Proceedings of the 3rd International Conference on Management Research and Economic Development
DOI: 10.54254/2754-1169/174/2025.21823

Gold Futures Price Forecast Based on Artificial Intelligence

Tianning He[1,a,*]
[1]*Woodsworth College, University of Toronto, Toronto, Ontario, Canada*
a. tianning.he@mail.utoronto.ca
**corresponding author*

Abstract: Gold futures prices are affected by many factors such as macroeconomics, market supply and demand, and financial markets. Their volatility is crucial to investment decisions and market stability. However, the complexity of the market makes it difficult for traditional forecasting methods to accurately capture the law of price changes. It is of great significance to study efficient forecasting methods. This paper systematically reviews the factors affecting gold futures prices and forecasting methods. The key driving factors are analyzed from the aspects of inflation rate, interest rate, crude oil price, and US dollar index, and three main forecasting methods are summarized: traditional time series models (ARIMA, GARCH, ARDL), hybrid models (MS-MIDAS-CJ, VMD-ICSS-BiGRU) and deep learning methods (SGRU-AM, DBN). Finally, this paper explores the optimization directions of model computational efficiency, generalization ability, and market sentiment integration. This study provides a systematic analysis of gold futures market forecasting. In the future, the combination of deep learning and market sentiment analysis is expected to improve forecasting accuracy and provide support for investors and market decision-making.

Keywords: Gold futures, Prices, Forecasts, Gold.

1. Introduction

As an important part of the global financial system, the price fluctuations of the gold futures market are affected by many factors such as macroeconomics, market supply and demand, financial markets, and technical analysis. Gold not only has a safe-haven property, but is also widely used in investment, industry, and jewelry manufacturing [1]. Therefore, its price trend has attracted the attention of investors, policymakers, and researchers. With the increasing complexity of financial markets, how to accurately predict gold futures prices has become an important research topic in the fields of financial engineering and economics [2, 3, 4].

In recent years, researchers have used a variety of methods to predict gold futures prices, including traditional time series analysis, hybrid model-based methods, and emerging technologies such as deep learning. Traditional methods such as ARIMA and GARCH are mainly based on historical data for modeling, which are suitable for price prediction in the stable market period, but have certain limitations in dealing with market mutations and nonlinear characteristics. The hybrid model method improves the prediction accuracy and applicability by integrating time series analysis, machine learning, and market structure identification. For example, MS-MIDAS-CJ and VMD-ICSS-BiGRU have shown superior performance in market volatility prediction and trading strategy optimization. In addition, deep learning methods such as SGRU-AM and DBN further enhance the nonlinear

DOI: 10.54254/2754-1169/174/2025.21823

modeling capabilities of the model, and can make more accurate predictions using multivariate data and market sentiment.

This paper systematically reviews the factors affecting gold futures prices and prediction methods. First, the key driving factors affecting gold futures prices are sorted out from four aspects: macroeconomics, market supply and demand, financial markets, and technical analysis, and their short-term and long-term effects on price fluctuations are analyzed. Secondly, different types of gold price prediction methods are discussed, including traditional methods, hybrid model methods, and deep learning methods, and their advantages and disadvantages and applicable scenarios are compared. Finally, this paper summarizes the limitations of current research and proposes future improvement directions, including improving model computational efficiency, combining transfer learning, using market sentiment analysis, and improving model interpretability to further optimize the accuracy and reliability of gold futures price prediction.

Through this review, this paper aims to provide investors, researchers, and policymakers in the gold futures market with a systematic analytical framework, reveal the core factors affecting gold prices, and explore the advantages and challenges of cutting-edge prediction technologies. Future research can further combine multiple methods to improve the accuracy and adaptability of prediction models to cope with complex and changing financial market environments.

2. Influencing Factors

Gold futures prices are affected by a variety of macroeconomics, market supply and demand, financial market variables and technical analysis indicators. Existing studies use different statistical and machine learning methods to analyze the volatility of gold prices and identify key driving factors. These factors not only affect the short-term volatility of the gold futures market but also determine the long-term price trend. The following will review the four aspects of macroeconomic factors, market supply and demand factors, financial market factors and technical analysis factors.

2.1. Macroeconomic Factors

As a global safe-haven asset, the price of gold is widely affected by macroeconomic variables. The inflation rate (CPI) is one of the key factors affecting the price of gold. When inflation rises, the purchasing power of currency decreases. Investors often choose gold for value preservation, so the price of gold usually rises with inflation . In addition, the Federal Funds Rate also has a significant impact on the price of gold. Gold does not generate interest income, so when interest rates rise, investors are more inclined to hold high-yield assets, and the price of gold may fall. Studies have found that the price of gold is negatively correlated with interest rates [5].

At the same time, crude oil prices have a significant positive impact on gold prices. High oil prices are usually accompanied by rising global inflation, which increases the safe-haven demand for gold [6]. The US dollar index is also an important factor affecting gold futures prices. The relationship between the US dollar and gold is usually negatively correlated. When the US dollar depreciates, the price of gold rises, and vice versa[7]. In addition, Treasury Bill Rates may affect gold prices, although some studies have found that its impact is weak and has not been significantly supported in the Granger causality test[7].

2.2. Market Supply And Demand Factors

The supply and demand changes in the gold market directly affect its price trend. Gold demand is one of the important variables for predicting gold prices. It is mainly determined by jewelry manufacturing, industrial applications, and investment demand (ETF and physical gold investment). When the market's investment demand for gold increases, the gold price rises [8]. In addition, the

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central bank's gold reserve policy will also affect market supply. A large amount of gold purchases by the central bank may push up prices, while selling gold may cause prices to fall[9].

2.3. Financial Market Factors

Financial market fluctuations are often closely related to gold futures prices. Stock market volatility affects the safe-haven properties of gold. When the stock market falls sharply, investors tend to transfer funds to the gold market, thereby pushing up gold prices[8]. For example, the Dow Jones Industrial Average (DJI) and the Standard & Poor's 500 Index (S&P 500) have a certain negative correlation with gold prices. In addition, market risk premiums and speculative trading are also important factors affecting the gold futures market. When the positions of speculative traders increase, market volatility may rise, which in turn affects the gold price [9].

2.4. Technical Analysis Factors

Technical analysis indicators are an important basis for short-term traders and algorithmic trading systems. In the gold futures market, moving averages (SMA, EMA) are used to identify trend directions, while relative strength index (RSI) and Williams %R are used to determine overbought or oversold conditions [9]. In addition, market structure mutations (ICSS detection) are also used to identify key turning points in the market and improve the stability of the model [7]. Gold futures prices are affected by multiple factors including macroeconomics, market supply and demand, financial markets and technical analysis. Macroeconomic variables such as inflation rate, interest rate, crude oil price and US dollar index play a decisive role in the long-term trend of gold prices, while gold demand, central bank reserves, market risk premium and speculative behavior play a key role in short-term fluctuations. In addition, technical analysis indicators and the identification of structural changes in the market also play an important role in short-term forecasts.

3. Forecasting Methods

The gold futures price forecasting methods can be roughly divided into traditional methods, methods based on hybrid models, and other methods. Traditional methods are mainly based on time series analysis and econometric models, which are suitable for price forecasting in stable market periods, but have difficulty in dealing with market mutations and nonlinear characteristics. The hybrid model-based method combines time series, machine learning, and market structure identification technology, which is suitable for complex market environments and improves forecasting accuracy. Other methods, such as deep learning, machine learning, and sentiment analysis, can use large-scale data to optimize gold price forecasts from the perspective of multivariate relationships and market sentiment.

3.1. Traditional Gold Price Forecasting Methods

Traditional methods mainly include time series models (such as ARIMA and GARCH) and econometric methods (such as ARDL and stochastic mean regression). Time series models assume that gold price data is predictable and rely on historical data for modeling. Among them, Gold Price Forecasting Using a Multivariate Stochastic Model[4] uses the ARIMA(6,1,1) model to forecast gold prices. It is found that ARIMA performs well in short-term forecasts, but due to the inability to capture market mutations, the long-term forecast error is large (RMSE = 0.219). Another time series method, GARCH (generalized autoregressive conditional heteroskedasticity model), is mainly used for volatility prediction in financial markets. For example, in the study of Forecasting Volatility of China Gold Futures Price[5], GARCH was used to model the volatility of the gold market, but its prediction error was high and its performance was inferior to that of machine learning methods.

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In addition to time series models, econometric methods are also widely used in gold price forecasting. Gold Price Forecasting Using a Multivariate Stochastic Model uses an autoregressive distributed lag (ARDL) model for forecasting, combining gold demand, Treasury bond interest rates and lagged gold prices[7]. The study found that ARDL can effectively capture the impact of long-term economic variables and has the lowest prediction error (RMSE = 0.076), which is better than ARIMA. In addition, the study also used stochastic mean regression (Ornstein-Uhlenbeck process) to simulate the characteristics of gold prices fluctuating around the long-term mean, but due to the slow mean regression speed, the prediction is delayed (RMSE = 0.173). Overall, ARIMA is suitable for short-term forecasting but not for market mutations, GARCH is suitable for volatility modeling but has large errors, and ARDL is suitable for long-term trend forecasting, with the lowest error and the best prediction effect.

3.2. Gold Price Prediction Method based on Hybrid Model

Researchers have also proposed some hybrid models to improve the accuracy of gold futures price prediction by combining time series, machine learning and market structure identification. Among them, the research on gold futures market volatility prediction based on Markov and mixed data models proposed the MS-MIDAS-CJ combined model, which uses mixed data sampling (MIDAS) to allow data modeling of different time frequencies to improve the applicability of short-term and long-term predictions[10]. At the same time, it combines the Markov mechanism (MS) to identify market state changes (high volatility/low volatility). The final model MS-MIDAS-CJ performs best in market volatility prediction and has the lowest error.

Another study, A New Hybrid VMD-ICSS-BiGRU Approach for Gold Futures Price Forecasting and Algorithmic Trading, proposed a VMD-ICSS-BiGRU combination model[9]. This model uses variational mode decomposition (VMD) to process market signals and improve data stability. It also combines the cumulative sum of squares(ICSS) to identify market structure mutations and uses BiGRU (bidirectional GRU) for time series prediction. The results show that this model performs well in trading strategy optimization, with an annualized return of 20.41%, which is better than traditional trading strategies. In general, MS-MIDAS-CJ is suitable for market volatility prediction, while VMD-ICSS-BiGRU is suitable for gold futures price prediction and trading strategy optimization.

3.3. Other Gold Price Prediction Methods

In addition to traditional methods and hybrid models, methods such as deep learning, attention mechanism and sentiment analysis have been gradually applied to gold futures price prediction in recent years. These methods can handle nonlinear market characteristics, market sentiment and multivariate interactions, and perform well in both short-term and long-term predictions. A Gold Futures Price Forecast Model Based on special gated recurrent unit + attention mechanism (SGRU-AM) proposed the SGRU-AM model, in which special gated recurrent uni (SGRU t) is an improved version of GRU with enhanced long-term memory capacity, while attention mechanism(AM) selects key features and improves prediction accuracy[6]. The study found that the SGRU-AM model has the lowest error (RMSE = 4.79), which is better than LSTM and ordinary GRU.

Another study, Deep Belief Network for Gold Price Forecasting, uses deep belief network(DBN) to predict gold prices, combines restricted Boltzmann machine (RBM) for unsupervised pre-training to improve feature extraction capabilities, and fine-tunes through backpropagation(BP)[8]. The results show that DBN has the lowest prediction error (RMSE = 0.0557), which is better than BP neural network and ARIMA, and is suitable for long-term trend prediction. Overall, SGRU-AM

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combines the attention mechanism to improve short-term prediction accuracy, while DBN is suitable for long-term trend prediction and has the lowest prediction error.

Gold futures price prediction methods can be divided into traditional methods, hybrid model-based methods, and other methods. Traditional methods such as ARIMA, GARCH, and ARDL are suitable for time series analysis, but have limitations in dealing with market mutations and nonlinear characteristics. Hybrid model-based methods, such as MS-MIDAS-CJ and VMD-ICSS-BiGRU, improve prediction accuracy and trading strategy optimization capabilities by combining market structure identification and machine learning. Other methods, such as SGRU-AM and DBN, rely on deep learning and attention mechanisms and perform well in both short-term and long-term predictions. Future research can further combine deep learning, hybrid models, and market sentiment analysis to build a more efficient gold futures price prediction framework and improve trading strategy optimization capabilities.

Although current research has proposed a variety of gold futures price prediction methods, including traditional time series models, hybrid model-based methods, and deep learning methods, various methods still have certain limitations, affecting their prediction accuracy and reliability in complex market environments. Therefore, further improving these methods and combining the latest machine learning and financial modeling techniques will be an important direction for future research.

4. Analysis of Limitations of Existing Forecasting Methods

4.1. Existing Limitations

4.1.1. Limitations of Traditional Time Series Methods

Time series models such as ARIMA and GARCH mainly rely on historical data for modeling and assume that market price changes are linearly predictable. However, gold market prices are affected by sudden events, policy changes and market sentiment, showing high nonlinearity and randomness, which makes traditional time series models have large errors in long-term forecasts. For example, the Gold Price Forecasting Using Multivariate Stochastic Model study found that ARIMA(6,1,1) performs well in the short term, but has large errors in the long term (RMSE = 0.219), and the GARCH method performs poorly in a highly volatile market environment. Therefore, these models are difficult to cope with market mutations and nonlinear dynamics, and their scope of application is relatively limited [8].

4.1.2. Limitations of Hybrid Model-based Methods

Hybrid models combine time series analysis, machine learning, and market structure identification to improve prediction accuracy, but they still have limitations. Although the MS-MIDAS-CJ and VMD-ICSS-BiGRU methods have improved the ability to predict gold market volatility and optimize trading strategies, their computational complexity is high and they require high hyperparameter selection and model structure optimization. For example, A New Hybrid VMD-ICSS-BiGRU Approach for Gold Futures Price Forecasting and Algorithmic Trading found that although the VMD-ICSS-BiGRU model performed best in trading strategy optimization (annualized return of 20.41%), it consumed a lot of computing resources and was difficult to apply to real-time prediction[9]. In addition, these hybrid models usually rely on a large amount of training data, and the prediction accuracy may decrease when there is insufficient data or the market environment changes suddenly.

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4.1.3. Limitations of Deep Learning Methods

Deep learning methods, such as SGRU-AM and DBN, can capture the nonlinear dynamics of the market and improve the accuracy of short-term and long-term forecasts. However, deep learning methods usually require a large amount of data for training and the model has low interpretability. For example, A Gold Futures Price Forecast Model Based on SGRU-AM found that SGRU-AM has the lowest prediction error (RMSE = 4.79), but its training process is complex and it is difficult to explain specific market behaviors [6]. In addition, Deep Belief Network for Gold Price Forecasting uses DBN to predict gold prices. Although it has the lowest prediction error (RMSE = 0.0557), this method has a large amount of computation and is highly sensitive to abnormal data. These problems limit the application of deep learning methods in actual trading systems[8].

4.2. Improvement Methods and Optimization Directions

4.2.1. Improve the Computational Efficiency of the Model

Since the computational complexity of hybrid models and deep learning methods is high, model pruning and lightweight neural networks can be considered for optimization. For example, in VMD-ICSS-BiGRU, the attention mechanism can be used to optimize feature extraction, reduce the amount of computation, and improve real-time prediction capabilities. In addition, AutoML (automatic machine learning) can be used to automatically optimize hyperparameters and network structures, reduce manual intervention, and improve model adaptability.

4.2.2. Combine Transfer Learning to Improve the Generalization Ability of the Model

Since deep learning methods have a high demand for data volume, transfer learning can be introduced to improve the generalization ability of the model. For example, in SGRU-AM and DBN predictions, the model can be pre-trained on global financial market data and then fine-tuned on specific market data, thereby reducing dependence on large-scale data and improving the adaptability of the model under different market conditions.

4.2.3. Using Few-Shot Learning and Data Augmentation

To address the problem of insufficient data, Few-Shot Learning (FSL) and Data Augmentation techniques can be used. For example, the MS-MIDAS-CJ method relies on high-quality time series data and can generate simulated market data through Generative Adversarial Networks (GAN) or Synthetic Data Augmentation to improve the robustness of the model.

4.2.4. Improving the Interpretability of the Model

A major problem with deep learning methods is the black box nature of the model, which makes it difficult to explain its prediction results. Therefore, Explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations), can be combined to analyze the contribution of different factors in the gold market to price prediction. For example, in the SGRU-AM prediction process, SHAP values can be used to analyze which market variables have the greatest impact on the prediction, thereby enhancing investors' trust in the model's predictions.

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4.2.5. Combining Sentiment Analysis and Market Sentiment Data

Existing research mainly relies on historical data for prediction, while market sentiment and news events are equally important in affecting gold prices. Natural language processing (NLP) technology can be combined to extract sentiment information from text data such as financial news and social media. For example, BERT (Bidirectional Encoder Representations from Transformers) or financial text sentiment analysis models can be used to input market sentiment data into the gold price prediction model to improve the real-time and accuracy of the prediction.

5. Conclusions

The complexity and high volatility of the gold market make it difficult for a single forecasting method to fully and accurately predict price trends. Future research directions should focus on further optimization of hybrid models, efficient training of deep learning, and the combination of data enhancement technology and market sentiment analysis. First, ensemble learning may be an important direction in the future, which improves the stability and generalization of forecasts by integrating traditional time series, machine learning and deep learning models. Second, reinforcement learning may become an important tool for optimizing trading strategies, continuously optimizing trading decisions through adaptive learning. In addition, the development of blockchain and smart contract technology will make market data more transparent and real-time, which will further improve the accuracy of the forecasting model.

In terms of practical application, future gold price forecasting models should have efficient computing, interpretability and real-time performance to meet the needs of the financial market. For example, combining quantitative trading strategies and smart investment advisory systems can make gold futures trading more intelligent. With the continuous development of artificial intelligence, computational finance and big data technology, gold futures price forecasts will be more accurate, intelligent and automated, providing investors and policymakers with more reliable market decision-making basis.

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