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Review of the Evolution and Cutting-Edge Research in Price Forecasting Methods

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Abstract. Price forecasting holds crucial decision-making value across various sectors, such as finance, commodities, retail, and energy. Accurate price forecasts are essential for optimizing inventory management, mitigating risks, formulating effective strategies, and improving overall profitability. This paper provides a systematic view of the evolution of price forecasting methods, tracing their development from traditional statistical time series models to modern machine learning approaches, as well as cutting-edge deep learning and their hybrid models. Using a comprehensive literature review and comparative analysis methods, different categories of forecasting models are organized and compared. The study finds that a single forecasting model is difficult to adapt to all market conditions. In contrast, hybrid models, especially those that integrate the feature extraction capabilities of deep learning with the interpretability of traditional models or combine multi-source data, demonstrate higher accuracy and robustness. These approaches are therefore identified as the mainstream research direction for future research in price forecasting.

Keywords: Price Forecasting, Time Series Analysis, Machine Learning, Deep Learning, Hybrid Models

1. Introduction

Against the backdrop of global economic integration, price forecasting has become a core prerequisite for decision-making in fields such as finance and trade. Currently, the field of price forecasting has formed three mainstreams methodological paradigms: traditional statistical models, machine learning approaches, and deep learning techniques. However, traditional models show insufficient adaptability to complex and volatile markets; machine learning methods often suffer from weak generalization and interpretability; and deep learning models face challenges related to model complexity and adaptability. Existing research mostly focuses on optimizing single models, while systematic reviews of the developmental trajectory and applicable boundaries of various methods remain limited. Moreover, the fusion logic underlying hybrid models has not been sufficiently synthesized, making it difficult to provide a holistic and cross-domain methodological reference.

This paper addresses the core issue of the evolutionary logic and cutting-edge paradigm of price forecasting methods. It adopts a literature review method to clarify the historical development of forecasting techniques and employs comparative analysis to compare the advantages and

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disadvantages of models from multiple dimensions. By systematically sorting out the core principles and application scenarios of the three types of methods, this study can make up for the fragmentation of existing research, provide practitioners with a basis for method selection, and clarify the challenges and future directions of the field.

2. Traditional price forecasting methods

2.1. Statistical models based on time series

2.1.1. Autoregressive Integrated Moving Average model and its variants

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used linear model in the field of forecasting. Its core logic is to transform non-stationary series into stationary series through differencing and then use historical observations to characterize the evolution pattern of the series. The standard ARIMA model is expressed as ARIMA (p, d, q), where p, d, and q correspond to the autoregressive order, differencing order and moving average order, respectively. Zhang et al. constructed an ARIMA model based on China's polysilicon price data from January 2016 to June 2025, and the empirical results show that the model is effective in capturing linear dependencies and short-term forecasting performance [1].

For price series with significant seasonal fluctuations, the Seasonal ARIMA (SARIMA) model introduces seasonal autoregressive, differencing, and moving average terms into the ARIMA framework. It can simultaneously capture non-seasonal changes and periodic fluctuations, improving the ability to model monthly or quarterly price data.

ARIMA and SARIMA are essentially linear models. However, real price fluctuations are affected by multiple factors such as supply and demand, market sentiment, and macro policies, showing complexity including nonlinearity and dynamic structural changes. Zhong et al.'s studies show that there are significant regime differences in the price fluctuations of non-ferrous metals, which simple ARIMA-type models find difficult to capture accurately [2]. Therefore, such models are more suitable for short-term forecasting and scenarios dominated by clear linear trends. For series with structural breaks or nonlinear dependencies, more complex nonlinear or variable parameter models are required.

2.1.2. Generalized Autoregressive Conditional Heteroskedasticity model family

Traditional time series models usually assume homoscedastic residuals, but empirical studies show that financial and bulk commodity price series generally exhibit volatility clustering. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model emerged as the times require and has gradually developed into a model family containing multiple variants.

The standard GARCH(p, q) model can effectively capture volatility clustering and persistence, which is of significant value in risk measurement, volatility forecasting, and asset pricing, and is often combined with mean models to build forecasting frameworks. In the prediction of monthly railway freight turnover, Jiang constructed a SARIMA-GARCH hybird model [3]. Specifically, SARIMA was used to depict trend and seasonal characteristics, while GARCH was used to describe the residual volatility structure of the residuals. The results show that the combined model significantly outperforms the single model in prediction accuracy, proving that GARCH can improve the robustness of forecasting for volatility clustering series.

2.2. Structured models based on econometrics

2.2.1. Vector Autoregression model (VAR)

ARIMA and GARCH mainly target univariate time series, while prices in economic and financial systems are often dynamically related to multiple variables. The VAR model expresses each endogenous variable as a linear combination of its own lagged values and those of other variables, depicting the dynamic evolution of multivariable systems. VAR models relax strict prior theoretical constraints, emphasize data-driven modeling, and are well suited for variable interaction analysis, impulse response, and joint forecasting.

VAR models are widely used in price linkage and market function analysis. Liao et al. constructed a VAR system of futures and spot prices and found that futures prices have a significant guiding relationship with spot prices, verifying the price discovery function of the futures market [4]. When exploring the volatility characteristics of corn futures yields, Liang et al. first used ARIMA-GARCH to depict volatility clustering and leverage effects of a single series, and then incorporated corn futures prices and macrovariables such as "the added value of the secondary industry" into a VAR system for analysis [5].

2.2.2. Cointegration analysis and Error Correction Model (ECM)

Most multivariable price series are non-stationary, and direct regression is prone to "spurious regression." Cointegration analysis tests the long-term equilibrium relationship between non-stationary variables; if a cointegration relationship exists, an ECM can be constructed to simultaneously depict the long-term equilibrium and short-term dynamic adjustment processes.

ECM incorporates the degree of the system's deviation from the long-term equilibrium into the short-term change mechanism through the error correction term, which has both forecasting ability and economic interpretability. Song et al. analyzed the long-term and short-term correlation between the stock market and the real economy using a ARDL-ECM model, and confirmed the long-term cointegration relationship between industrial added value and the Shanghai A-share index and trading volume through the bound cointegration test [6]. Further results show that, in the long run, stock market index and industrial added value have a positive equilibrium relationship, and the stock market is the Granger cause of the long-term changes in the real economy; in contrast, short-term impacts are insignificant, and no short-term Granger causality is observed. These findings highlight the core value of ECMs: deviations caused by short-term fluctuations are gradually corrected toward long-term equilibrium through the error correction mechanism.

2.3. Advantages and common limitations of traditional methods

Traditional methods such as ARIMA/SARIMA, GARCH, VAR, and ECM are characterized by strong economic interpretability and can provide reliable benchmark forecasts and policy-relevant insights in stable scenarios; however, they generally rely on linear and stationarity assumptions, have limited ability to depict non-linear relationships, structural mutations, and high-dimensional features, and their forecasting accuracy is limited when facing complex and rapidly changing price systems.

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3. Application of modern machine learning methods in price forecasting

3.1. Classic supervised learning models

3.1.1. Support Vector Machines and Support Vector Regression

Support Vector Machines (SVM) and their regression form, Support Vector Regression (SVR) are classic supervised learning algorithms. Unlike traditional linear regression that "minimizes the sum of squared errors of all data points," SVR focuses on finding the optimal hyperplane, so that most sample points fall within the bandwidth range and maximize the boundary. Through kernel function technology, non-linear problems in the original space can be implicitly mapped to a high-dimensional feature space and transformed into linear solutions, solving the problem of non-linear modeling.

Yu et al. proposed a hybrid "information granulation + support vector machine" approach for stock price forecasting [7]. Through information granulation, the core trend of the price series is extracted and noise is reduced. The processed features are then fed into the SVM to build an opening price forecasting model. Empirical results show that this method can effectively predict the fluctuation range of stock prices, verifying the feasibility of SVR in handling nonlinear problems in financial time series. Moreover, the "data preprocessing + modeling" paradigm provides a useful framework for addressing high-noise and high-volatility data commonly observed in financial markets.

3.1.2. Random Forest and Gradient Boosting Decision Trees

Ensemble learning models, such as Random Forest and Gradient Boosting Decision Tree (GBDT), are based on decision trees and improve forecasting accuracy and robustness through diverse ensemble strategies, compensating for the shortcomings of single decision trees. Decision trees form decision structures through recursive data partitioning based on if-then rules. Their main advantages include strong interpretability, minimal assumptions about data distributions, and the ability to automatically capture interaction effects among features. Fan et al. constructed a "K-means + decision tree" model to evaluate rural inclusive financial credit risks [8]. The farmer data after cluster preprocessing were input into the decision tree, and the consistency between model predictions and manual review verified its performance in processing complex, high-dimensional data.

However, a single decision tree is prone to overfitting and weak generalization. Random Forest adopts a Bagging strategy by generating independent training subsets through bootstrap sampling and training multiple decision trees in parallel. The final output is obtained through voting or averaging, which reduces variance, enhances generalization, and enables the estimation of feature importance. GBDT adopts the Boosting serial strategy in which decision trees are constructed sequentially. Each new tree fits the residuals of the previous model to reduce bias, optimizing the loss function through gradient descent. The final prediction is produced by a weighted aggregation of all treesm resulting in high prediction accuracy.

These two types of models are widely used in price forecasting. They can automatically capture the non-linear relationships and interaction effects between prices and technical indicators and macro variables without presetting function forms, and are suitable for price forecasting tasks driven by multiple factors. They can also lock core variables through feature importance analysis and improve modeling efficiency.

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3.2. Evolution of machine learning models

The application of machine learning in price forecasting shows a clear evolutionary logic: from single classic models to ensemble models, and then to the current mainstream hybrid model architecture. The core driving force is to cope with the high noise, non-stationarity, non-linearity, and multi-scale characteristics of price data, and improve forecasting stability and accuracy.

Chen et al. proposed a "data preprocessing-component forecasting-result integration" framework in precious metal futures price forecasting [9]. This hybrid paradigm of "signal decomposition + machine learning" has become an advanced strategy for dealing with non-stationary financial time series. It can strip noise, separate fluctuation components of different frequencies, provide regularized input for the model, and improve modeling efficiency and reliability.

Compared with deep neural networks and SVR models that require fine parameter tuning, the Extreme Learning Machine (ELM) provides an efficient predictor for hybrid architectures. After superimposing the prediction results of each component, the full-scale information is integrated. In the forecasting of gold and silver futures, the error indicators are better than traditional models, verifying the effectiveness of architectural innovation [9]. This evolution marks the entry of price forecasting from the stage of "model selection and parameter tuning" to "system engineering design."

4. Deep learning hybrid forecasting framework

4.1. Deep learning sequence modeling methods

Deep learning models automatically learns complex patterns through multi-layer non-linear transformations, and has significant advantages in time series forecasting. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer are the core sequence modeling paths: CNN extracts local temporal patterns through one-dimensional convolutions, reduces parameter complexity via weight sharing, and achieves translation invariance and hierarchical feature learning, and is often used as a feature extractor suitable for data with local correlation and fixed cycles; RNN transmits historical information through cyclic connections. However, basic RNN suffers from gradient disappearance and explosion problems.

Long Short-Term Memory (LSTM) solves the long-term dependency through the gating mechanism. Gated Recurrent Unit (GRU) further simplifies the LSTM structure, reduces parameters and maintains performance. Both are mainstream models for financial time series forecasting, good at depicting long-term trends and periodic cycles; Transformer abandons cyclic and convolutional structures, establishes global dependencies based on the self-attention mechanism, can improve efficiency through parallel computing, has the potential for interpretability, has significant advantages in ultra-long sequence modeling, and its variants are suitable for multi-variable forecasting.

4.2. Combination of deep learning and hybrid forecasting paradigms

4.2.1. Multi-source heterogeneous data fusion

One of the core advantages of the deep learning-based hybrid frameworks is to realize the unified encoding and fusion of multi-source heterogeneous data, breaking through the limitations of traditional structured data. In terms of text information fusion, Yu et al. improved the LSTM-based prediction accuracy through sentiment analysis of stock bar comments [10]; Jiang et al. proposed the

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MTAE framework, which used Word2Vec to convert text into word vectors and combined multi-task learning to realize supervised dimensionality reduction of text features, and integrated with economic indicators to improve the forecasting effect of crude oil futures [11]. In terms of multi-modal fusion, the DMAF model proposed by Huang et al. excavates the complementary relationship between image and text information through single-modal and cross-modal attention layers [12]; Zhang et al. integrated time series, text semantics, and sentiment features to build a corn futures forecasting model, confirming the synergistic effect of multi-feature fusion [13]. Current forecasting research has shifted from pursuing "better single models" to building "intelligent hybrid systems," and improving the fault tolerance, adaptability, and accuracy of the framework through the integration of multi-source information.

4.2.2. Hybridization of model architectures

Model-level hybridization addresses complex forecasting challenges through the collaboration of functionally specialized modules. In the classic cascading mode of "feature extractor + sequence modeler," the CNN-LSTM-Attention model proposed by Jing et al. extracts local patterns through CNN, learns long-term dependencies through LSTM, and weights key information through the attention mechanism, with better performance than single models [14]; the MCGAT model proposed by Luo et al. adopts parallel paths to extract static and dynamic features, and dynamically weights and fuses them through the attention mechanism to improve adaptability to complex markets [15]. Higher-level hybrid frameworks integrate multiple technical paradigms. The crude oil futures forecasting framework constructed by Lin et al. integrates variational mode decomposition, a pool of deep learning base models, and reinforcement learning, and improves forecasting accuracy through "divide and conquer" and intelligent collaboration [16]. The deep learning hybrid forecasting paradigm marks the transformation of price forecasting from relying on expert experience to design models to systematically building adaptive systems. Through multi-source data fusion and model architecture hybrid, it enhances adaptability and forecasting accuracy to complex market environments.

5. Conclusion

This paper systematically reviews the three core methods in the field of price forecasting. Traditional statistical models have solid theories and strong interpretability, but are limited by linear and stationarity assumptions and have insufficient ability to adapt to complex markets. Modern machine learning models break through the bottleneck of non-linear modeling and improve forecasting accuracy, but have the problem of weak interpretability; deep learning hybrid frameworks realize the upgrading of information dimensions and modeling capabilities through multi-source data fusion and modular architecture, with better robustness. The central conclusion is that a single model is difficult to adapt to all market conditions. Hybrid models that integrate the advantages of multiple models and multi-source information are the key to improving forecasting performance, representing the future mainstream direction.

Current price forecasting faces three core challenges: at the data level, the problems of noise and non-stationarity have not been completely solved, and there are new difficulties such as alignment and semantic ambiguity in multi-source heterogeneous data fusion; at the model level, deep learning frameworks have a large number of parameters and high computing costs, are prone to overfitting, and the "black box" characteristic leads to insufficient interpretability, which restricts practical application; at the application level, there is an adaptation gap between the static assumptions of the

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model and the dynamic evolution of the market, which is difficult to cope with structural mutations and black swan events, and is prone to failure.

Future research can focus on four directions: first, integrate causal reasoning and explainable AI to build transparent forecasting models; second, develop adaptive, lightweight, and meta-learning frameworks to improve the market adaptability and deployment efficiency of models; third, deepen the fusion of multi-modal and alternative data, and combine industry large models to explore the value of new data; fourth, build "virtual market" environments and train more robust forecasting agents through reinforcement learning.

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