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Forecasting the LNG Manufacturing Price Index from a Supply and Demand Perspective: The Case of Peoples Republic of China

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ABSTRACT

As a low-carbon fossil energy source, natural gas plays a crucial role in mitigating climate change and improving air quality, making it a key element in China's strategy to achieve its "carbon peaking and carbon neutrality" goals. Liquefied natural gas (LNG) has become a vital component of the global energy system due to its favorable transportation and storage characteristics and wide range of applications, particularly in facilitating the transition of energy structures. With the continuous increase in LNG consumption, accurately forecasting LNG manufacturing prices has become a central issue in the industry, as it provides a crucial reference basis for both enterprise production and industry development. This paper analyses the LNG ex-factory price, identifies six influencing factors including international crude oil futures prices, domestic crude oil spot prices, international natural gas futures prices, CSI 300 Index, domestic LNG production and domestic LNG sales based on typical correlation analysis. Using historical LNG production price data from 2016 to 2022, a Nonlinear Auto Regressive with Exogenous Inputs (NARX) neural network model is developed, integrating both historical price data and the identified influencing factors. The performance of the NARX model is compared to a traditional BP neural network model, demonstrating its high accuracy and stability in forecasting LNG production prices. The findings suggest that the proposed forecasting framework can effectively guide LNG producers in price forecasting and production planning, providing more accurate decision-making support for the industry.

Keywords: LNG; NARX Model; Natural Gas Price; Neural Network Prediction Model
JEL Classifications: C63, D700

1. INTRODUCTION

LNG has emerged as a crucial component of the natural gas sector, experiencing year-on-year increases in both trade volume and seaborne demand, thereby playing a vital role in the global energy transition (Miu, 2023). Historically, the natural gas industry in China has been heavily regulated, with LNG prices dictated by government policy. However, the implementation of various pricing mechanisms has resulted in notable discrepancies in trading prices (Wu, 2015). While domestic investigations into energy price forecasting have predominantly concentrated on crude oil prices (Xu et al, 2022; Zhang et al, 2019; Fan et al, 2017), there remains a scarcity of studies specifically focused on forecasting natural gas prices. The prices of natural gas are influenced by an array of factors, including international geopolitical developments and supply-demand dynamics, rendering this field a challenging area of academic pursuit. The most effective models and methodologies for predicting natural gas prices have yet to be established within the scholarly community. As the marketization of the LNG industry continues to advance, it becomes imperative to analyze price trends and investigate the factors that impact LNG prices, as this knowledge is essential for the further growth of the natural gas sector and the operational strategies of related enterprises.

Current studies on forecasting models for natural gas prices can be generally divided into three primary categories: statistical models, artificial-intelligence (AI) models, and hybrid forecasting models. Statistical models, predominantly founded on linear assumptions, are frequently utilized for short- to medium-term energy price predictions due to their swift processing capabilities (Hu et al., 2009). Fan and Liu (1999) were pioneers in incorporating relevant oil prices as factors influencing natural gas prices, employing a multidimensional autoregressive model to forecast these prices. This work represented the initial effort to model and predict natural gas prices in China. Since then, Wu and Zhu (2017) developed a heterogeneous autoregressive model for predicting natural gas prices, taking into account the inherent heterogeneity of the natural gas market, which resulted in positive forecasting outcomes. Shi et al. (2021) examined the fluctuation mechanism of natural gas spot prices using a dynamic Bayesian network model. Li and Kong (2023) employed various time series models to forecast the prices of natural gas, concluding that time series models demonstrate strong forecasting capabilities. Similarly, Lv and Shan (2013) utilized a time-series framework to forecast the volatility of natural gas spot prices. Wang and Lei (2020) put forward an improved pattern of sequence similarity search approach for natural gas price prediction relying on data mining techniques. Additionally, some scholars have used the structural vector autoregressive model (Wiggins and Etienne, 2017) and the structural heterogeneous autoregressive model (Hailemariam and Smyth, 2019) to forecast the natural gas producer price index.

Statistical models effectively capture the linear traits of natural gas price series but often struggle to account for their nonlinear features. In contrast, neural networks that utilize machine learning algorithms offer a significant advantage in enhancing prediction performance (Salehnia et al, 2013). Consequently, many researchers have shifted their focus to artificial intelligence models for forecasting natural gas prices. For instance, Jiang et al. (2021) employed wavelet analysis to predict U.S. natural gas spot and futures prices, achieving a relative prediction error of <10%. Similarly, Čeperić et al. (2017) used a feature selection algorithm to identify crucial input variables and applied support vector regression for short-term predictions of Henry Hub spot natural gas prices, demonstrating improved prediction precision in contrast to conventional time-series models. Furthermore, Su et al. (2019) examined various artificial intelligence algorithms, including artificial neural networks, support vector machines (SVM), gradient boosting techniques (such as XGBoost and CatBoost), and Gaussian process regression, to predict the Henry Hub spot price of natural gas from 2001 to 2018. This research represents a groundbreaking initiative in employing multiple AI models for natural gas price forecasting.

Given the influence of various factors on natural gas prices, which exhibit both cyclicality and non-linearity, a single model is often insufficient to fully capture the complexity of the price series. Consequently, hybrid models that integrate multiple forecasting methodologies have gained significant popularity among researchers (Jin and Kim, 2015). For example, Wang et al. (2020) presented a weighted hybrid model driven by data, which combines support vector regression (SVR), long short-term memory (LSTM) recurrent neural networks, and data analysis techniques to predict the daily Henry Hub Natural Gas Spot Price. Wang et al. (2021) introduced a novel approach that combines fully adaptive noise ensemble empirical mode decomposition (EEMD) with a gated recurrent unit (GRU), optimized using a particle swarm optimization algorithm. This integration demonstrated a high degree of prediction accuracy for weekly natural gas prices. Zhang et al. (2021) employed a CEEMD-ELM-ARIMA model to forecast the Henry Hub natural gas price, combining machine learning and time series approaches to enhance both prediction accuracy and model stability. Additionally, Li et al. (2021) proposed a hybrid prediction model relying on variational modal decomposition, particle swarm optimization, and deep networks to forecast the monthly Henry Hub natural gas price, outperforming traditional models in terms of prediction performance.

Previous research has significantly advanced natural gas price forecasting by offering a range of predictive models and methods. However, investigations specifically addressing China's LNG factory gate price remain relatively scarce. Most existing approaches rely on limited historical time series and do not adequately consider the numerous market forces affecting LNG prices, highlighting gaps in both focus and methodology. To address these shortcomings, this paper concentrates on predicting the LNG manufacturing price index using a NARX neural network from a supply-and-demand perspective, incorporating historical price data as well as various price-influencing factors. By taking these elements into account, the proposed approach provides a more comprehensive framework for price prediction. The main contributions of this paper are as follows: (1) A comprehensive LNG price forecasting framework based on the NARX neural network model is proposed, integrating historical price data and multiple influencing factors from a supply-and-demand perspective, filling the gap in research on LNG factory gate prices in China; (2) Six key influencing factors for LNG production prices are quantitatively analyzed, constructing a systematic framework for impact factor analysis, advancing LNG price forecasting research; (3) The superior performance of the NARX neural network model is validated through a comparison with the traditional BP neural network, demonstrating its efficiency and stability in practical applications.

2. RESEARCH METHODOLOGY AND MODELLING

LNG manufacturing prices generally reflect supply-side, demand-side, and market economic conditions. This paper examines the key determinants of LNG commodity pricing in light of these market characteristics and proposes a NARX neural network model for price forecasting.

2.1. Factors Affecting LNG Prices

As an energy commodity, natural gas prices are influenced by multiple elements, including supply-side, demand-side, and market economy factors (Liu and Wang, 2002). On the supply side, costs and reserves play a key role; on the demand side, consumption levels and the prices of alternative commodities are critical. Market economy factors encompass unexpected events affecting trading activities and shifts in consumer mentality.

The supply and consumption of natural gas are the primary factors that directly impact its price, among both supply-side and demand-side influences (Yu, 2003). The price of alternative energy sources serves as a secondary, yet significant, factor affecting natural gas prices (Cong, 2012). As a fossil fuel, natural gas has several substitutes, including refined oil, coal, liquefied petroleum gas (LPG), and electricity (Li et al., 2013). Natural gas prices are closely correlated with oil prices, and there is also a substitution relationship with coal, LPG, and fuel oil (Yan, 2016). In China, national policies, production costs, supply and demand dynamics, the economic cycles of alternative energy prices, and consumers' affordability for gas all play crucial roles in determining natural gas prices. Studies indicate that the factors influencing natural gas prices are closely linked to its pricing mechanism. In the early stages of natural gas market liberalization, China's import prices largely followed the crude oil-linked pricing method. Data analysis suggests that China's liquefied natural gas prices are influenced by both the long-term impact of WTI crude oil prices and short-term lagging effects (Wang, 2019).

On the market economic side, consumer sentiment plays a significant role in energy pricing. Energy market participants' psychological expectations can influence futures prices, which reflect these expectations. For example, Tang Baojun and Tao Quan used various analytical methods, such as correlation coefficients and the G-S model, to analyze the price discovery function in the New York Mercantile Exchange (NYMEX) natural gas futures market. Their results showed a strong correlation between NYMEX natural gas futures and spot prices (Tang and Tao, 2013). Zhang Yang further examined the impact of the natural gas futures market and the crude oil market on the fluctuations of natural gas spot prices, confirming that both markets are primary influencers of natural gas price volatility (Zhang, 2022), highlighting the influence of trading sentiment. Additionally, emergencies such as pandemics, wars, extreme weather events, or natural disasters can significantly affect energy market prices. These emergencies not only disrupt the energy market but also impact the broader market economy. Stock prices are a key indicator of market developments (Gatfaoui, 2016). Acaravci et al. (2012) demonstrated a substantial long-term connection between natural gas prices and natural gas stock prices across 15 European Union countries, while Zhang and Chevallier (2017) found a correlation between natural gas prices and the stock market volatility index. This paper, therefore, uses stock indices as a measure to assess the influence of unexpected events on natural gas prices.

2.2. NARX Neural Network

The NARX (Nonlinear Autoregressive Exogenous) model is used to forecast the LNG manufacturing price. The model uses weekly data on several variables as predictors, including the crude oil futures price, crude oil spot price, natural gas futures price, the CSI 300 index, domestic LNG production, and domestic LNG sales volume. These variables are averaged over the weeks to form the response variable—the LNG manufacturing price index.

The NARX model is a type of dynamic neural network featuring a nonlinear autoregressive structure. Similar to other neural networks, it comprises an input layer, a hidden layer, and an output layer. By means of the hidden layer and activation functions, the model achieves complex nonlinear mappings (Yan and Zhang, 2018). As a "black-box" model, the internal calculation process and working principles cannot be fully explained by a simple model or function. The hidden layers and node weights are abstract in their mathematical meaning. Therefore, the performance of such models should be evaluated based on prediction accuracy, that is, by comparing the predicted results with actual outcomes.

Dynamic neural networks, like the NARX model, have the ability to preserve and backpropagate information over time. They can incorporate historical time-series data into the model, allowing the system to learn from past observations and reflect those results in future predictions. This feature strengthens the model's capacity to grasp the temporal dynamics of the system.

The NARX model employs recursive thinking to integrate both the historical sequence of response variables and external factors into a unified framework. This combination of time series modeling and regression techniques allows for a more comprehensive analysis of the underlying system. Additionally, the model uses actual output values and error values during the training process. By interrupting backpropagation at certain points, the model avoids falling into local optima, which improves computational efficiency and enhances overall predictive performance (Li et al., 2020).

$$y(t) = f[y(t-1), y(t-2),..., y(t-h), x(t-1), x(t-2),..., x(t-h)]$$

where x(t) is the predictor variable of the external input and y(t) is the response variable of the neural network model output. The value of the response variable y(t) is jointly determined by y(t−1) and x(t−1) of the previous cycle; f(·) is a function obtained from the historical data training of multiple predictor and response variables.

For a neural network with m input values, n output values, N output node layers, and H hidden layer nodes, the model internally includes:

(1) Input layer state

$$\alpha = [\alpha_1, \alpha_2,...,\alpha_\phi] \quad (1)$$

The total number of input layer states is:

$$\varphi = H\cdot(m\cdot l_X+n\cdot l_Y) \quad (2)$$

(2) Input layer bias

$$\beta^H = [\beta_1, \beta_2,..., \beta_H] \quad (3)$$

(3) Input weights W^1

The weights of the hidden node i and input node j of the connected input layer, denoted as $w_{i,j}$.

(4) Hidden layer weights

The weights linking the hidden layer node i and the output layer node k are denoted as $w_{k,i}$. The total number of hidden layer connection weight values is equal to H·N.

(5) Output layer bias

$$\beta^N = [\beta_1, \beta_2, ..., \beta_N] \quad (4)$$

The full number of parameters to be determined during training is the sum of the number of input layer connection weights, input layer deviations, output layer hidden layers, connection weights and output layer deviations.

$$M_p = H{\cdot}N+H+N \quad (5)$$

(6) Output values and residuals

The output of the hidden layer is:

$$h_i = \prod\left[\sum_{j=1}^{N} w_{i,j}x_j + b_i^H\right] \quad (6)$$

The output of the output layer is:

$$y_k = \prod\left[\sum_{j=1}^{H} w_{k,i}h_i + b_i^N\right] \quad (7)$$

The residuals are:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^2 = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_k - y_k)^2 \quad (8)$$

The NARX neural network model is constructed using MATLAB. The data samples are divided into three independent subsets: The training set, the validation set, and the test set. During the model training process, the training set is utilized to train the neural network and determine the weights of the network nodes. The validation set is employed to optimize the network structure by adjusting the number of hidden nodes, thereby improving the accuracy of the prediction model. The test set is reserved solely for evaluating the final performance of the model. The training set comprises 70% of the total samples, while both the validation set and the test set each account for 15%.

3. EMPIRICAL ANALYSIS

We first analyze the factors that influence the LNG manufacturing price and assess the degree of correlation between these factors and the LNG manufacturing price using typical correlation analysis. Subsequently, we train a NARX neural network prediction model using historical data on LNG manufacturing prices and their influencing factors.

3.1. Data Sources and Data Processing

The predictor variables in the model used in this paper include international crude oil futures prices (x_1, USD/tonne), domestic crude oil spot prices (x_2, CNY/tonne), international natural gas futures prices (x_3, USD/tonne), the CSI 300 Index (x_4), domestic LNG production (x_5, million tonnes), and domestic LNG sales (x_6, million tonnes), covering the period from November 2015 to October 2023. All four price series are sourced from the Wind database.

After performing principal component analysis, it was found that the trends of major energy trading crude oil futures prices are similar. Therefore, a representative crude oil futures price is selected to represent the overall price level of crude oil futures. In this case, Brent crude oil futures prices are chosen. Similarly, Daqing crude oil spot prices are selected for domestic crude oil spot prices, and US natural gas futures prices are selected for international natural gas futures prices. The CSI 300 Index is used to measure macroeconomic market sentiment and contingencies. For domestic LNG supply, production data is used, while apparent consumption is used to represent domestic LNG demand; both datasets are provided by OilChem.

Before training the neural network model, the data must be normalized to remove the effect of varying data magnitudes, which could otherwise impact model training and fitting. In this paper, we apply Min-Max normalization to scale the data, ensuring that all variables are mapped to the interval (−1, 1). This normalization is calculated as follows:

$$x^{map} = \frac{x_i(t) - \bar{x}_i}{s_i} \quad (9)$$

where x^{map} is the result of the data obtained after normalization; $x_i(t)$ is the initial time series data; $\bar{x}_i$ is the mean of the sample of time series data; s_i is the standard deviation of the sample of time series data.

3.2. Typical Correlation Analysis of Influencing Factors

Typical correlation analysis studies the linear correlation among the column vectors of two matrices. This approach is not confined to examining the correlation between separate vectors, but can also be extended to analyze the relationships between two sets of variables, with each set comprising multiple vectors.

The method assumes the existence of two vectors, U and V, which are linear combinations of two sets of original variables, X and Y, respectively. These are referred to as the latent variables corresponding to X and Y. The correlation coefficients between each vector in X and U (as well as each vector in Y and V) are called structural coefficients, while the correlation coefficient between U and V is known as the typical correlation coefficient.

The formula is expressed as:

$$U_i = a_1X_1+...+a_pX_p \quad (10)$$

$$V_i = b_1Y_1+...+b_qY_q \quad (11)$$

Where $a_1,..., a_p, b_1,...,b_q$ are typical structural coefficients respectively.

Typical correlation coefficients are:

$$\rho_i = \frac{cov(U,V)}{\sigma_u\sigma_v} \quad (12)$$

where $cov(U,V)$ is the covariance of U and V; σ_u and σ_v represent the standard deviation of U and V, respectively.

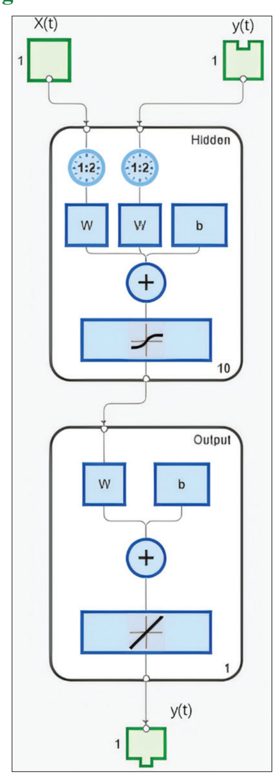
In typical correlation analysis, a strong correlation is indicated if the correlation coefficient ($\rho > 0.7$), a moderately strong correlation by ($0.7 > \rho > 0.5$), a moderate correlation by ($0.5 > \rho > 0.3$), and a poor correlation by ($\rho < 0.3$) (Hazra and Gogtay, 2016).

The data for the LNG manufacturing price forecasting model is divided into two parts: one consists of the time-series weekly data of the predictor variables, denoted as ($x_1[t],...,x_6[t]$); the other is the response variable, which is the historical series of LNG ex-works prices, denoted as ($y[t]$). The independent variables ($x_1[t],..., x_6[t]$) form a vector group of independent variables, and the LNG price serves as the dependent variable. After incorporating the data, the typical correlation coefficient between the independent variable vector group and the dependent variable is calculated to be 0.8185, with a $P < 0.01$. This indicates a strong correlation between the data in the independent variable vector set and LNG prices. Therefore, the six independent variables selected in this study can effectively explain and predict the level of LNG manufacturing prices.

3.3. NARX Forecast Results and Analysis

The data for the LNG manufacturing price forecasting model is divided into two parts: one consists of the weekly time-series data for the predictor variables, denoted as ($x_1[t],..., x_6[t]$), and the other is the response variable, which is the historical series of LNG manufacturing prices, denoted as ($y[t]$). MATLAB is used to construct and train the neural network model. The structure of the NARX model is shown in Figure 1.

Figure 1: NARX model structure



Due to the randomness of the data selected by the neural network in the training, testing and validation of the model, the results of the model obtained from each training will be slightly different, After six training iterations, the model achieves its optimal validation performance, featuring a mean squared error (MSE) of 0.15604, as shown in Figure 2.

The predicted values of LNG weekly data generated by the NARX model are close to the actual values, with only minor discrepancies between the predicted and real data points. This suggests that the model's overall prediction and fitting performance are quite good. A comparison of the predicted values with the actual values is illustrated in Figure 3.

When the model achieves optimal training, the overall fitting accuracy is 0.98437 for the training set, 0.92779 for the test set,

Figure 2: Training performance

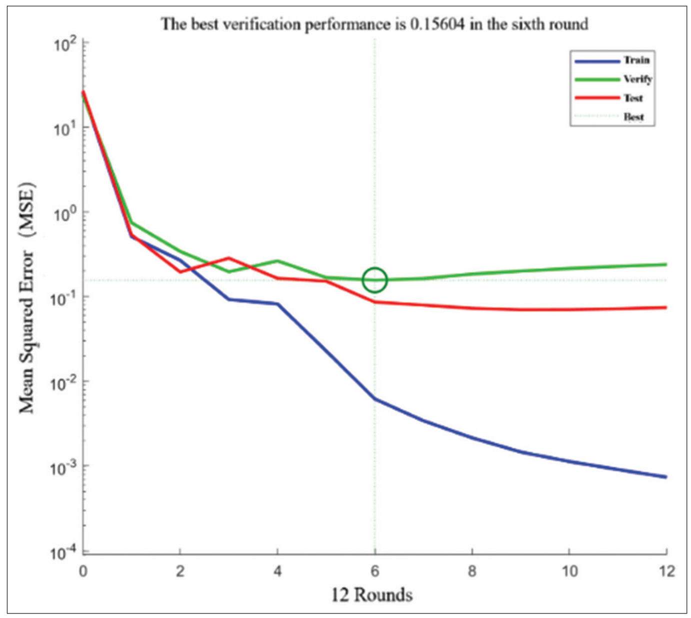


Figure 3: NARX model predictions versus actual values

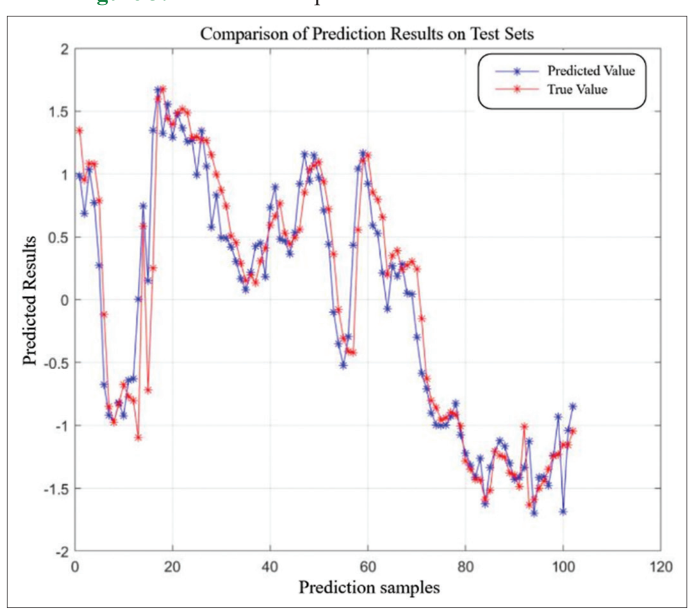


Figure 4: R^2 of the fitted model.

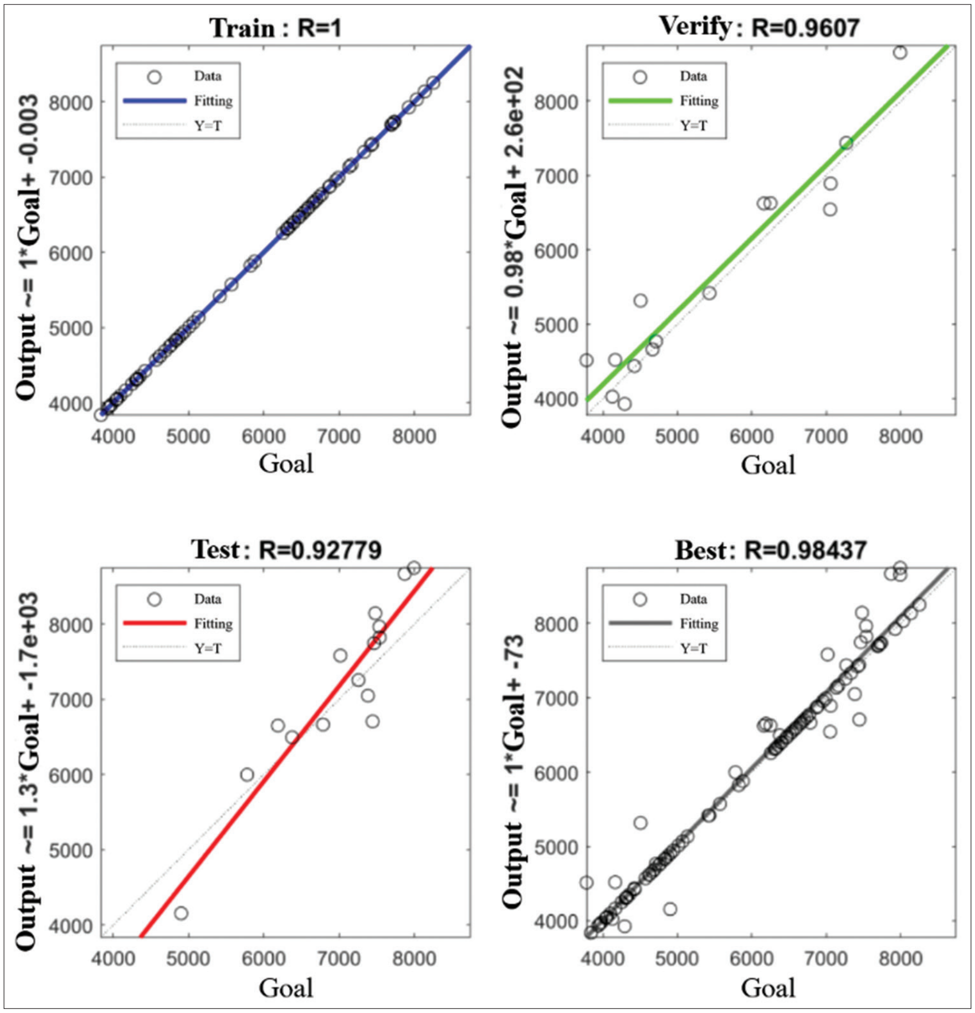


Figure 5: Time series response plot

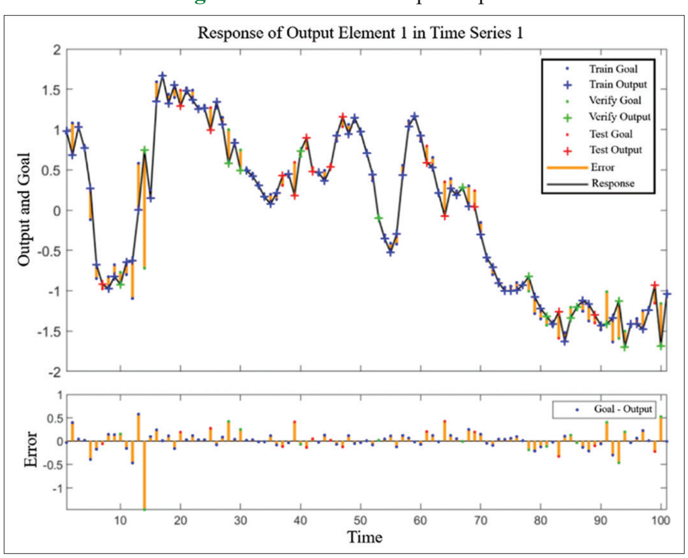
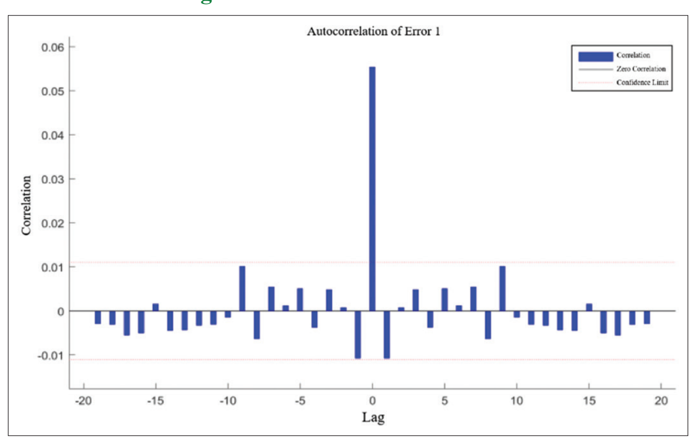


Figure 6: Autocorrelation of errors



and 0.9607 for the validation set. The accuracy of the fitted model is shown in Figure 4.

Figures 5-7 illustrate the time-series response plot of the model, the autocorrelation histogram of the errors, and the cross-correlation histogram between the input variables and the errors, respectively. In the error time-series plot, the yellow line represents the error, i.e., the difference between the true and predicted values. Shorter yellow lines indicate higher model accuracy and better fitting performance.

In the error autocorrelation plot, the largest error occurs when the input delay is 0. The model performs best when the delay value is non-zero, with the error remaining within the confidence interval.

Figure 7: Reciprocal correlation between input variables and errors

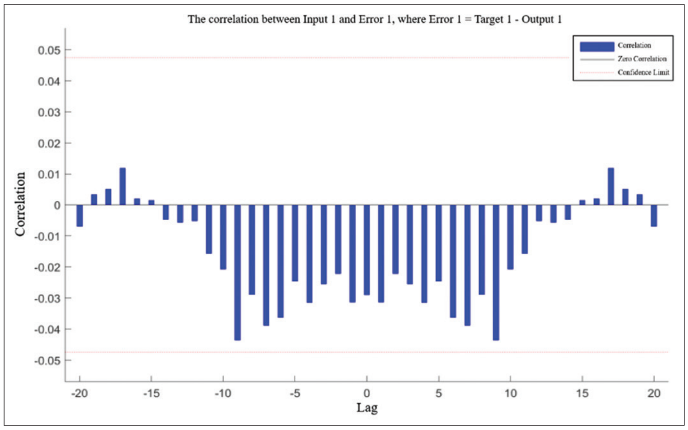


Figure 8: Comparison of BP model and NARX model prediction results

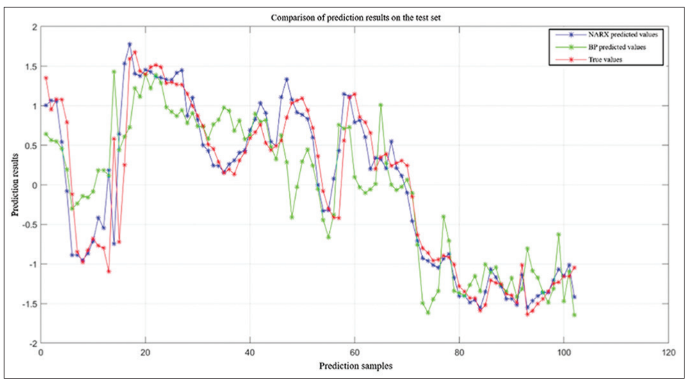


Table 1: Comparison of parameters associated with the BP model and the NARX model

Evaluation indicators	NARX	BP
MES	0.15604	0.28894
R	0.98437	0.9423

The intercorrelations between the input variables and the errors are all below 0.05 and fall within the confidence interval. This indicates that the errors in model fitting are random, and there is no systematic error arising from variable selection or model construction.

3.4. Model Testing

To further assess the prediction performance and fitting accuracy of the NARX neural network, a BP neural network regression model was constructed using the same time series data for both the predictor and response variables. As shown in Table 1, the mean squared error (MSE) of the BP neural network was 0.28894, which is slightly higher than the MSE of the NARX model. A comparison of the prediction results from both the BP neural network and the NARX temporal network is shown in Figure 8. From the figure, it is evident that the predicted values from the NARX model are closer to the actual values in contrast to the BP model. Additionally, the NARX model exhibits no signs of overfitting or underfitting, indicating superior prediction accuracy over the BP neural network.

4. CONCLUSION

Begins by examining the factors influencing LNG manufacturing prices. It selects six key indicators from the supply side, demand side, and market economy perspective, while also considering the historical manufacturing prices of LNG. A typical correlation analysis is conducted on these influencing factors, and then a NARX neural network is constructed based on the historical LNG price sequence and its influencing factors. The prediction performance of the NARX model is contrasted with that of a BP neural network. The research findings are as follows:

(1) The selected variables—crude oil futures, spot prices, Shanghai and Shenzhen stock indices, natural gas futures prices, and national natural gas production and consumption—show strong correlations with LNG manufacturing prices. These variables can be effectively used as independent predictors in an LNG manufacturing price forecasting model.
(2) The NARX neural network is capable of integrating the historical LNG manufacturing price sequence with its influencing factors. The model demonstrates high fitting accuracy and minimal prediction error, outperforming the BP regression neural network in prediction accuracy. This model can be applied to forecast LNG manufacturing prices, providing valuable insights for LNG production and enterprise operations.
(3) Across different phases, the NARX neural network consistently shows outstanding performance, especially in markets with large swings, as it can quickly adapt to shifting market trends. In practical operations, anticipating market turning points in advance is a critical criterion for model usability. As such, considering the forecast results across all stages, the NARX neural network superior performance.

This study provides a systematic framework for LNG market price prediction research and proposes new prediction ideas, expanding the depth and breadth of existing research; At the same time, it provides new methods and tools for predicting LNG production prices, which can help enterprises optimize production plans and pricing strategies more scientifically. However, there are still certain limitations. This study only focuses on the Chinese market, and future research can consider the market characteristics of more countries and regions for horizontal comparative analysis. Future research directions can further integrate more macroeconomic variables, market volatility indicators, and combine advanced technologies such as deep learning to improve prediction accuracy and model universality.

REFERENCES

Acaravci, A., Ozturk, I., Kandir, S.Y. (2012), Natural gas prices and stock prices: Evidence from EU-15 countries. Economic Modelling, 29, 1646-1654.

Čeperić, E., Žiković, S., Čeperić, V. (2017), Short-term forecasting of natural gas prices using machine learning and feature selection algorithms. Energy, 140, 893-900.

Cong, R. (2012), Research on influencing factors of world natural gas prices. Western Economic Management Forum, 23(4), 61-69.

Fan, Q., Wang, T., Zhang, Z. (2017), Application of quantum particle swarm intelligence algorithm in international Brent crude oil price prediction [J]. Fuzzy Systems and Mathematics, 31(4), 84-90.

Fan, Y., Liu, B. (1999), Application of multidimensional autoregressive modelling in natural gas price forecasting. Systems Engineering Theory and Practice, 11, 92-96.

Gatfaoui, H. (2016), Linking the gas and oil markets with the stock market: Investigating the U.S. Relationship. Energy Economics, 53, 5-16.

Hailemariam, A., Smyth, R. (2019), What drives volatility in natural gas prices? Energy Economics, 80, 731-742.

Hazra, A., Gogtay, N. (2016), Biostatistics series module 6: Correlation and linear regression. Indian Journal Dermatology, 61(6), 593-601.

Hu, C., Zhang, Y., Wu, Z. (2009), An empirical study of natural gas futures price trend prediction--an analysis based on Markov model. Price Theory and Practice, 9:59-60.

Jiang, X., Qiao, J., Wang, X. (2021), Natural gas price prediction based on wavelet analysis. Gas and Heat, 41(06):34-37.

Jin, J., Kim, J. (2015), Forecasting natural gas prices using wavelets, time series, and artificial neural networks. PLoS One, 10(11), e0142064.

Li, F., Zhu, H., Li, Z. (2013), Analysis of factors affecting natural gas distribution price in China. Energy Technology and Management, 38(1), 166-167.

Li, H., Sun, S., Luo, C. (2020), Grain yield prediction model based on NARX neural network. Jiangsu Agricultural Science, 48(22), 228-232.

Li, J., Wu, Q., Tian, Y., Fan, L. (2021), Monthly henry hub natural gas spot prices forecasting using variational mode decomposition and deep belief network. Energy, 227, 120478.

Li, M., Kong, Y. (2023), Natural gas price forecasting based on time series modelling. Oil Gas and New Energy, 35(1), 61-66.

Liu, Y., Wang, H. (2002), Analysis of factors affecting future natural gas prices in China. Price Theory and Practice, 2, 29-30.

Lv, X., Shan, X. (2013), Modeling natural gas market volatility using GARCH with different distributions. Physica a Statistical Mechanics and its Applications, 392(22), 5685-5699.

Miu, Y. (2023), Analysis and outlook of international LNG transportation market. International Petroleum Economy, 31(7), 79-84.

Salehnia, N., Falahi, M.A., Seifi, A., Mahdav, M.H. (2013), Forecasting natural gas spot prices with nonlinear modeling using Gamma test analysis. Journal of Natural Gas Science and Engineering, 14, 238-249.

Shi, H., Chai, J., Lu, Q. (2021), Analysis of the volatility mechanism and volatility prediction of North American natural gas spot price. Theory and Practice of Systems Engineering, 41(12), 2828.

Su, Z., Liu, E., Xu, Y., Xie, P., Shang, C., Zhu, Q. (2019), Flow field and noise characteristics of manifold in natural gas transportation station. Oil and Gas Science and Technology-Revue D'IFP Energies Nouvelles, 74, 70.

Tang, B., Tao, Q. (2013), Research on price discovery function of natural gas futures market of New York mercantile exchange--an empirical analysis based on G-S model. China Energy, 35(3), 30-34.

Wang, J., Cao, J., Yuan, S., Cheng, M. (2021), Short-term forecasting of natural gas prices by using a novel hybrid method based on a combination of the CEEMDAN-SE-and the PSO-ALS-optimized GRU network. Energy, 233, 121082.

Wang, J., Lei, C. (2020), Research on natural gas price prediction method based on data mining technology. China Mining, 29(2), 52-58.

Wang, J., Lei, C., Guo, M. (2020), Daily natural gas price forecasting by a weighted hybrid data-driven model. Journal of Petroleum Science and Engineering, 192, 107240.

Wang, T.(2019) Research on Pricing Mechanism and Influencing Factors in Natural Gas Market. China: Southwest University of Finance and Economics Press.

Wiggins, S., Etienne, X.L. (2017), Turbulent times: Uncovering the origins of US natural gas price fluctuations since deregulation. Energy Economics, 64, 196-205.

Wu, D., Zhu, B. (2017), Natural gas price forecasting based on HAR-RV-CJ model. Statistics and Decision Making, 23, 83-87.

Wu, Q. (2015), LNG supply and demand situation and price forecast at home and abroad. Shanghai Gas, 1, 33-38.

Xu, Y., Xu, D., Chen, S. (2022), Medium and long-term crude oil price forecast, management and suggestions of domestic and foreign oil companies. China Energy, 44(10), 17-22.

Yan, H., Zhang, Z. (2018), Interest rate term structure forecasting, treasury bond pricing and treasury bond portfolio management. Statistical Research, 35(3), 23-37.

Yan, Q. (2016), Influencing factors of natural gas prices in China and future operation trends. International Petroleum Economics, 24(6), 45-51.

Yu, X. (2003), Analysing natural gas price influencing factors with ISM. Chemical Technology and Economy, 10, 30-32.

Zhang, J., Li, D., Tan, Z. (2019), Research on international crude oil price forecasting based on hybrid model. Journal of Beijing Institute of Technology Social Science Edition, 21(1), 59-64.

Zhang, J.L., Liu, Z.Y., Wang, M.X. (2021), Research on natural gas price prediction model based on CEEMD-ELM-ARIMA. Natural Gas and Oil, 39(4), 129-136.

Zhang, Y. (2022) Multi-scale analysis of the impact of North American crude oil price on natural gas price based on transfer entropy network. China: Jiangsu University Press.

Zhang, Y., Chevallier, J., (2017), "De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets. Energy Economics, 68, 228-239.