analysis can be used to evaluate the contributions of industrial structure, energy structure, technological innovation, environmental regulation, carbon emission intensity, and energy prices to the prediction results. For the j-th feature, its contribution can be expressed as:

$$\text{Importance}_j = \frac{1}{N}\sum_{i=1}^{N}|\phi_{ij}| \tag{26}$$

where ϕ_{ij} denotes the contribution value of the j-th feature to the prediction result of the i-th sample. This method can further answer which factors promote the improvement of manufacturing energy allocation efficiency and which factors lead to efficiency decline. Finally, scenario simulation is designed to examine future changes in manufacturing energy allocation efficiency under different policy or management conditions. The adjusted variables are input into the trained Transformer model to obtain efficiency prediction results under different scenarios.

IV. RESULTS AND DISCUSSION

A. EFFICIENCY MEASUREMENT RESULT

Based on the SBM-DEA model with undesirable outputs, the manufacturing energy allocation efficiency from 2012 to 2023 was measured. The results show the overall energy allocation efficiency of the manufacturing sector presents a steadily increasing trend during the sample period. As shown in Figure 1, the average efficiency increased from 0.612 in 2012 to 0.815 in 2023, indicating that the manufacturing sector has gradually improved its ability to transform energy input into desirable economic output under environmental constraints. This improvement may be attributed to industrial upgrading, technological progress, cleaner production, and stricter environmental regulation. From a regional perspective, significant heterogeneity can be observed. The eastern region consistently maintains the highest energy allocation efficiency, increasing from 0.707 in 2012 to 0.942 in 2023. The central region follows closely and shows a relatively stable upward trend. In contrast, the western region remains at a lower efficiency level, although its efficiency also improves from 0.529 to 0.735 during the same period. This pattern suggests that regions with stronger industrial foundations, higher technology intensity, and better energy management capacity tend to achieve higher energy allocation efficiency (Table III).

TABLE 3. Regional Manufacturing Energy Allocation Efficiency

Year	Overall	Eastern region	Central region	Western region
2012	0.612	0.707	0.620	0.529
2014	0.641	0.742	0.652	0.554
2016	0.671	0.779	0.686	0.582
2018	0.713	0.825	0.734	0.623
2020	0.744	0.863	0.770	0.657
2022	0.791	0.915	0.823	0.708
2023	0.815	0.942	0.850	0.735

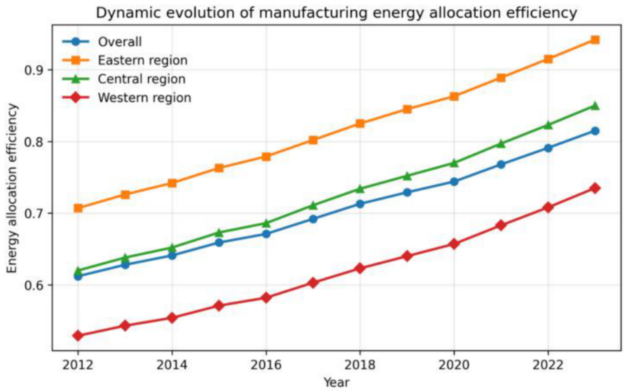

FIGURE 1. Dynamic Evolution of Manufacturing Energy Allocation Efficiency

The regional comparison indicates that manufacturing energy allocation efficiency is not only affected by energy consumption itself, but also closely related to factor allocation quality, technological innovation, industrial structure, and environmental governance capacity. The eastern region has a more advanced manufacturing structure and stronger technological innovation capability, which helps reduce energy redundancy and undesirable outputs. The western region, however, still faces constraints such as relatively high energy dependence, insufficient technological input, and slower industrial transformation.

B. DYNAMIC EVOLUTION CHARACTERISTICS

To further examine the internal structural differences in manufacturing energy allocation efficiency, the efficiency levels of representative manufacturing subsectors were compared. As shown in Figure 2, high-technology and equipment-related industries, such as electronics, equipment manufacturing, and

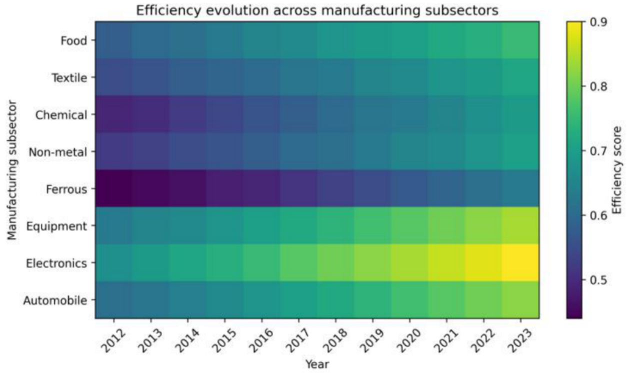

FIGURE 2. Efficiency Evolution across Manufacturing Subsectors

automobile manufacturing, show higher efficiency levels and faster improvement. In contrast, traditional energy-intensive industries, such as ferrous metal processing, chemicals, and non-metallic mineral products, exhibit relatively lower efficiency levels. This result suggests that the dynamic evolution of manufacturing energy allocation efficiency is strongly associated with industrial characteristics. Industries with higher technology intensity and stronger innovation capacity can achieve more efficient energy conversion through process optimization, digital manufacturing, and cleaner production technologies. By contrast, energy-intensive industries usually rely more heavily on fossil energy and have greater pressure from carbon emissions and pollutant discharge, which leads to lower efficiency scores under the SBM-DEA framework with undesirable outputs.

From the temporal perspective, most manufacturing subsectors show a gradual upward trend, indicating that energy allocation efficiency improvement is a common phenomenon across the manufacturing system. However, the speed of improvement differs among sectors. Electronics manufacturing shows the most significant improvement, increasing from 0.67 in 2012 to 0.90 in 2023. Ferrous metal processing also improves but remains at the lowest level among the selected subsectors, increasing from 0.44 to 0.63. This indicates that energy-intensive industries still have considerable room for improvement in terms of energy-saving technology, production process upgrading, and emission reduction.

C. PREDICTION PERFORMANCE COMPARISON

To validate the proposed Transformer model, it is compared with ARIMA, SVR, Random Forest, XGBoost, LSTM, GRU, and TCN using MAE, RMSE, MAPE, and R^2, as shown in Table IV and Figure 3.

The comparison results show the Transformer model achieves the best prediction performance. Transformer model obtains the lowest MAE of 0.028, the lowest RMSE of 0.038, and the lowest MAPE of 3.74%, while its R2 reaches 0.936. Compared with ARIMA, the Transformer reduces RMSE by 53.66%, indicating that traditional linear time-series models have limited ability to capture nonlinear changes in manufacturing energy allocation efficiency. Compared with LSTM and GRU, the Transformer also achieves lower prediction errors, suggesting that the self-attention mechanism is more effective in modeling long-term dependencies and multivariate interactions.

Figure 4 further compares the observed and predicted values of the Transformer model during the testing period. The predicted curve is highly consistent with the observed curve, indicating that the model can effectively capture the upward trend and short-term fluctuations of manufacturing energy allocation efficiency. Although slight deviations appear in some years, the overall prediction error remains small. This demonstrates that the Transformer model has good applicability for dynamic prediction of energy allocation efficiency.

TABLE 4. Prediction Performance Comparison of Different Models

Model	MAE	RMSE	MAPE (%)	R2
ARIMA	0.061	0.082	8.74	0.721
SVR	0.053	0.071	7.56	0.783
Random Forest	0.049	0.066	7.03	0.812
XGBoost	0.045	0.061	6.41	0.841
LSTM	0.041	0.056	5.78	0.866
GRU	0.039	0.054	5.51	0.874
TCN	0.036	0.049	4.96	0.896
Transformer	0.028	0.038	3.74	0.936

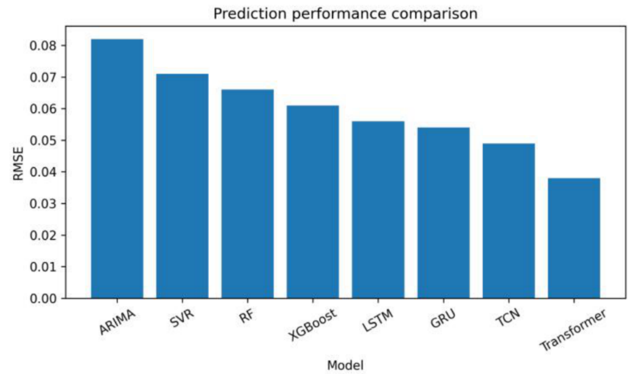

FIGURE 3. Prediction Performance Comparison

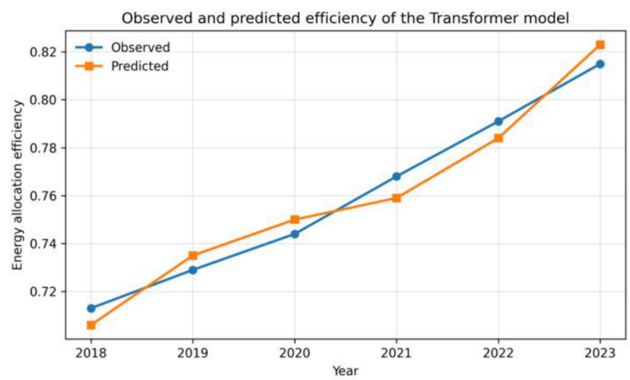

FIGURE 4. Observed and Predicted Efficiency of the Transformer Model

TABLE 5. Feature Contribution Ranking

Rank	Feature	Mean absolute contribution
1	Technology innovation	0.218
2	Energy structure	0.184
3	Industrial structure	0.157
4	Environmental regulation	0.139
5	Carbon intensity	0.121
6	Energy price	0.083
7	Capital input	0.062
8	Labor input	0.036

D. KEY DRIVING FACTORS

To improve the interpretability of the prediction results, feature contribution analysis was conducted to identify the key factors affecting manufacturing energy allocation efficiency. As shown in Figure 5, technology innovation has the highest contribution value, followed by energy structure, industrial structure, environmental regulation, and carbon intensity. This indicates that the improvement of manufacturing energy allocation efficiency depends not only on reducing energy consumption, but also on enhancing technological capability, optimizing energy structure, and improving environmental governance (Table V).

The dominant role of technology innovation suggests that R&D investment, patent output, and digital transformation can improve energy allocation efficiency by promoting process optimization, energy-saving equipment application, and intelligent production management. Energy structure also plays an important role. A higher proportion of clean energy and electricity substitution can reduce undesirable outputs and improve the environmental performance of manufacturing energy use. Industrial structure affects efficiency mainly through the share of high-value-added and low-energy-consumption industries. When manufacturing shifts from traditional heavy industries to advanced manufacturing and high-tech industries, the overall efficiency tends to improve. Environmental regulation has a relatively high contribution, indicating that regulatory pressure can promote enterprises to reduce energy redundancy and pollutant emissions. However, the effect of regulation may depend on its intensity and implementation mechanism. Moderate environmental regulation can stimulate green innovation, whereas excessive or poorly designed regulation may increase compliance costs. Carbon intensity also shows a clear impact, suggesting that reducing carbon emissions per unit output remains a key pathway for improving energy allocation efficiency under carbon neutrality targets.

E. SCENARIO SIMULATION AND POLICY IMPLICATIONS

To further explore the future evolution of manufacturing energy allocation efficiency, four policy scenarios were designed: technology innovation improvement, energy structure optimization, stronger environmental regulation, and combined improvement. The trained Transformer model was used to predict energy allocation efficiency from 2024 to 2030 under different scenarios. The simulation results are presented in Table VI and Figure 6.

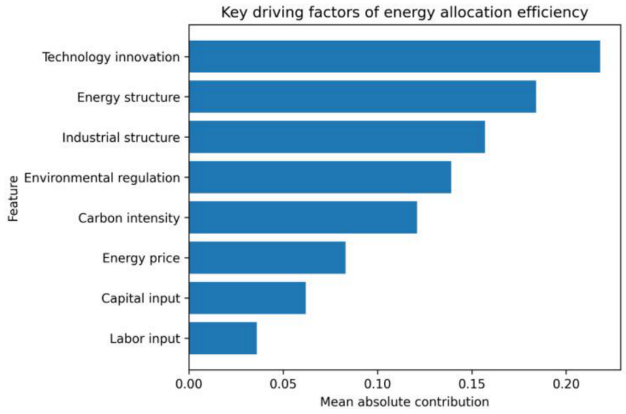

FIGURE 5. Key Driving Factors of Manufacturing Energy Allocation Efficiency

TABLE 6. Scenario Simulation Results of Manufacturing Energy Allocation Efficiency

Scenario	2024	2026	2028	2030	Change vs baseline in 2030
Baseline	0.828	0.850	0.872	0.892	0.000
Technology innovation	0.838	0.877	0.916	0.952	0.060
Energy structure optimization	0.836	0.872	0.909	0.942	0.050
Stronger regulation	0.834	0.869	0.904	0.935	0.043
Combined scenario	0.849	0.908	0.966	1.018	0.126

The baseline scenario indicates that manufacturing energy allocation efficiency will continue to improve gradually, reaching 0.892 by 2030. Under the technology innovation scenario, the predicted efficiency increases to 0.952 in 2030, which is 0.060 higher than the baseline. This suggests that technological progress is the most direct driver of efficiency improvement. Under the energy structure optimization scenario, the efficiency reaches 0.942 in 2030, indicating that reducing fossil energy dependence and increasing the share of clean energy can effectively improve energy allocation performance. The stronger regulation scenario also improves efficiency, but its effect is slightly weaker than technology innovation and energy structure optimization.

The combined scenario produces the most significant improvement, with predicted efficiency reaching 1.018 in 2030. This result suggests that a single policy measure may have limited effects, whereas coordinated policies involving technological innovation, energy structure adjustment, and environmental regulation can generate stronger synergistic effects. Therefore, manufacturing energy efficiency improvement should not rely solely on energy consumption control. Instead, it should be achieved through a comprehensive pathway that integrates technological upgrading, cleaner energy substitution, industrial structure optimization, and carbon emission control. Overall, the empirical results indicate that manufacturing energy allocation efficiency shows a clear upward trend, but regional and sectoral differences remain significant. The Transformer model outperforms traditional

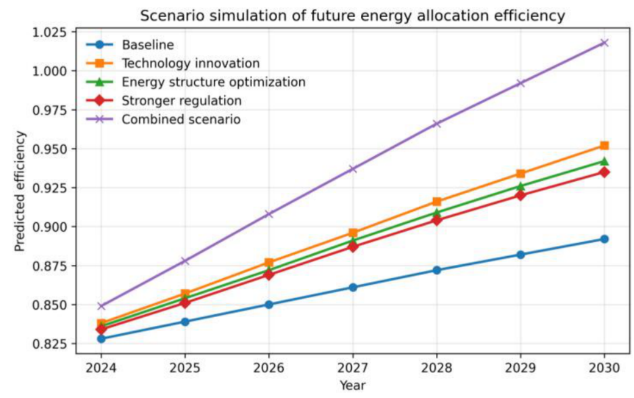

FIGURE 6. Scenario Simulation of Future Manufacturing Energy Allocation Efficiency

statistical models, machine learning models, and recurrent neural network models in dynamic prediction, demonstrating its advantage in capturing long-term dependencies and multivariate interactions. The interpretability analysis further reveals that technology innovation, energy structure, industrial structure, environmental regulation, and carbon intensity are the key factors affecting efficiency changes. These findings provide useful evidence for promoting manufacturing energy optimization, reducing carbon emissions, and supporting green industrial transformation.

V. CONCLUSION

This study proposed a Transformer-based dynamic prediction framework for manufacturing energy allocation efficiency. By integrating the SBM-DEA model with undesirable outputs and a multivariate time-series forecasting model, the study first measured manufacturing energy allocation efficiency under the joint constraints of energy input, economic output, and environmental emissions, and then predicted its future evolution using the Transformer model. The results show that manufacturing energy allocation efficiency generally presents an upward trend, indicating that technological progress, industrial upgrading, and environmental governance have gradually improved the efficiency of energy use in the manufacturing sector. However, clear regional and sectoral differences remain, suggesting that energy allocation efficiency improvement is still uneven across different manufacturing systems. The prediction results demonstrate that the Transformer model achieves better performance than traditional statistical models, machine learning models, and recurrent neural network models. This indicates that the self-attention mechanism can effectively capture long-term dependencies, nonlinear changes, and multivariate interactions in energy allocation efficiency series. The interpretability analysis further shows that technological innovation, energy structure, industrial structure, environmental regulation, and carbon intensity are the main factors affecting the dynamic changes in manufacturing energy allocation efficiency. Among them, technological innovation plays the most important role, while energy structure optimization and environmental regulation also provide important support for efficiency improvement and carbon reduction. Overall, this study provides a feasible analytical framework for linking energy efficiency evaluation with dynamic prediction, which can offer decision-making support for manufacturing energy optimization, green transformation, and low-carbon policy design. Nevertheless, there are still several directions for further improvement. Future research can incorporate more fine-grained enterprise-level or high-frequency energy consumption data to improve the temporal resolution of prediction. In addition, advanced Transformer variants such as Informer, Autoformer, PatchTST, and iTransformer can be further compared or integrated to enhance long-sequence forecasting performance. Future studies may also combine causal inference, policy simulation, and multi-scenario optimization to better reveal the mechanisms through which technological innovation, environmental regulation, and energy structure adjustment jointly affect manufacturing energy allocation efficiency.

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