ORIGINAL PAPER

DOI: 10.26794/2587-5671-2026-30-4-97-112
UDC 338.27(045)
JEL E37, C54

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Improving the Accuracy of Precious Metal Prices Forecasts When Used as Stabilization Assets

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ABSTRACT

Precious metals are key elements of the asset class in the international financial market. They have a number of advantages: they are a valuable tool for preserving wealth, they are not at risk of default, and they provide effective protection against inflation. In addition, they are considered safe-haven assets during periods of unfavorable geopolitical conditions. **The purpose** of this research is to find methods for improving the accuracy of predicting the price of precious metals through the use of advanced machine learning models. **The methodological basis** is the concept of predicting the effectiveness of precious metals as a stabilizing asset (and a safe-haven asset) in the context of future financial instability. The research methodology is based on evaluating the effectiveness of machine learning models using information criteria such as AIC and BIC, determination coefficients R2 and Adj-R2, and RMSE and MAPE as measures of the closeness between the actual and predicted values of time series and error measures. The information base for this study was based on daily data on the prices of four precious metals (gold, silver, platinum, and palladium), provided by Investing.com. Given the increasing importance of precious metals as indicators of investor sentiment and the state of the global economy, and in light of the escalating geopolitical tensions from 2020 to 2025, we conducted a comparative analysis using modern machine learning models. The results obtained demonstrate the advantages of the KAN model as a promising tool for improving the accuracy of forecasts and the interpretability of results in various scenarios. This is highly significant for the development of an effective investment strategy in the precious metal markets.

Keywords: precious metal market; price forecasts; investment strategy; stabilization assets; machine learning models; LSTM network; Kolmogorov-Arnold network

For citation: **Kireeva E.F., Karaev A.K., Ponkratov V.V. Improving the accuracy of precious metal prices forecasts when used as stabilization assets. *Finance: Theory and Practice*. 2026;30(4):97-112. DOI: 10.26794/2587-5671-2026-30-4-97-112**

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INTRODUCTION

Since the beginning of 2020, the global economy has been affected by various economic and humanitarian shocks, which have triggered geopolitical risks and uncertainty, leading to a fundamental change in the investment landscape in financial markets. The search for hedging assets to address challenges and threats of an economic and humanitarian nature highlights the attractiveness of the precious metals market, which is being explored by many economists [1, 2]. Precious metals have become important financial assets and investments due to their safe haven characteristics from potential market risks [3–5].

Precious metals have several advantages over other investment assets. They are not affected by currency devaluation, unlimited issuance, or credit risk, making them safer than stocks and bonds. Unlike real estate, which can be less liquid over long periods, gold can not only preserve but also increase your capital. Precious metals are considered a reliable investment and are less volatile than cryptocurrencies due to regulatory risks and technological disruptions.

In recent years, a new geopolitical factor has added to these traditional arguments. The freezing of Russia's foreign exchange reserves showed that foreign currency assets held in foreign banks may be unavailable for political reasons. Gold reserves provide a stable foundation for state strategic independence, reducing dependence on volatile oil and gas revenues and creating sustainable protection against external shocks.

The stabilizing role of precious metals extends beyond gold. Silver, platinum, and palladium are all used to diversify investment portfolios, providing both protective assets and industrial metals. Over the past few years, all four of these precious metals have seen steady price increases on both the global and Russian markets.

Gold has led the way in absolute growth, with silver and platinum leading in relative growth. These metals have shown steady and significant increases over time, confirming their status as safe assets. Despite their volatility and occasional price fluctuations, silver, platinum, and palladium remain attractive for diversifying investment portfolios and potentially earning higher returns.

The global financial markets, including the market for precious metals, are becoming more complex and volatile. These markets are characterized by speculative transactions that increase systemic and price risks. Under these circumstances, it is crucial for investors, policymakers, and experts to accurately forecast the prices of precious metals.

Traditional statistical methods for predicting the price of precious metals have limitations when dealing with multidimensional, non-linear, non-stationary time series that contain significant noise. These methods typically operate under the assumption of time series stationarity, linear relationships, and normal probability distributions, making it difficult to accurately predict future trends based on historical data.

Recent advances in machine learning and deep learning have led to new breakthroughs in this area, with models based on recurrent neural networks (RNNs) with long- and short-term memory (LSTMs) and the Kolmogorov-Arnold Network (KAN) showing promising results [6]. These models are able to learn complex patterns and rules from high-dimensional, nonlinear data, leading to improved prediction accuracy compared to traditional methods.

The aim of the research is to discover methods to enhance the accuracy of predicting the price of precious metals through the use of advanced machine learning algorithms.

To achieve this goal, the study has identified the following objectives:

- Identification of precious metals as a tool for capital protection during periods of market volatility and uncertainty.
- Investigation of the role of machine learning techniques in scientific and practical studies on forecasting precious metal prices.
- Comparative analysis of the accuracy of predictions made by the LSTM and KAN models for precious metal prices for the period from January 1, 2024 to May 1, 2025.
- Discussion of the findings and justification of conclusions regarding the use of the KAN model as a potential tool for improving the accuracy of precious metal price forecasts.

PRECIOUS METALS AS A STABILIZING ASSET IN A VOLATILE ECONOMY: LITERATURE REVIEW

Precious metals have unique properties that make them a reliable investment tool. They retain or even increase in value when other financial instruments suffer significant losses. This makes precious metals a valuable asset for protecting investment portfolios from systemic risks.

Among all precious metals, gold is the most resilient, demonstrating its value even during times of financial crisis. Gold is characterized by its high liquidity and stability in conditions of geopolitical and economic uncertainty. Silver, on the other hand, is often used to diversify investment portfolios due to its relatively low investment cost. Now, both gold and silver are included in many investment strategies and are considered strategically important assets. This is supported by scientific studies that show silver's potential as a stabilizing asset in investment portfolios [7].

Platinoids (platinum and palladium) also form a significant share of investment portfolios, taking into account the rarity of these metals and the wide range of uses both in the jewelry industry and in the manufacturing sector. The platinum market is facing several challenges: limited stocks, logistical difficulties due to sanctions, price fluctuations, and increasing demand in the automotive industry. Despite these challenges, innovations are opening up new opportunities for growth that align with the principles of sustainable development and the transition towards a "green" economy in various countries [8]. Platinum group metals are considered safe assets around the world due to their high profitability and their ability to diversify portfolios [9].

Global Economic Policy Uncertainty (GEPU) increases the risk of unexpected changes, especially in fiscal and regulatory policies. Due to the ongoing rise in geopolitical tensions, increased uncertainty has become a significant factor in financial markets. When uncertainty is high, the risk of investing in speculative assets increases [10]. GEPU influences the precious metals market in several ways, affecting the investment and purchasing decisions of economic actors. This, in turn, can lead to significant fluctuations in the price of these metals in the commodity market [11].

Precious metals are important investments for an expanded portfolio, however, they are very sensitive to economic uncertainty. Since January 2020 (during the COVID-19 pandemic), prices for precious metals have shown an upward trend. For example, gold prices rose from almost $ 1,500 (USD) to $1,900 per ounce at the end of 2020.

T. Nuunkh, T. Burggraf and M. Nasir [12] revealed that economic uncertainty increases the demand for precious metals during the crisis. Similarly, S. Thongkairat, V. Yamaka, and S. Sribonchitta [13] identified the strong influence of GEPU on the gold market. In addition, the GEPU shock is more volatile for gold prices in developing countries compared to developed economies. Thus, it is assumed that precious metals are assets that counteract market risks [14]. Therefore, numerous modern studies focus on the use of precious metals as a stabilizing asset in order to identify and use their capabilities in conditions of financial instability [15, 16]. Global financial markets are interconnected through a variety of channels. One of the key factors integrating the foreign exchange and precious metals markets is the dynamics of oil prices [17].

A wide variety of research methods were used to predict the prices of precious metals. For example, T. Mingming and Z. Yingliang [18] used the MWRNN (Multiple Wavelet Recurrent Network) model to predict the price of crude oil, taking into account the price of gold. In the work of V.A. Al-Dhuraibi and J. Ali [19] used both traditional statistical methods and machine learning methods for short-term forecasting of the gold price trend: Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Linear Regression (LR).

In the article [20], gold price trends were studied using the ICA-GRUNN hybrid method, which combines the methods of Independent Component Analysis (ICA) and Gate Recurrent Unit Network (GRUNN).

B. Guha and G. Bandepadhyay [21] used the classical ARIMA method to predict the price of gold. G. Tsokhen [22] tried to predict the prices of precious metals using approaches such as Bollinger bands (BB), Darvas boxes (DB) and linear regression (LR). In his work, F. Weng, Y. Chen, Z. Wang, and others [23] proposed using data from open sources to predict gold prices using the Genetic Algorithm Regulation Online Extreme Learning Machine (GA-ROSEUM) model. T. Duts Huynh, T. Burggraf, M. Wang [24] investigated the possibility of predicting the ratio of gold and platinum using the multiple wavelet correlation method in the short term.

MACHINE LEARNING METHODS IN SCIENTIFIC AND PRACTICAL RESEARCH ON PREDICTING THE PRICE OF PRECIOUS METALS

The use of machine learning techniques provides powerful new tools for analyzing and predicting the behavior of financial and commodity markets. Predicting the prices of precious metals using machine learning algorithms has become a crucial tool for investors, central banks, and mining companies. This has led to increased interest in scientific research in this field [25].

In a scientific article [26], the authors analyzed and predicted daily prices for precious metals using the method of artificial neural networks (ANN). They found that the ANN-based model demonstrated high accuracy and efficiency in predicting the value of gold and palladium, but forecasts for silver and platinum were less accurate. The study emphasizes the potential of ANNs as a promising tool for predicting precious metals prices.

A. Varshini, P. Kayal, and M. Maiti [27] used machine learning and deep learning models, such as Stacked LSTM, Convolutional LSTM, Bidirectional LSTM, SVR EGB, and Gated Recurrent Unit, to predict future metal prices in commodity markets. The effectiveness of these models was assessed using three indicators: RMSE, MAE, and MAPE. Their results showed that the accuracy of the forecasts varied significantly depending on the type of metal being forecasted, the time period being forecasted over, and the specific input data used.

T. Liu and Z. Zheng [28] proposed a three-stage hybrid learning method to predict the price of silver, palladium, and platinum. They found that their hybrid model outperformed other models, emphasizing the importance of combining different components to improve forecasting accuracy and generalization power.

P. Sarangi, R. Verma, S. Inder and N. Mittal [29] evaluated the effectiveness of a hybrid model based on machine learning and ANN-PSO particle swarm optimization for predicting the monthly gold price in India. Their results showed that the model can effectively predict future gold prices.

S. Oztoprak and Z. Orman [30] reviewed the use of explainable artificial intelligence (XAI) for predicting precious metal values, as well as conducting a thorough review of existing research on this topic.

S. Kangalli Uyar, U. Uyar and E. Balkan [31] described a two-stage approach to forecasting price bubbles in the precious metals markets. They used various machine learning methods to detect and evaluate factors contributing to bubble formation. These methods included logistic regression, SVM, CART, random forests, EGB and neural networks. Their study showed that macroeconomic factors influenced monthly fluctuations in prices of gold, silver, palladium and platinum between 1990 and 2022. This led to the formation of price bubbles.

The paper [32] explores the use of machine learning techniques to predict the price of precious metals, including gold, silver, palladium, and platinum, from 2017 to 2023. The authors employed machine learning algorithms, specifically the Gaussian mixture model (GMM), for evaluation. The effectiveness of these models was assessed using various metrics, such as entropy, log likelihood, normalized entropy criterion (NEC), integrated complete likelihood (ICL), Akaike information criterion (AIC), and Bayesian information criterion (BIC).

The findings indicate that machine learning models have the potential to achieve high accuracy in predicting precious metal prices. The results also suggest that prices have significantly increased during the COVID-19 pandemic, driven by factors such as increased demand for safe investment, industrial usage of metals, favorable monetary policies, concerns about inflation, and the devaluation of the US dollar [33].

Based on the results of a review of scientific publications, it can be concluded that modern machine learning methods are actively used to model investment strategies and predict price dynamics in precious metals markets [34, 35]. Scientific approaches for analyzing and evaluating this field are constantly improving, and their results are finding wide practical application and further development, contributing to the deepening of scientific research and the use of hybrid models in the learning processes.

However, taking into account multiple influencing factors, it is difficult to determine which machine learning model is most effective. There are still many unanswered questions regarding the use of these methods, making it necessary to continue studying this topic and conducting comprehensive scientific research.

INITIAL DATA AND RESEARCH METHODS

To conduct a scientific study, the initial data of the daily values of the price of gold (XAU), silver (XAG), platinum (XPT), palladium (XPD) in US dollars (USD) were uploaded from the website Investing.com.[1]

Figure 1 shows the dynamics of the price per gram, the time series XAU, XAG, XPT, XPD from 01.01.2020 to 01.05.2025. According to the data presented, the largest increase in gold and silver prices was observed from the beginning of 2024 to the beginning of 2025. During this time interval, the cost of one gram of gold increased from 50 to more than 100 dollars, and silver — from 0.85 to 1.1 dollars. This significant increase in precious metals prices is a record over the past five years and is due to several factors such as geopolitical instability, inflationary processes and changes in the market structure.

In this regard, reliable estimates of the prospects for further price increases for gold and other precious metals are extremely important.

In order to provide a theoretical basis for analyzing price trends for precious metals, the paper provides a comparative analysis of the accuracy of forecasts of the price of 1 gram of XAU, XAG, XPT, XPD for the period 01.01.2024–05.01.2025 (*Fig. 2*).

The research question is to find methods to improve the accuracy of predicting the price of precious metals using advanced machine learning models. To answer the research question, the article tests the hypothesis about the advantages of forecasting methods by conducting a comparative analysis of the accuracy of time series forecasting models based on daily values of precious metals: gold (XAU), silver (XAG), platinum (XPT), palladium (XPD) for the period 01.01.2024–05.01.2025.

[1] Investing.com. Futures prices for metals. URL: https://ru.investing.com/commodities/metals (accessed on 06.09.2025).

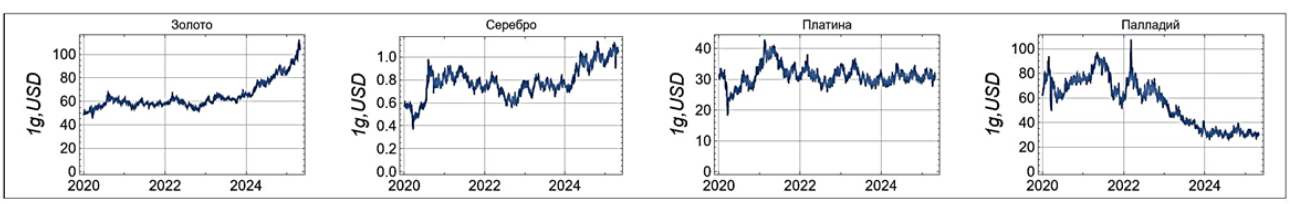

Fig. 1. **Price Dynamics of 1 Gram of Precious Metals, in USD, (01.01.2020–01.05.2025)**

Source: Authors' calculations based on data from Investing.com. Metal futures prices. URL: https://ru.investing.com/commodities/metals (accessed on 06.12.2025).

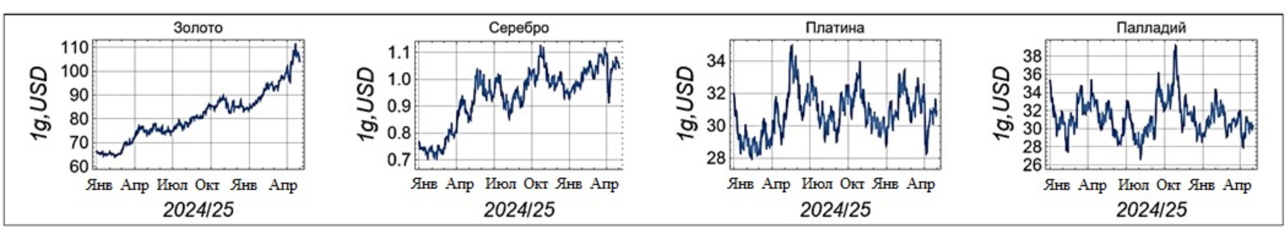

Fig. 2. **Price Dynamics of 1 Gram of Precious Metals, in USD (01.01.2024–01.05.2025)**

Source: Authors' calculations based on data from Investing.com. Metal futures prices. URL: https://ru.investing.com/commodities/metals (accessed on 06.12.2025).

Hypothesis testing is based on an assessment of the strengths and weaknesses of the most advanced modern forecasting models such as LSTM and KAN.

The effectiveness of the models is evaluated taking into account information criteria (AIC and BIC), coefficient of determination (R2 and Adj-R2) and RMSE, MAPE indicators, as a measure of proximity between actual and predicted time series values and error measures.

The KAN Forecasting Model

To create the KAN prediction model, the main conclusions of the Kolmogorov-Arnold superposition theorem are applied. This theorem states that any continuous function of several variables can be represented as a finite set of continuous functions of one variable [36, 37]. Formally, for any continuous function f of n variables $f:[0,1]^n \rightarrow R$ there are continuous functions of one variable: ϕ_i and ψ_{ij}, so that:

$$f(x_1, x_2,...,x_n)=\sum_{i=1}^{2n+1}\phi_i\left(\sum_{j=1}^{n}\psi_{ij}(x_j)\right). \quad (1)$$

This theorem provides a formal justification for the possibility of neural networks to approximate complex functional dependencies [38].

Input layer: processing of input variables

The KAN input layer accepts multidimensional input data $\boldsymbol{x}=(x_1,x_2,...,x_n)$ and prepares them for processing through hidden layers. Each input variable x_j is individually transformed by a set of one-dimensional functions ψ_{ij}.

Hidden layers: the role of functions ψ_{ij}

The hidden layers in KAN are responsible for applying one-dimensional functions ψ_{ij} to input variables: each function ψ_{ij} transforms one input variable x_j into an intermediate representation.

Mathematically:

1. For each input variable x_j, calculate:

$$\psi_{ij}(x_j) \text{ для } I = 1, 2,..., 2n + 1.$$

Calculate the intermediate sums by combining the results of applying the functions ψ_{ij}:

$$z_i=\sum_{j=1}^{n}\psi_{ij}(x_j),$$

where each z_i is a combination of transformed input variables.

Output layer: the role of functions ϕ_i

The KAN output layer takes the intermediate sums z_i and applies another set of one-dimensional functions ϕ_i to them. These functions ϕ_i produce the final results, which are then summarized to produce the output of the network.

Mathematically:

1. For each intermediate sum z_i, calculate: $\phi_i(z_i)$ for $I = 1, 2,..., 2n + 1$

2. The functions ϕ_i are summed to obtain the final result:

$$f(x)=\sum_{i=1}^{2n+1}\phi_i(z_i). \quad (2)$$

KAN activation functions. MLP-based neural networks usually use a single activation function (for example, Sigmoid, $S(x)=\frac{1}{1+e^{-x}}$), which is used by all nodes of the network. In contrast, KAN uses activation functions for each node that combine a smooth basis function *b(x)* with a component based on B-*splines*:

$$\phi(x)=\omega_b\, b(x)+\omega_s\, spline\, x, \quad (3)$$

where ω_b and ω_s are trainable scaling factors. The basis function *b(x)* is usually chosen as:

$$b(x)=\frac{x}{1+e^{-x}}. \quad (4)$$

The spline function *spline x* is a linear combination of basic B-*spline* functions:

$$spline\, x=\sum_i c_i B_i(x), \quad (5)$$

where the coefficients c_i are the trainable parameters. In practice the parameters $\{\omega_b; \omega_s; c_i\}$ are trained through standard backpropagation, providing reliable flexibility while maintaining interpretability. Moreover, this activation function design facilitates locally accurate approximation of complex relationships and enhances the model's ability to capture even excessively nonlinear function behavior [39].

For practical application and development of a forecasting model based on KAN in the WolframMathematica system, the method proposed by A. Hafver was used [40].

Hafwer's approach indicates that the K-A (Kolmogorov-Arnold) theorem can be interpreted as a two-layer neural network of direct propagation. Based on this, a way is proposed to expand it to more layers. The second important element of the approach is the idea of representing the basis function in each layer using B-*splines* [0,1], where ***m*** is the number of intervals, ***i*** is the index of the basis function, and ***p*** is the order of the B-*spline* polynomial.

Ultimately, the Kolmogorov-Arnold network layer design is implemented, **KANlayer** [*inputs_, outputs_, m_, p_*], on the basis of which models of forecasting the price of precious metals are formed:

kan_xau = NetTrain [NetChain [{KANlayer [1, 1, 170, 2]}], x(xau)→y(xau)]
kan_xag = NetTrain [NetChain [{KANlayer [1, 1, 170, 2]}], x(xag) →y(xag)]
kan_xpt = NetTrain [NetChain [{KANlayer [1, 1, 170, 2]}], x(xpt) →y(xpt)]
kan_xpd = NetTrain [NetChain [{KANlayer [1, 1, 170, 2]}], x(xpd) →y(xpd)].

In the considered models for predicting the price of precious metals based on the Kolmogorov-Arnold network (KAN): ***m*** is the number of intervals = 170; ***p*** is the order of the B-spline polynomial = 2.

The forecast of the time series compiled from the daily values of the price of 1 gram in USD: XAU; XAG; XPT; XPD is presented for the period from January 1, 2024 to May 1, 2025. Calculations were carried out with the division of the entire data set (observations) – 487 points into 2 sections, including training and test datasets, in the ratio of 90/10:

- from 1 to 437 – training data collection (01.01.2024–11.03.2025);
- 438 to 487 – test data collection (12.03.2025–01.05.2025).

A Forecast Model Based on a Recurrent LSTM Network

The study uses a forecasting model based on the LSTM algorithm, developed in accordance with the methodology proposed by S. Nagpal [41]. The software implementation of this model is performed using the Wolfram Mathematica system.

Data preparation for neural network training

To prepare the initial data for training neural networks, you first need to apply the Enhanced Dickey-Fuller test (ADF, Test) to verify the stationarity of the time series. The ADF test returns the probability of a null hypothesis that confirms the existence of a single root. *Table 1* shows the results of applying the ADF test to verify the stationarity of the original time series.

Table 1

TheAugmented Dickey–Fuller (ADF) Test for Stationarity of the Original Time Series

***p*-Value of Null Hypothesis**			
XAU	**XAG**	**XPT**	**XPD**
0.783	0.671	0.7565	0.798

Source: Compiled by the authors.

Table 2

The Augmented Dickey–Fuller (ADF) Test for Stationarity of Transformed Time Series

***p* - Value of Null Hypothesis**			
XAU	**XAG**	**XPT**	**XPD**
7.*10^−8	4.*10^−7	1.6*10^−8	5*10^−10

Source: Compiled by the authors.

As can be seen from Table 1, the *p*-Value of Null Hypothesis values are high, and therefore, the initial time series are unstable and are not suitable for direct use in neural network training.

To improve the normality of the data, we apply the Box-Cox transform with λ = 0 (logarithmic transformation) of all the original time series and evaluate the stationarity of the transformed time series by applying the ADF test to the transformed time series (*Table 2*).

As can be seen from *Table 2*, the logarithmic transformation of the data gives very small *p*-values for the null hypothesis, which confirms the existence of a unit root, and, therefore, the transformed time series can be considered stationary, and, therefore, suitable for training neural networks.

Next, we need to divide the source data into parts that we can feed to the input of neural networks for their training. It is also necessary to determine the delay (lag) of the training data. *The lag* can be assumed to be three (lag = 3), based on the assumption that differentiation of the order above three is extremely unlikely for any time series.

Just like in the KAN model, the calculations were carried out with the division of the entire data set (observations) — 487 points, into 2 sections:

- from 1 to 437 – training data collection (01.01.2024–11.03.2025);
- from 438 to 487 – test data collection (12.03.2025–01.05.2025).

Data preparation for neural network training:

The next step is to create associations that use three consecutive values from each time series and associate them with a fourth, neighboring value. This procedure is repeated for all precious metals (gold, silver, platinum, palladium).

For the design of the LSTM model, the approach [41] uses a 10-layer neural network LSTM, which can be trained on time series data of individual precious metals:

```
model1 =
 NetChain [{ReshapeLayer [{1, lag}],
   ConvolutionLayer [16, 2, "Input" –> {1, lag}],
   PoolingLayer [2, "Function" –> Mean], LongShortTermMemoryLayer [50],
   BatchNormalizationLayer [], DropoutLayer [0.4], LinearLayer [64],
   BatchNormalizationLayer [], DropoutLayer [0.2], LinearLayer [1]]
```

Next, the model is trained on precious metals data with 500 training iterations:

$$\text{xautrained1} = \text{NetTrain}\left[\textbf{model}1, \text{xautrain}, \text{ValidationSet} \to \text{xautest}, \text{MaxTrainingRounds} \to 500\right]$$
$$\text{xagtrained1} = \text{NetTrain}\left[\textbf{model}1, \text{xagtrain}, \text{ValidationSet} \to \text{xagtest}, \text{MaxTrainingRounds} \to 500\right]$$
$$\text{xpttrained1} = \text{NetTrain}\left[\textbf{model}1, \text{xpttrain}, \text{ValidationSet} \to \text{xpttest}, \text{MaxTrainingRounds} \to 500\right]$$
$$\text{xpdtrained1} = \text{NetTrain}\left[\textbf{model}1, \text{xpdtrain}, \text{ValidationSet} \to \text{xpdtest}, \text{MaxTrainingRounds} \to 500\right]$$

It should be noted that after the neural network data is trained on the corresponding test sets for 500 iterations, the ***p***-values of the null hypothesis that the residuals are random are also calculated.

Since the Box-Cox transformation (logarithmic) was initially applied to the source data, then the inverse exponential transformation is used to obtain the predicted market values of precious metals, as well as visualization of the predicted market values in comparison with real data.

RESULTS AND DISCUSSION

The results obtained from a comparative analysis of the accuracy of forecasts of the price of 1 gram in USD of precious metals (XAU, XAG, XPT, XPD) of the LSTM and KAN models for the period 01.01.2024–01.05.2025 are presented in *Table 3*, taking into account information criteria and accuracy measures: AIC (Akaike Information Criterion); BIC (Bayesian Information Criterion); Adj-R^2 (adjusted coefficient of determination); R^2 (coefficient of determination); RMSE (Root Mean Square Error); MAPE (Mean Absolute Percentage Error).

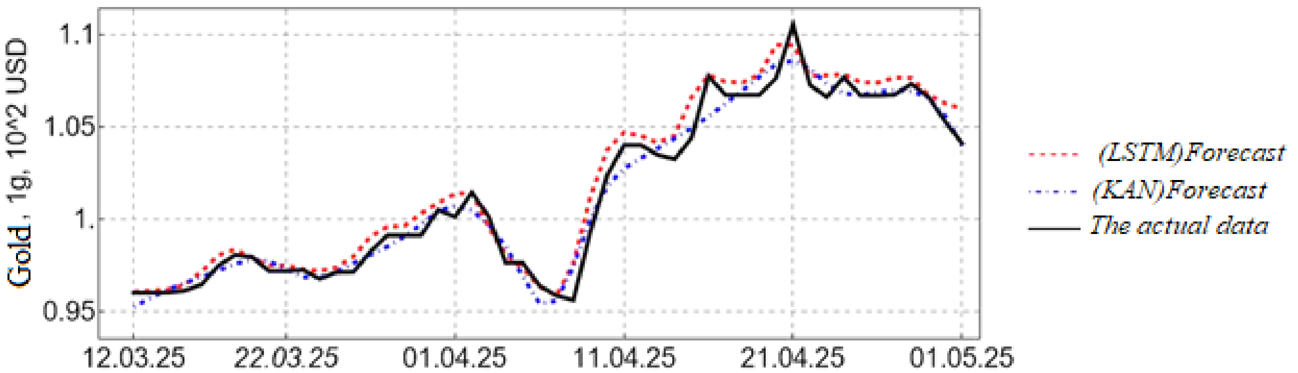

Fig. 3. **The Dynamics of the Fit Between Forecast Data: LSTM Model; KAN Model; and the Actual Daily Gold Prices of 1 g (in 10^2 USD) from March 12, 2025, to May 1, 2025**

Source: Authors' calculations.

Fig. 4. **The Dynamics of the Fit of Forecast Data: LSTM Model, KAN Model and the Actual Daily Prices of 1 g of Silver (in USD) from March 12, 2025, to May 1, 2025**

Source: Authors' calculations.

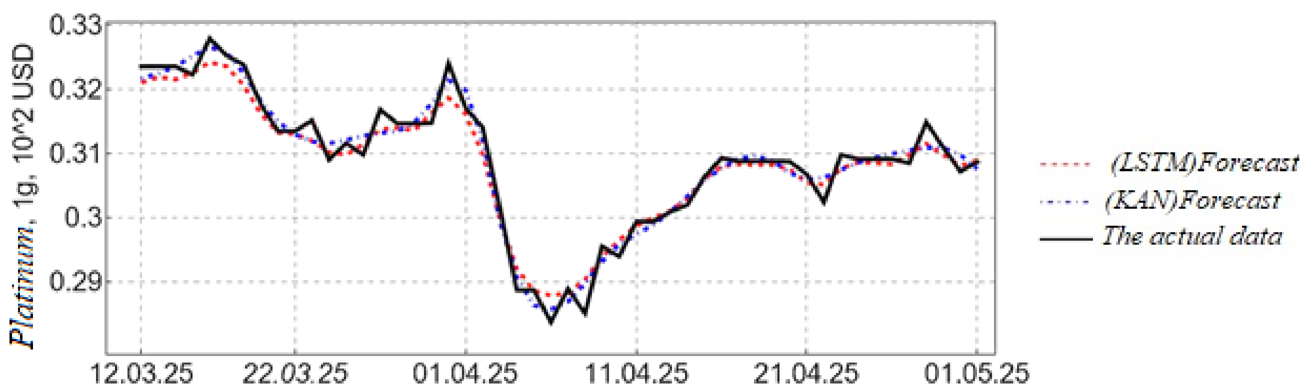

Fig. 5. **The Dynamics of the fit Between Forecast Data: LSTM Model; KAN Model; and the Actual Daily Platinum Prices of 1 g (in 10^2 USD) from March 12, 2025, to May 1, 2025**

Source: Authors' calculations.

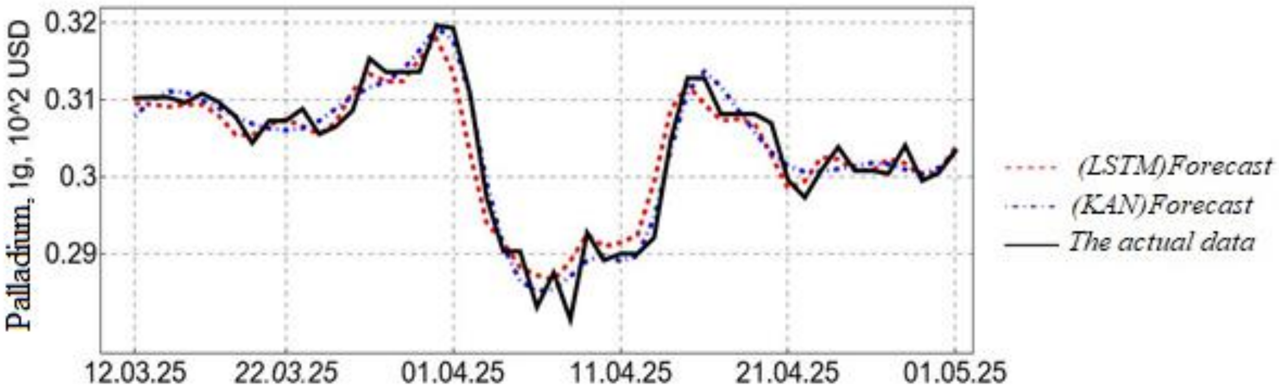

Fig. 6. **The Dynamics of the fit Between Forecast Data: LSTM Model; KAN Model; and the Actual Daily Palladium Prices of 1 g (in 10^2 USD) from March 12, 2025, to May 1, 2025**

Source: Authors' calculations.

Forecasting the gold price. The results of efficiency — matching the predicted values based on the KAN and LSTM models to the actual values of a time series made up of daily values of the price of 1 gram of gold (in 10^2 USD) from 12.03.2025 to 01.05.2025 are shown in *Fig. 3* and in *Table 3*. As can be seen from *Fig. 3*, both models are visually characterized by high accuracy in matching large-scale changes in the predicted values to the actual ones. It should be noted that the high-frequency actual changes are more accurately reproduced by the predictive LSTM model. As follows from *Table 3*, the LSTM model surpasses the KAN model in terms of AIC (–359.62), BIC (–353.89), R^2 (0.980), Adj R^2 (0.979). At the same time, according to the RMSE and MAPE error metrics, the KAN model predicts test values with lower errors: 0.0074 and 0.5593 versus 0.0088 and 0.6550, respectively.

Hence, calculations have shown that in forecasting the gold price, the LSTM forecasting model is characterized by a higher degree of conformity - proximity to actual values compared to the KAN forecasting model.

Forecasting the price of silver. The results of the correspondence of the forecast values obtained on the basis of the KAN and LSTM models to the actual values of the time series made up of the daily values of the price of 1 gram of silver (USD) from 12.03.2025 to 01.05.2025 are shown in *Fig. 4* and in *Table 3*. As can be seen from *Fig. 4*, both models are visually characterized by high accuracy of matching large-scale changes the predicted values are actual. However, the high-frequency actual changes are more accurately reproduced by the KAN predictive model. As we can observe in *Table 3*, the KAN model surpasses the LSTM model in terms of AIC (–323.22), BIC (–317.48), R^2 (0.956), Adj R^2 (0.955). According to the RMSE and MAPE error metrics, the KAN model also predicts test values with lower errors: 0.0090 and 0.6670 versus 0.0160 and 1.1308, respectively.

Consequently, the conclusion suggests itself that in forecasting the silver price, the KAN forecasting model is characterized by a higher degree of correspondence between the forecast values and the actual test values compared to the LSTM forecasting model.

Forecasting the platinum price. The results of efficiency — the correspondence of the predicted values to the actual values of a time series made up of the daily values of the price of 1 gram of platinum (in 10^2 USD) from 12.03.2025 to 01.05.2025 are shown in *Fig. 5* and in *Table 3*. Both models are visually characterized by high accuracy in matching large-scale changes in predicted values to actual ones (see *Fig. 5*). At the same time, high-frequency actual changes are more accurately reproduced by the LSTM predictive model. The LSTM model surpasses the KAN model in terms of AIC (–490.06), BIC –484.33), R^2 (0.9743), Adj R^2 (0.9738), and in terms of error metrics RMSE and MAPE, the KAN model predicts test values with lower errors than the LSTM model: 0.00201 and 0.5403 versus 0.0021 and 0.5428, accordingly (*Table 3*).

Table 3

The Effectiveness of KAN and LSTM Models in Predicting Daily Prices of 1 Gram of Gold (XAU), Silver (XAG), Platinum (XPT), and Palladium (XPD) for the Period 12.03.25–01.05.25

Precious metal	Forecasting model	AIC	BIC	Adj-R^2	R^2	RMSE	MAPE
Gold, XAU	LSTM	–359.62	–353.89	0.9798	0.980	0.0088	0.655
	KAN	–343.21	–337.47	0.9720	0.9725	0.0074	0.5593
Silver, XAG	LSTM	–273.90	–268.16	0.8798	0.882	0.0160	1.1308
	KAN	***–323.22***	***–317.48***	***0.955***	***0.956***	***0.0090***	***0.6670***
Platinum, XPT	***LSTM***	***–490.06***	***–484.33***	***0.9738***	***0.9743***	***0.0021***	***0.5428***
	KAN	–472.87	–467.14	0.963	0.964	0.00201	0.5403
Palladium, XPD	LSTM	–451.21	–445.47	0.922	0.924	0.0027	0.6360
	KAN	***–469.62***	***–463.89***	0.946	0.947	0.00207	0.5590

Source: Authors' calculations.

Conclusion: in predicting the platinum price, the LSTM model is characterized by a higher degree of correspondence and proximity of forecast values to actual *Forecasting the palladium price*. The results of efficiency — matching the predicted values based on the KAN and LSTM models to the actual values of a time series made up of daily values of the price of 1 gram of palladium (in 10^2 USD) from 12,03.2025 to 01.05.2025 are shown in *Fig. 6* and in the *Table 3*. Both models are visually characterized by high accuracy in matching large-scale changes in the predicted values to the actual ones. The high-frequency actual changes are more accurately reproduced by the KAN predictive model. As follows from *Table 3*, the KAN model surpasses the LSTM model in all information indicators and error metrics: AIC (–469.24), BIC (–463.45), R^2 (0.947), Adj R^2 (0.946), RMSE (0.00207), MAPE (0.5590).

In this way, in forecasting the price of 1 gram of palladium, the KAN forecasting model is characterized by a higher degree of accuracy compared to the LSTM model, i.e., it is close to the actual values.

For all the analyzed precious metals for the period 12.03.25–01.05.25, the KAN model demonstrated its effectiveness, reaching the lowest values of the average absolute percentage error (MAPE) and RMS error (RMSE). In addition, the KAN model surpasses the LSTM model in predicting the price of 1 gram of silver and palladium in terms of AIC, BIC, Adj-R^2, R^2. These results confirm the ability of the KAN model to effectively predict and capture complex nonlinear dependencies of changes in the price of precious metals, surpassing advanced neural network architectures such as the LSTM network, not to mention traditional statistical methods such as ARMA/ARIMA.

However, for gold and platinum, the LSTM model showed the best results in terms of AIC, BIC, Adj-R^2, R^2. In terms of error metrics (MAPE) and (RMSE) it also showed higher values compared to the KAN model, although in these cases the KAN model demonstrated its competitiveness.

The results obtained in the work show that traditional advanced machine learning models, in particular the LSTM model, can be effective in predicting the behavior of objects that are described by a simple set of data. The KAN model demonstrates high efficiency in analyzing objects with an extensive and diverse array of data, which makes it suitable for complex economic forecasts.

The KAN network makes it possible to solve critical predictive modeling tasks by identifying complex nonlinear relationships and providing a theoretically sound basis for feature decomposition. It shows a clear advantage by using its spline-based architecture to train one-dimensional functions that are composable, scalable, and interpretable. Unlike LSTM models, the KAN network-based model provides a flexible framework for modeling nonlinear dependencies with theoretical rigor and empirical stability, and also works excellently with multidimensional nonlinear data, as evidenced by its high performance.

CONCLUSIONS

In the context of geopolitical instability, it is particularly important to obtain accurate forecasts of the dynamics of prices for precious metals. This information is crucial for the formation of effective investment strategies, both at the state level and for private investors. The use of modern analysis methods allows not only to minimize potential risks and reduce volatility, but also to identify new investment opportunities in the precious metals market.

The research question was to select and evaluate the application of methods to improve the accuracy of forecasting prices for precious metals through the use of advanced machine learning models. A significant problem with ML-based forecasting models is the interpretability of the results obtained due to their opacity, the so-called "black box nature". Machine learning models are referred to as a "black box" in the scientific literature, because the assumptions and calculations used in them may not always be fully understood. In this context, they can be assessed as a step forward in accuracy and a step back in interpretability of the results obtained [42]. As one of the most advanced AI technologies, the KAN network [43] opens up new opportunities for improving the interpretability of ML models [44].

As part of this research, the hypothesis that using a model based on the Kolmogorov-Arnold network (KAN) could improve the accuracy and transparency of forecasts for precious metal prices was tested. To achieve this goal, a comparative analysis of forecasting accuracy for time series, including daily values of precious metal prices, was conducted. The effectiveness and drawbacks of modern advanced forecasting models, such as recurrent neural networks with long- and short-term memory (LSTM), and Kolmogorov-Arnold networks, were evaluated.

The study aimed to compare the accuracy and efficacy of the two most advanced models for forecasting precious metal prices. It revealed the significant potential of the KAN model in improving forecast accuracy in real-world conditions.

The research conducted has convincingly demonstrated that the KAN model has extensive analytical capabilities and adaptability, making it a valuable tool for working with large data sets. The KAN model can be used for making management decisions within the framework of selecting an investment strategy.

To predict prices in the precious metals market, the use of the KAN model provides more accurate forecasts in uncertain conditions, explains market mechanisms by taking into account both objective and subjective factors, and allows for the use of flexible risk management strategies.

It can be concluded that the KAN accumulates innovative methods and approaches to analyzing complex financial and economic data, including that of the precious metals market, through the use of a new neural network architecture. The main advantage of the KAN model is its high ability to perceive and adapt to complex relationships.

From a practical standpoint, the research findings have significant implications for developing an optimal investment strategy in precious metal markets [45]. This strategy should be based on accurate forecasts of price fluctuations and provide for effective risk management. To ensure informed decision-making in a dynamic international trade and financial system, it is necessary to integrate advanced technological solutions with the results of empirical research [46].

As future research directions, it is suggested to investigate the impact of investor sentiment during periods of economic and geopolitical uncertainty on the dynamics of precious metal prices. Research based on investor behavior could contribute to more accurate market forecasts. In this regard, analysis of public sentiment in social media and assessment of financial transactions could be promising areas for research. These approaches could significantly expand analytical and practical tools, and improve the accuracy of forecasting models.

ACKNOWLEDGEMENTS

The article was prepared as part of research conducted at the expense of the Research Fund of the Financial University. Financial University under the Government of the Russian Federation, Moscow, Russian Federation.

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A.K. Karaev — conducted model calculations and configured them, and formulated the conclusions.
V.V. Ponkratov — collected data and analyzed scientific research on precious metal price forecasting, described the model and experiments, and performed pre-processing and post-processing of the data.

Conflicts of Interest Statement: The authors have no conflicts of interest to declare.

The article was submitted on 03.03.2026; revised on 29.04.2026 and accepted for publication on 22.05.2026.
The authors read and approved the final version of the manuscript.

Translated by N.I. Sokolova