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Forecasting Slovak GDP based on metal commodity prices as a tool for policymakers

Pronóstico del PIB eslovaco basado en los precios de los metales como herramienta para los responsables políticos

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Abstract: the paper examines the development of selected metal commodity prices in the global market in the context of the development of Slovakia´s GDP as a macroeconomic indicator GDP and identify which of the analyzed metal commodities are most closely linked to the Slovak economy. Research data were obtained from website Investing and Eurostat and converted into time series. Metal commodity prices were expressed in US dollars per ton, while GDP values were expressed in millions of US dollars. The data were processed using artificial intelligence, specifically recurrent neural networks with a Long Short Term Memory layer, which have strong potential to predict such types of time series. The experiment included predictive models based on artificial neural networks. Metal commodities also play a crucial role in the Slovak economy, and the research confirms that the development of copper, zinc and aluminum prices is correlated with Slovakia´s economic performance. Therefore, the country´s GDP can be forecasted with high accuracy based on the price movements of these selected metal commodities. The findings may assist policymakers as well as top management in the manufacturing industry, where input prices can be compared with developments in the national economy.

Keywords: copper, aluminum, zinc, prices, prediction, neural networks, GDP, Slovakia.

Resumen: el artículo examina la evolución de los precios de determinados metales en el mercado global en el contexto del desarrollo del PIB de Eslovaquia como indicador macroeconómico e identifica cuáles de los metales analizados están más estrechamente vinculados a la economía eslovaca. Los datos de la investigación se obtuvieron del sitio web Investing y de Eurostat y se convirtieron en series temporales. Los precios de los metales se expresaron en dólares estadounidenses por tonelada, mientras que los valores del PIB se expresaron en millones de dólares estadounidenses. Los datos se procesaron mediante inteligencia artificial, concretamente redes neuronales recurrentes con una capa de memoria a largo plazo (MPM), que poseen un gran potencial para predecir este tipo de series temporales. El experimento incluyó modelos predictivos basados en redes neuronales artificiales. Los metales también desempeñan un papel crucial en la economía eslovaca, y la investigación confirma que la evolución de los precios del cobre, el zinc y el aluminio está correlacionada con el desempeño económico de Eslovaquia. Por lo tanto, el PIB del país puede pronosticarse con gran precisión basándose en las fluctuaciones de los precios de estos metales. Los hallazgos pueden ser de utilidad tanto para los responsables políticos como para la alta dirección del sector manufacturero, donde los precios de los insumos pueden compararse con la evolución de la economía nacional.

Palabras clave: cobre, aluminio, zinc, precios, predicción, redes neuronales, PIB, Eslovaquia.

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Introduction

A country's gross domestic product (GDP) is shaped by domestic economic factors and external sectors (Gupta & Kumar, 2023). Commodity prices, including those of metals and raw materials, have a significant impact on GDP per capita across different income groups (Sen *et al*., 2024). These prices also serve as valuable indicators of current and future global economic activity, as factors derived from commodity price movements provide useful information for short-term forecasting of global GDP and industrial production (Matsumoto *et al*., 2023). Dependence on commodities is positively associated with economic growth, whereas commodity price volatility shows a negative relationship with economic growth. Moreover, commodity dependence is positively linked to long-term commodity price volatility (Wanzala and Obokoh, 2024). Metals such as steel, which is an indispensable and durable material used across all sectors and contributes significantly to the global economy, must exhibit enhanced mechanical properties to meet contemporary industrial requirements (Kumar and Sil, 2023). The price volatility of industrial metals shows dynamic transmission patterns and interconnectedness with other markets, which have been significantly affected by major global events such as the COVID-19 pandemic and the Russia-Ukraine war (Shao *et al*., 2024). Commodity price shocks also entail important macroeconomic consequences (Ybrayev *et al*., 2024). Commodity-specific demand factors and supply shocks represent key sources of confounding variables (Matsumoto *et al*., 2023).

Volatility in mineral prices can pose significant risks to developing countries, particularly those that are heavily dependent on mineral production, as evidenced by the high sensitivity of fiscal revenues to mineral price shocks (Urbina and Rodríguez, 2023). The depletion of mineral resources has tangible adverse effects on socio-economic outcomes, in particular through rising energy poverty, and thus disproportionately affects economies dependent on mineral extraction (Yasmeen *et al*., 2024). In the V4 countries, GDP growth has been strongly affected by a series of external shocks, including the COVID-19 pandemic and the Russia-Ukraine war, with forecasts indicating a major shock and a shift to a lower steady-growth trajectory (Apanovych *et al*., 2024). Improving the accuracy of macroeconomic expectations is essential for informing effective policy decisions, as information frictions can substantially shape macroeconomic dynamics and policy outcomes (Link *et al*., 2023). Accurate and reliable GDP forecasting is crucial for sound economic policy-making and risk management (Aisy *et al*., 2025). Between 1993 and 2012, the gross

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domestic product (GDP) of the Slovak Republic increased by 128%, and it continues to rise (Hájek and Rezny, 2014). The Slovak Republic can be characterized an industrially oriented economy, with the automotive industry playing one of the most important roles in it (Valásková and Kramárová, 2015). Metal price dynamics are very important for global economic activity, as metals serve as key inputs for industrial production and construction and reflect major global economic developments (Kara *et al*., 2023). Commodity prices have significant and time-varying effects on exchange rates, with the nature of these effects differing across countries, commodity sectors, and macroeconomic conditions (Wang and Cheung, 2023). The above studies clearly indicate that the ability to forecast developments in metal commodity prices and their impact on GDP is crucial for effective economic management and policymaking.

The application of machine learning methods to macroeconomic forecasting has produced promising results. For example, random forest regression was used to forecast medium-term developments in public debt in EU Member States using a broad range of macroeconomic, fiscal, and monetary indicators (Zarkova *et al*., 2023). Commodity prices reflect the process of information discovery related to the global business cycle and information frictions in financialized commodity markets (Peersman *et al*., 2021). Metal commodities are important for forecasting future GDP because they constitute essential inputs for industrial production, signaling trends in economic growth and development. Metals are an irreplaceable industrial raw material and hold strategic importance for economic advancement (Kahraman & Akay, 2023).

Numerous studies have employed various techniques or models to analyze and forecast GDP. Metal price dynamics are highly significant for global economic activity, given their role as key intermediate goods for industrial production and construction, as well as their function as investment assets (Kara *et al*., 2023). Zhang *et al*. (2023) examine the relationship between energy and economic indicators for GDP forecasting using a Long Short-Term Memory model with wavelet analysis. The analysis by Chang and Levinson (2023) identifies time-varying inefficiencies in GDP forecasts between FOMC meetings and provides evidence of inefficiencies in inflation forecasts. Szabo (2024) presents a fully probabilistic approach to combining model-based predictions with survey data, applying this method to estimate a real GDP growth model in the United States. Alkhareif and Barnett (2022) developed monthly GDP forecasts for Saudi Arabia by estimating a Generalized Dynamic Factor Model (GDFM) on a panel of 272 variables covering the period from January 2010 to June 2018.

Santos et al. (2021) used a Long Short-Term Memory (LSTM) architecture to predict Brazilian ethanol spot prices 3, 6, and 12 months ahead, finding that the 63-day model demonstrated the best convergence and produced the smallest forecast errors compared to the 126-day and 252-day models.

Cuaresma *et al*. (2024) developed an econometric framework for forecasting commodity prices that incorporates different dynamics across economic regimes. They tested regime-dependent threshold models on the Goldman Sachs commodity index and its five sub-indices. The results show that allowing for regime-dependent dynamics significantly improves prediction accuracy. Guo *et al*. (2024) developed an improved long short-term memory (LSTM) model combined with convolutional neural networks (CNNs) and multi-year meteorological data to predict complex spatio-temporal patterns. Li *et al*. (2023) demonstrated that the Long Short-Term Memory (LSTM) network architecture has proven to be very promising for forecasting Brazilian ethanol prices, showing strong predictive performance with minimal error. Jovanovic et al. (2025) proposed a fuel price forecasting model based on a multi-headed LSTM network optimized using a modified particle swarm optimization (PSO) algorithm. Li and Guo (2025) introduced a multi-factor method for warning against the risk of oil price volatility, combining risk factor analysis,

price prediction, and volatility risk alerts using an LSTM model. The proposed risk-alert mechanism achieves excellent accuracy and can provide a scientifically grounded reference for government intervention policies. Enilov (2023) use the time-varying mixed-frequency autoregressive interpretation vector model (TV-MF-VAR) to examine the causal relationship between monthly commodity prices and quarterly economic growth from January 1980 to March 2020. Wang and Zhang (2025) proposed an innovative hybrid approach to improve the accuracy of oil futures price forecasting. This approach integrates optimized variational mode decomposition, an attention mechanism, and a stochastic error correction algorithm into a deep bidirectional LSTM network. Zhao *et al*. (2025) introduced a three-step LSTM-Transformer-XGBoost fusion framework for highly accurate prediction of gold futures prices. The architecture integrates LSTM for long-term temporal dependencies.

Wang *et al*. (2023) proposed a hybrid EEMD-CNN-ILSTM forecasting model for the price of oil futures. The experimental results indicate that the model is more efficient and accurate compared to the seven benchmark prediction models. Ab Khalil and Abu Bakar (2023) found that among the deep learning algorithms tested for predicting the Malaysian stock market, Long Short-Term Memory (LSTM) model outperformed the Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) models. Song and Choi (2023) proposed new hybrid models for forecasting the closing prices of the DAX, DOW, and S&P500 indices. Kim and Jang (2023) concluded that for oil price forecasting, both LSTM-based and GRU-based models outperformed existing models, including vanilla LSTM and GRU models, as well as hybrid models incorporating CNN architecture. To improve the efficiency of the Long Short-Term Memory model (LSTM), Chen *et al*. (2023) applied a simulated annealing (SA) algorithm to determine the optimal combination of hyperparameters.

Based on the research carried out on suitable methods applicable for the prediction and analysis of the impact of metal commodities on national economies, the LSTM method was selected, as it appears to be the most appropriate for forecasting time series and for modelling selected metals indicators together with selected macroeconomic indicators in Slovakia. Subsequently, the metal commodity most closely associated with Slovakia´s macroeconomic indicators will be determined. This focus leads to the formulation of the first research question:

RQ1: How is the prediction of selected commodity prices related to the development of the Slovak economy?

Once the relationship between the prices of selected commodities and the Slovak economy has been established, it is necessary to determine which commodity price or which combination of commodity prices has the strongest impact on the economy of Slovakia. This leads to the second research question.

RQ2: Which of the selected metal commodities is most closely linked to the Slovak economy?

The structure of the present scientific article includes a literature review of the problem, followed by the methodology, and the calculation using neural networks. The discussions and final results address the research questions and provide further clarification. The topic is highly relevant for predicting the development of national economies in an uncertain international environment.

Materials and Method

The analysis is entirely focused on the macroeconomic variables of Slovakia. Two data sources were used for data collection, specifically, macroeconomic variables such as GDP, were obtained from the Eurostat database (2023) ec.europa.eu/eurostat while information on the selected commodities, namely copper, zinc, and aluminum, was retrieved from the investing.com (2023) website. Macroeconomic variables were extracted specifically for Slovakia. The price data for metal commodities, except aluminum, are available for the period from 3 January 2012 to 7 June 2024. For aluminum, the

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dataset covers the period from 1 July 2014 to 7 June 2024.

Artificial neural network (NN) models, especially the Long Short-Term Memory (LSTM) architecture, are used to predict the future development of macroeconomic indicators. The following parameters are required for constructing the neural network:

a) The number of elements in the neural network model depends on the input data and the model configuration. The input data refer to the dimensionality of the matrix, i.e.,

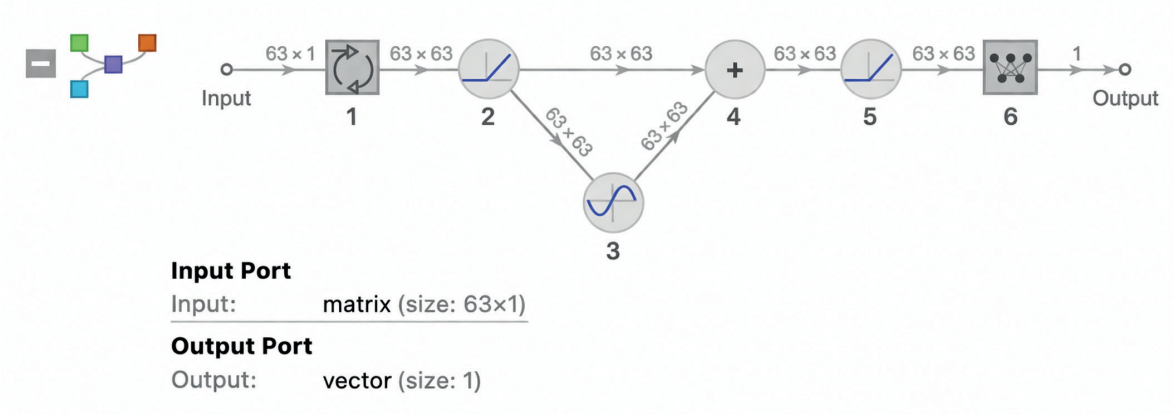
b) The activation function (Elementwise Layer) is used to facilitate signal propagation between individual NN layers. The selection of activation functions is based on the following options: Sine, Ramp (including the Rectified Linear Unit) and ArcTan.

c) A time series delay can be defined as a sequence of previous values used to predict future values. In this study, a delay of 63 days is applied.

The structure of the NN is identical except for the changes in the parameters. Figure 1 shows a diagram of the NN structure.

Figure 1

Neural network structure with LSTM layer



First, each commodity will be used separately to predict the macroeconomic variable. Subsequently, two variables will be combined, and finally all commodity prices whose inputs are processed correctly will be used together. The neural network consists of six main layers, in addition to the input and output layers. The six layers between the input and output layers are hidden ().

a) Input layer: A matrix representing commodity price data is provided. In the experiment, different matrix sizes will be examined, specifically, an array of size "63 x 2". The value "m" in the array represents the number of consecutive variables needed to calculate the next variable.

b) 1st hidden layer: This is the LSTM layer, which produces an output matrix with dimensions "m x n", where "m" is the time-series delay and "n" is chosen empirically. Here, the 63 x 2 input matrix generates a 63 x 63 output matrix). The value of "n" is incremented by 1.

c) 2nd hidden layer: This layer is built as an Elementwise Layer – Perceptron, which is a simple network acting as a perceptron. The activation functions of these layers will be selected randomly from the predefined set of activation functions.

d) 3rd hidden layer: This layer is another Elementwise layer with the same selection criteria as in the second hidden layer.

e) 4th hidden Layer: The fourth hidden layer, known as the "Plus" layer, performs ele-

mentwise addition. It receives input from the second and third hidden layers and transmits the output to the fifth hidden layer.

f) **5th hidden layer:** This layer is an Elementwise layer that uses the same activation function selection criteria as the second and third hidden layers.

g) **6th hidden layer:** The sixth hidden layer is a linear layer, which acts on the data matrix at the input (the picture shows a 63 x 63 matrix). Generates a vector with a single element as output.

h) **Output layer:** this layer predicts the macroeconomic variable.

The Long Short-Term Memory Layer is a network that consists of four components: Input Gate, Exit Gate, Forget Gate, and Memory Gate. LSTM processes an input matrix representing a sequence of vectors and generates a sequence of equal length. Each element of the input sequence element is represented as a vector of size k, while each output sequence element is a vector of size n.

Let denote the input sequence. The LSTM produces a sequence of states . The cell state is defined as follows:

$$c_t = f_t * c_{t-1} + i_t * m_t \quad (1)$$

Where:

c_t is the updated variable state at time t.
f_t Is the forget gate.
$c_{(t-1)}$ Is the initial state of the variable.
i_t Is the input gate.
m_i Is the memory gate.

$$i_t = \sigma[W_{ix}x_t + W_{is}S_{t-1} + b_i] \quad (2)$$

Where:

σ is Logistic Sigmoid.
W_{ix} is an input weight in the input gate matrix *n x k*.
x_t is an input variable, matrix *n x k*.
W_{is} Is the weight of the state in the input gate, matrix *n x n*.
$S_{(t-1)}$ Is the initial state.
b_i Is the bias, vector size *n*.

The state is defined as follows:

$$s_t = o_t * Tanh[c_t] \quad (4)$$

Where:

S_t Is a state of the variable.
O_t Is the output gate.
Tanh Is hyperbolic tangent.

The output gate is defined as follows:

$$o_t = \sigma[W_{ox}x_t + W_{os}S_{t-1} + b_o] \quad (5)$$

Where:

W_{ox} defines the input weight in output gate, matrix *n x k*.
W_{os} Is the weight of the state in output gate, matrix *n x n*.
b_o Is the bias, vector size *n*.

When compared to, for example, a Gated Recurrent Unit, the advantage of LSTM is in the forget gate:

$$f_t = \sigma[W_{fx}x_t + W_{fs}S_{t-1} + b_f] \quad (6)$$

Where:

W_{fx} Is an input weight in forget gate, matrix *n x k*.
W_{fs} Is an input weight in forget gate, matrix *n x n*.
b_f Is the bias, vector size *n*.

The main processes of LSTM include the memory gate (see below):

$$m_t = Tanh[W_{mx}x_t + W_{ms}S_{t-1} + b_m] \quad (7)$$

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Where:

W_{mx} defines the input weight in memory gate, matrix $n \times k$.

W_{ms} Is the weight of the state in memory gate, matrix $n \times n$.

b_m Is the bias, vector size n.

The prices of individual commodities were initially associated with one of the many macroeconomic factors for training the neural network. The analysis was subsequently expanded to include a broader set of commodity prices in the training dataset. First, the prices of individual commodities were selected and trained using an LSTM neural network to predict the GDP of Slovakia. Commodity prices were then combined to create multi-input configurations, allowing for the prediction of future GDP of Slovakia based on price combinations.

This complex procedure aimed to identify the most efficient model, measured by its accuracy in predicting the macroeconomic variable. The Pearson correlation coefficient was used to quantify both the strength and the direction of the linear relationship between actual and predicted macroeconomic values to assess the performance of the model. The most robust neural network configuration was then used to predict future macroeconomic data with greater accuracy and reliability.

The forecasting model is based on a Long Short-Term Memory (LSTM) neural network trained on daily copper, zinc, and aluminum prices, which were preprocessed through forward-fill interpolation and min–max normalization. A fixed 63-day sliding window was applied, where each sequence of 63 consecutive price observations served to predict the subsequent quarterly GDP value. All available historical data were used for training, as the objective of the study is a one-step-ahead forecast of GDP for the most recent quarter rather than generalized out-of-sample prediction. The network architecture follows the structure shown in Figure 1 and consists of an input layer (63 × n), a single LSTM layer with 63 hidden units, three nonlinear elementwise layers with activation functions drawn from {Sin, Ramp, ArcTan}, a combination layer, and a final linear output layer. The model was trained using the Adam optimizer, mean squared error loss, and standard hyperparameters applied uniformly across all commodity configurations.

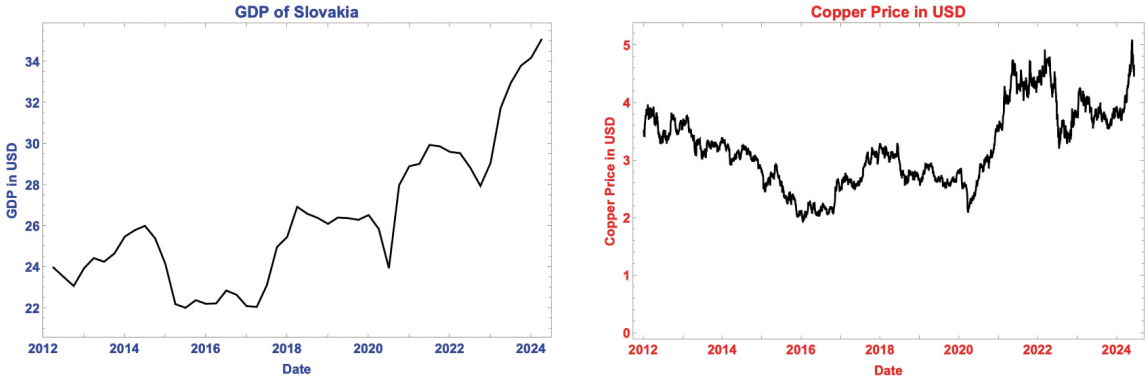
Results and Discussion

a) Prediction of GDP based on Copper Price

Figure 2 shows the quarterly GDP in one of the V4 countries, Slovakia, from 2012-Q1 to 2024-Q1 and the daily prices of copper recorded between 3 January 2012 and 7 June 2024. As shown in Figure 2, Slovakia's GDP exhibits a generally upward trend over the observed period, although several fluctuations are evident. Copper prices show smaller fluctuations.

Figure 2

Slovakia's GDP/Copper Price



Note. Prepared using the results of Smart PLS (p-value <0.05).

- **Prediction of GDP using copper price**
  The NN yields the corresponding correlation coefficients using a lag of 63 trading days, as summarized in Table 1.

Table 1

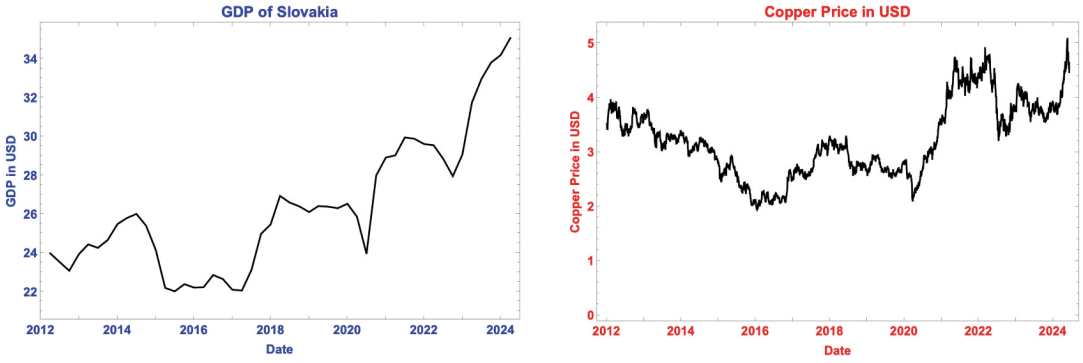
Basic configuration of network parameters and network performance

Network	Performance	1. Activation	2. Activation	2. Activation
1NN63	0.975244	Sin	Sin	Sin
2NN63	0.953500	ArcTan	ArcTan	Ramp
3NN63	0.995623	ArcTan	Sin	Ramp
4NN63	0.981382	Sin	Ramp	Ramp
5NN63	0.926517	ArcTan	ArcTan	ArcTan

Figure 3 shows the comparison between the actual GDP of Slovakia and the GDP predicted by the neural network.

Figure 3

Comparison between actual GDP and predicted GDP / Comparison between actual GDP and the best-performing prediction



Note. Prepared using the results of Smart PLS (p-value <0.05).

Table 2 shows the conditional distribution of actual and predicted GDP values.

Tabla 2

Conditional distribution of actual and forecast GDP values

Description	GDP	LSTM NN GDP Prediction
Minimum	22,0582	21.9548
Maximum	31,5854	31.5107
Mean	25,6355	25.6339

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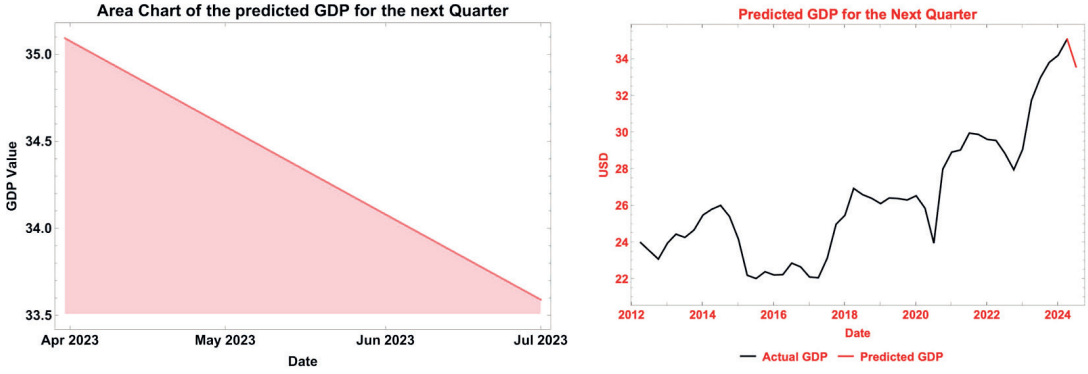
Variance	6,76356	6.67973
Standard Deviation	2,60068	2.58452
Quartile Deviation	1,87124	1.74199
Median Deviation	1,93460	2.21883
Mean Deviation	2,13635	2.10184

Figure 4 illustrates the predicted GDP of Slovakia for the next quarter of the year 2024 (Q2). Based on copper prices for the next quarter, the model estimates Slovakia´s GDP at $33,590.2 million.

Figure 4

Area chart for projected GDP for the second quarter of 2024 (2Q) / Line chart for projected GDP for the second quarter of 2024 (2Q)

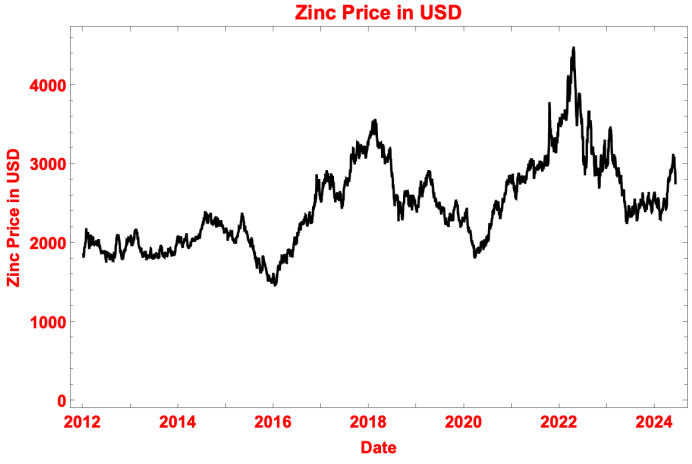


b) Prediction of GDP using zinc price

The NN provides the value of the correlation coefficient based on a lag of 63 trading days, as reported in Table 3.

Figure 5

Time series of zinc prices in USD



- **GDP forecast using the zinc price**

The neural network provides the correlation coefficient value based on a lag of 63 business days, as shown in Table 3.

Table 3
Basic configuration of network parameters and performance

Network	Performance	1. Activation function	2. Activation Function	3. Activation Function
1NN63	0.948407	ArcTan	Sin	Ramp
2NN63	0.958141	ArcTan	Sin	ArcTan
3NN63	0.943974	ArcTan	ArcTan	Ramp
4NN63	0.947254	Ramp	ArcTan	ArcTan
5NN63	0.976273	ArcTan	Sin	ArcTan

Figure 6 shows the comparison between the actual GDP of Slovakia and the predicted GDP values.

Figure 6
Comparison of actual and GDP prediction / Comparison with the most accurate GDP prediction

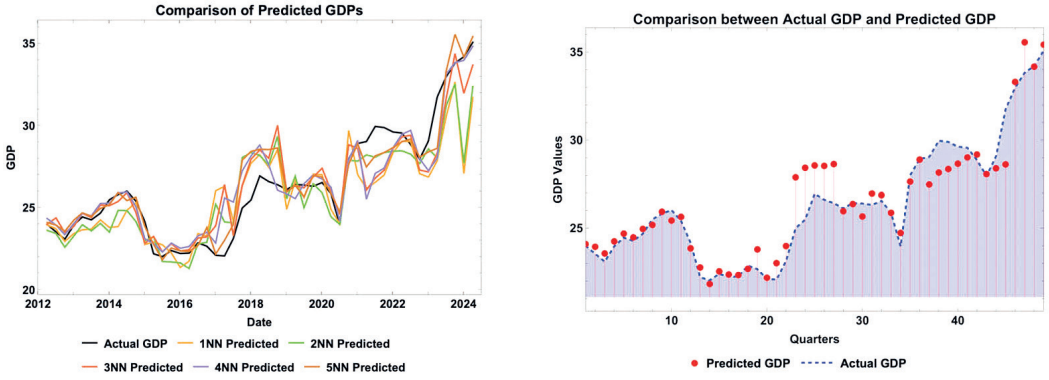


Table 4 shows the conditional distribution of both the actual GDP values and the predicted values.

Table 4
Conditional distribution of actual and GDP prediction values

Description	GDP	LSTM NN GDP Prediction
Minimum	22,0582	21,9913
Maximum	31,5854	30,3319
Mean	25,6355	25,6875
Variance	6,76356	6,33935

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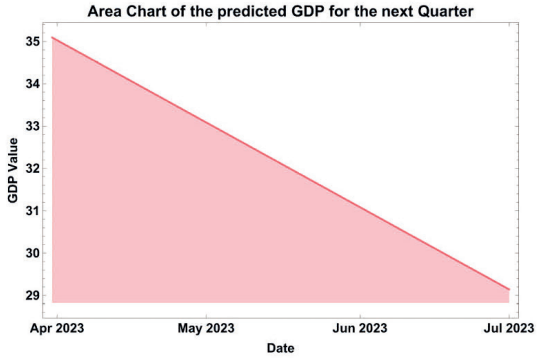
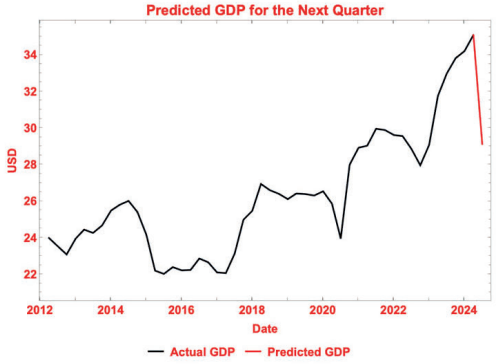
Description	GDP	LSTM NN GDP Prediction
Standard Deviation	2.60068	2.51781
Quartile Deviation	1.87124	2.06431
Median Deviation	1.93460	2.07049
Mean Deviation	2.13635	2.16407

Figure 7 shows the predicted GDP of Slovakia for the next quarter of the year 2024(Q2). Based on the predicted zinc prices, the estimated GDP value is $29,143.3 million.

Figure 7

Area chart and line chart of Slovakia's projected GDP for the second quarter of 2024 (Q2)



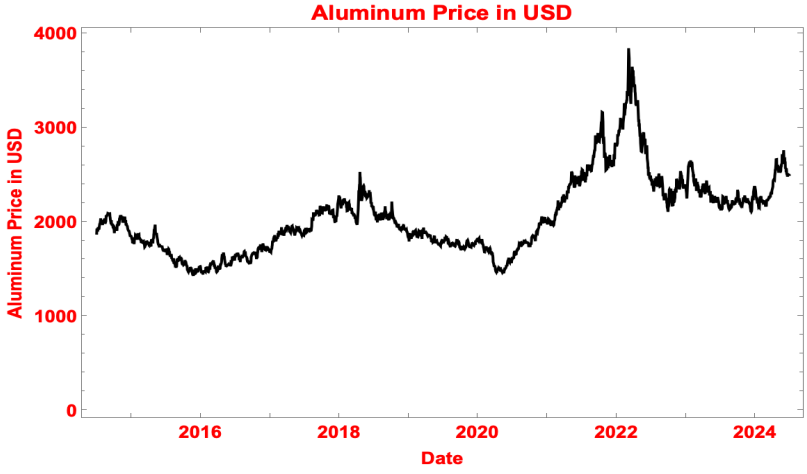


c) GDP forecast based on the price of aluminum

Figure 8 shows daily aluminum prices for the period from July 1, 2014, to June 7, 2024.

Figure 8

Aluminum price



- **Prediction of GDP based on aluminum prices**
  The NN generated correlation coefficients based on a considered lag of 63 trading days, presented in Table 5.

Table 5

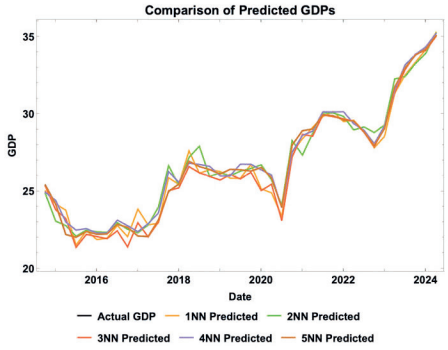
Basic configuration of network parameters and performance

Network	Performance	1. Activation function	2. Activation function	3. Activation Function
1NN63	0.985741	ArcTan	Sin	ArcTan
2NN63	0.999964	Ramp	Sin	Ramp
3NN63	0.999620	Ramp	ArcTan	Ramp
4NN63	0.977247	ArcTan	Ramp	ArcTan
5NN63	0.882652	Ramp	ArcTan	Sin

Figure 9 shows the comparison between actual GDP values in Slovakia and the value of GDP predicted by all five NNs, as well as the comparison between the most accurate prediction and actual GDP.

Figure 9

Comparison between actual and predicted GDP / Comparison between actual GDP and the most accurate prediction



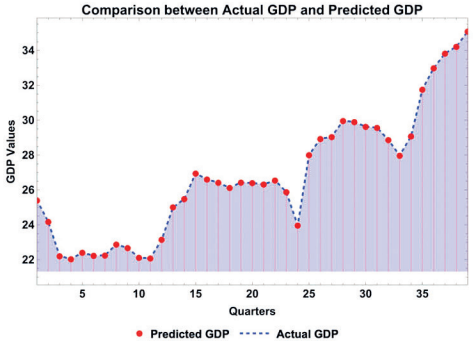


Table 6 summarizes the conditional distribution of actual GDP and predicted GDP values. The differences between the two distributions are minimal, with nearly identical minimum and maximum values.

Table 6

Conditional distribution of actual and predicted GDP values

Description	GDP	LSTM NN GDP Prediction
Minimum	22.0582	22.0539
Maximum	31.5854	31.5862
Mean	25.9508	25.9454
Variance	7.82051	7.81204

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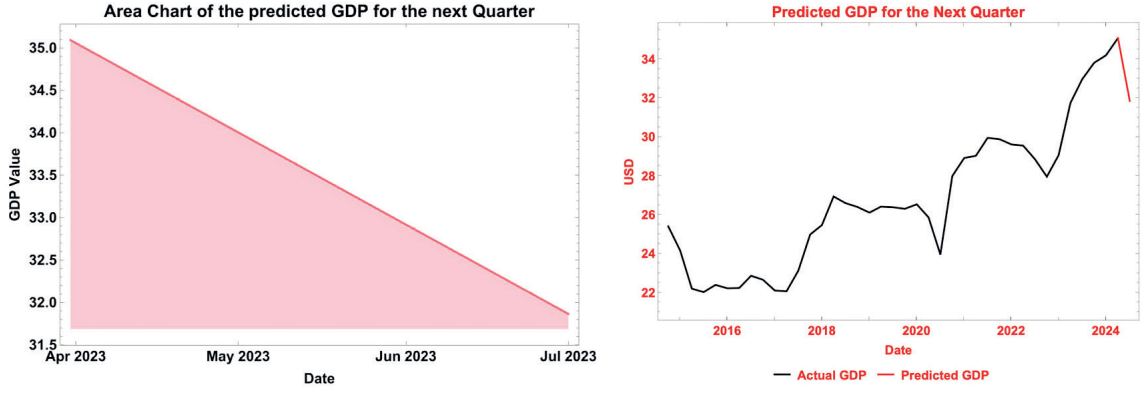
Description	GDP	LSTM NN GDP Prediction
Standard Deviation	2.79652	2.79500
Quartile Deviation	2.72840	2.72827
Median Deviation	2.66945	2.70400
Mean Deviation	2.29805	2.29627

Figure 10 shows the predicted GDP of Slovakia for the next quarter of the year 2024(Q2). Based on aluminum prices, the predicted GDP of Slovakia is $31,865.5 million.

Figure 10

Area chart and line chart of Slovakia's projected GDP for the second quarter of 2024 (Q2)



d) Prediction of GDP based on copper and zinc prices

Prediction of GDP using zinc and copper prices: The NN produced the correlation coefficient values with a considered lag of 63 trading days, shown in Table 7.

Table 7

Basic configuration of network parameters and performance

Network	Performance	Activation Function	Activation Function	Activation Function
1NN63	0.996931	ArcTan	ArcTan	Sin
2NN63	0.999334	Ramp	Sin	Ramp
3NN63	0.997197	Sin	Ramp	ArcTan
4NN63	0.999281	Ramp	Sin	ArcTan
5NN63	0.999350	ArcTan	Sin	Sin

Figure 11 shows the comparison between the actual GDP of Slovakia and the GDP values predicted by the five NNs, as well as the comparison between the most accurate result provided by the neural network and the actual GDP.

Figure 11

Comparison of actual and GDP prediction values / Comparison of actual GDP and the most accurate prediction value of Slovakia's GDP

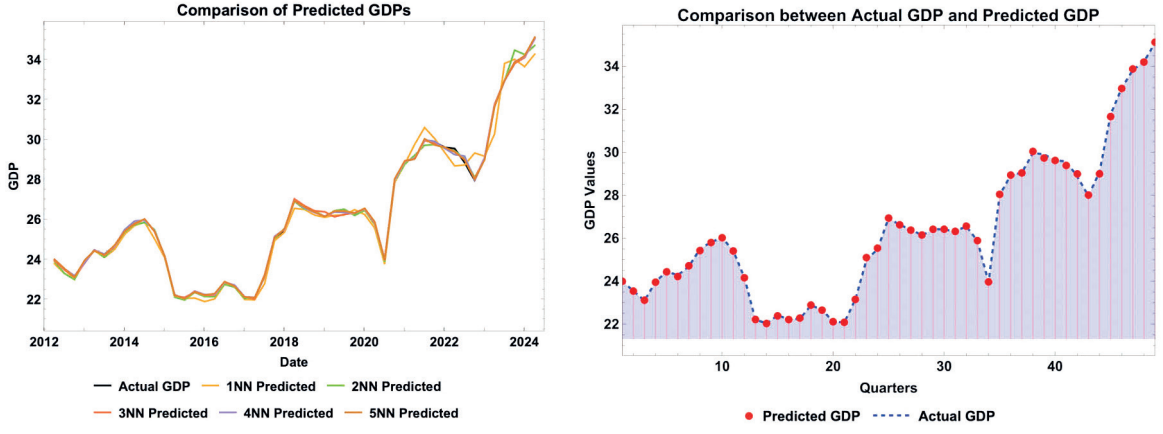


Table 8 shows the conditional distribution of the GDP and the predicted GDP. The differences in the conditional distribution of both GDP values are very small, and the minimum and maximum values are almost identical. This ensures very high accuracy, which is useful for future predictions and obtaining more precise values.

Table 8

Conditional distribution of actual and GDP prediction values

Description	GDP	LSTM NN GDP Prediction
Minimum	22.0582	22.0678
Maximum	31.5854	31.4099
Mean	25.6355	25.6336
Variance	6.76356	6.73464
Standard Deviation	2.60068	2.59512
Quartile Deviation	1.87124	1.87715
Median Deviation	1.93460	1.97280
Mean Deviation	2.13635	2.13894

Figure 12 shows the predicted GDP of Slovakia for the next quarter of the year 2024(Q2). Based on zinc and copper prices for the next quarter, the predicted GDP of Slovakia is $30,988.4 million.

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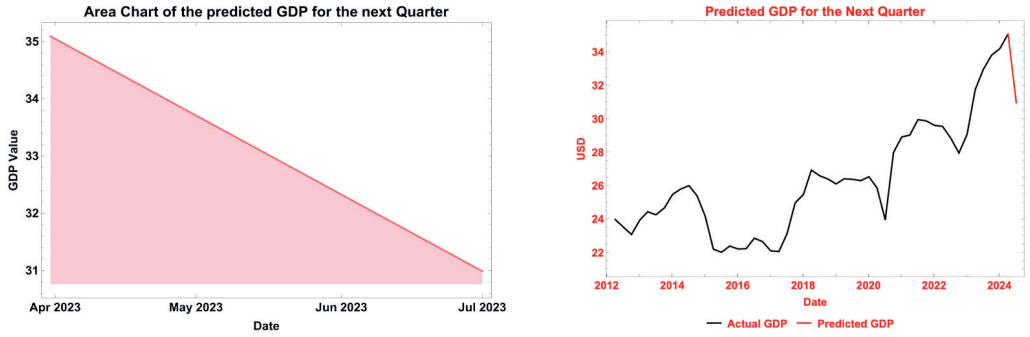
Figure 12

Area chart and line chart of Slovakia's projected GDP for the second quarter of 2024 (Q2)



e) Prediction of GDP based on copper and aluminum prices

- **Prediction of GDP using aluminum and copper prices:** The NN provides correlation coefficient values with a considered lag of 63 trading days, as shown in Table 9.

Table 9

Basic setting of network parameters and performance

Network	Performance	Activation function	Activation function	Activation function
1NN63	0.999553	Ramp	Sin	Ramp
2NN63	0.999655	Sin	ArcTan	Ramp
3NN63	0.986352	Sin	ArcTan	ArcTan
4NN63	0.997681	Ramp	Sin	Ramp
5NN63	0.999927	Ramp	ArcTan	Ramp

Figure 13 shows a comparison between Slovakia´s actual GDP and the predicted GDP values from all five NNs, as well as a comparison between the most accurate predicted value and the actual value of GDP.

Figure 13

Comparison between actual and GDP prediction / Comparison between actual GDP and the most accurate prediction

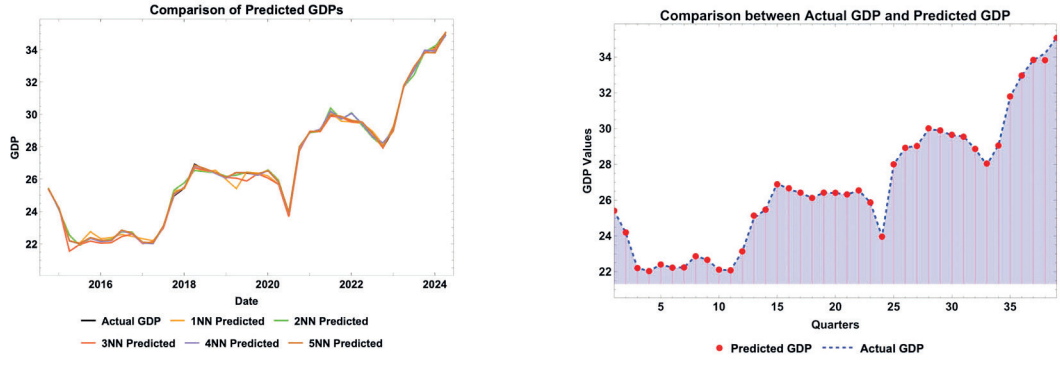


Table 10 shows the conditional distribution of actual and predicted GDP. The differences in the conditional distribution of both GDPs are minimal, with the minimum and maximum values nearly identical.

Table 10

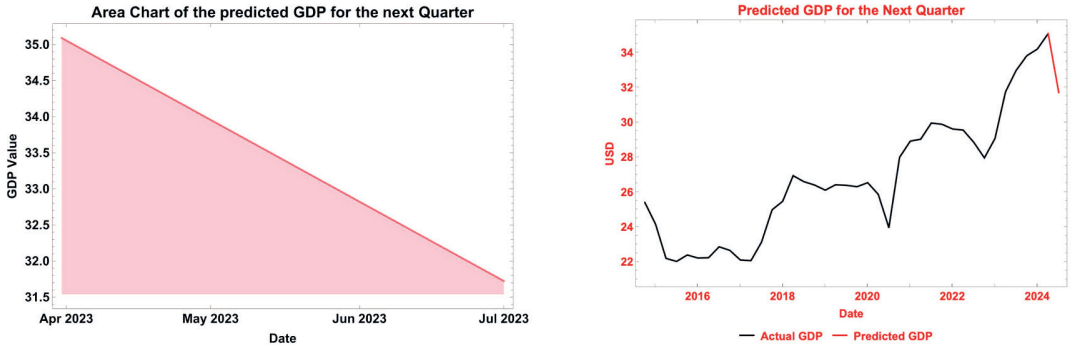
Conditional distribution of actual and GDP prediction

Description	GDP	LSTM NN GDP Prediction
Minimum	22.0582	22.0465
Maximum	31.5854	31.5866
Mean	25.9508	25.9621
Variance	7.82051	7.86151
Standard Deviation	2.79652	2.80384
Quartile Deviation	2.72840	2.72584
Median Deviation	2.66945	2.63684
Mean Deviation	2.13635	2.30752

Figure 14 shows the predicted GDP of Slovakia for the next quarter of 2024 (Q2). Based on aluminum and copper prices for the next quarter, the predicted GDP value is $31,724.1 million.

Figure 14

Area chart and line chart of projected GDP for the second quarter of 2024 (Q2)



f) Prediction of GDP based on aluminum and zinc prices

- **Prediction of GDP using aluminum and zinc prices:** The NN generates correlation coefficients with a considered lag of 63 trading days, shown in Table 11.

Table 11

Basic configuration of network parameters and performance

Network	Performance	Activation function	Activation function	Activation function
1NN63	0.999577	Ramp	ArcTan	Ramp
2NN63	0.997978	Sin	Ramp	Ramp

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Network	Performance	Activation function	Activation function	Activation function
3NN63	0,997074	Ramp	ArcTan	ArcTan
4NN63	0,999543	Ramp	ArcTan	Ramp
5NN63	0,982891	ArcTan	Sin	Sin

Figure 15 shows a comparison between Slovakia's real GDP and the projected GDP value.

Figure 15

Comparison of actual and GDP predicted values/Comparison of actual GDP and the most accurate GDP predicted value

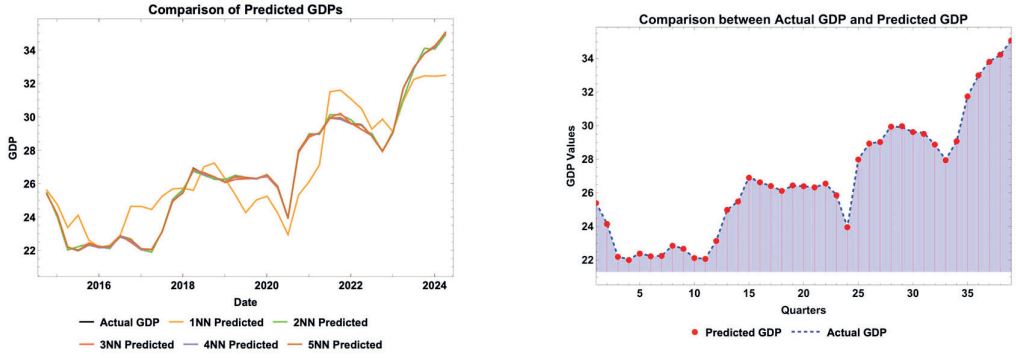


Table 12 shows the conditional distribution of actual and GDP predicted values. The differences in the conditional distribution are minimal, with nearly identical minimum and maximum values.

Table 12

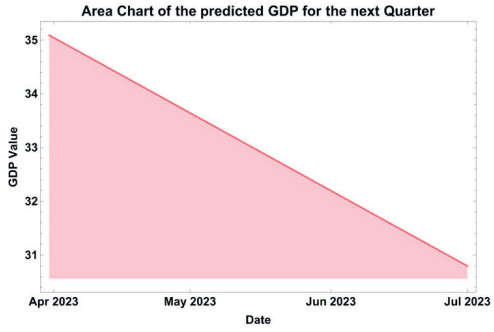
Conditional distribution of actual and GDP predicted values

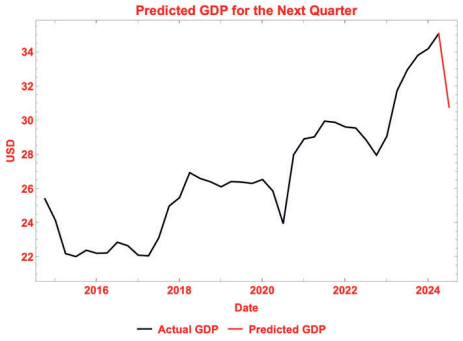
Description	GDP	LSTM NN GDP predicted
Minimum	22.0582	22.0799
Maximum	31.5854	31.3627
Mean	25.9508	25.9503
Variance	7.82051	7.73149
Standard Deviation	2.79652	2.78056
Quartile Deviation	2.72840	2.72928
Median Deviation	2.66945	2.65914
Mean Deviation	2.29805	2.29061

Figure 16 shows Slovakia's GDP predicted for the second quarter of 2024 (Q2). Based on aluminum and zinc prices, Slovakia's predicted GDP is $30,795.6 million.

Figure 16

Area chart and line chart of GDP predicted for the second quarter of 2024 (Q2)





g) Prediction of GDP based on zinc, copper, and aluminum prices

- **Prediction of GDP using aluminum, zinc, and copper prices:** The NN provides correlation coefficients with a lag of 63 trading days, shown in Table 13.

Table 13

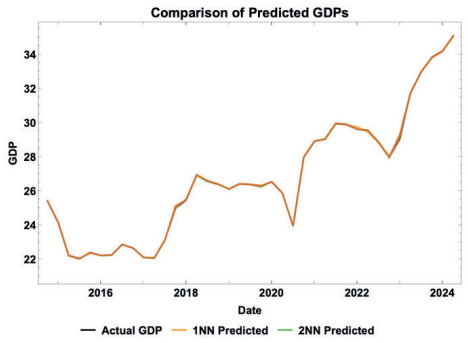
Basic configuration of network parameters and performance

Network	Performance	Activation function	Activation function	Activation function
1NN63	0.999899	Sin	Sin	Sin
2NN63	0.999987	ArcTan	Ramp	Ramp
3NN63	0.999124	Sin	Ramp	ArcTan
4NN63	0.999964	Ramp	Sin	Ramp
5NN63	0.999999	Ramp	ArcTan	Sin

Figure 17 shows the comparison between actual and predicted values of Slovakia´s GDP.

Figure 17

Comparison of actual and predicted GDP / Comparison of actual GDP and the most accurate GDP prediction



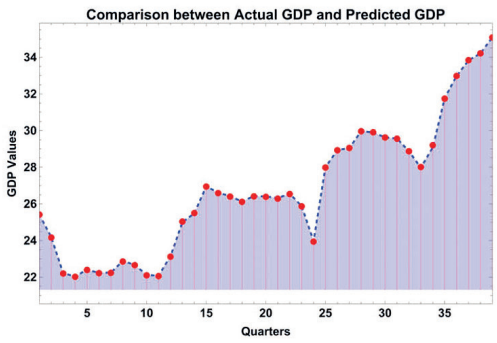


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Table 14 shows the conditional distribution of actual and predicted GDP values. The differences in the conditional distribution of both GDPs are minimal.

Tabla 14

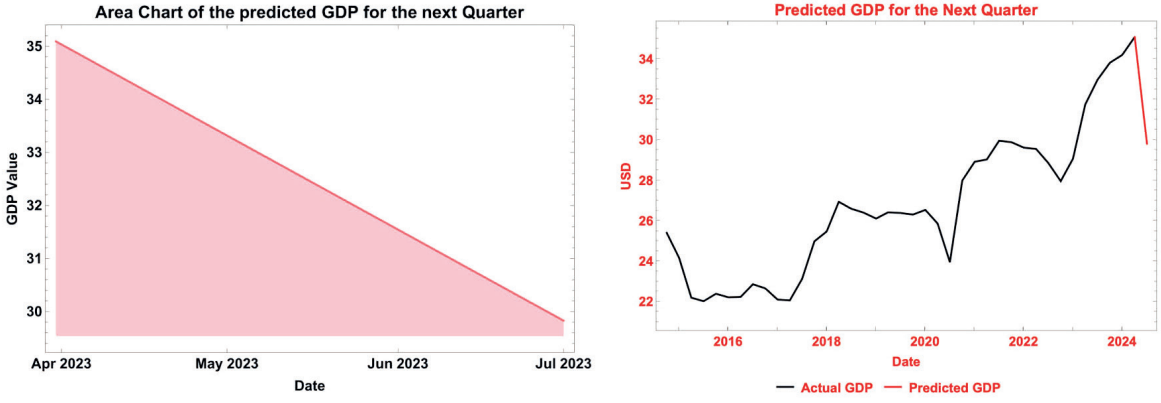
Conditional distribution of actual and predicted GDP

Description	GDP	LSTM NN GDP Predicted
Minimum	22.0582	22.0520
Maximum	3.5854	31.5857
Mean	25.9482	25.9488
Variance	8.05027	8.04900
Standard Deviation	2.83730	2.83708
Quartile Deviation	2.86282	2.86139
Median Deviation	2.60780	2.60935
Mean Deviation	2.36135	2.36104

Figure 18 shows the predicted GDP of Slovakia for the next quarter of the year 2024 (Q2). Based on aluminum, zinc, and copper prices, the predicted GDP of Slovakia is $29,828.4 million.

Figure 18

Area chart and line chart of predicted GDP for the second quarter of 2024



The comparison of prediction accuracy based on combinations of metal commodities yields the most accurate GDP prediction for the next quarter, as shown in Table 15.

Table 15
Accuracy of GDP Forecasts

Metal commodities	Accuracy	Predicted value
Zinc	0,976273	28,3054
Copper	0,995600	29,3196
Aluminum	0,999964	27,1593
Zinc and copper	0,999350	27,4339
Zinc and aluminum	0,999577	29,8282
Aluminum and copper	0,999927	28,9072
Aluminum, copper, and zinc	1,000000	30,1207

When forecasting Slovakia's future GDP based on individual metal commodities, the predicted GDP values exhibit fluctuations. The predictive method indicates that Slovakia's GDP for Q2 2024 is expected to decrease by between $1.5028 and $5.9497, suggesting a decline in economic output.

Although no additional statistical models were applied, internal robustness is supported by the consistency of results across all 15 LSTM configurations. Regardless of the activation functions or combinations of commodities used, all models produce extremely high correlation coefficients (0.97–1.00), and the conditional distributions of predicted GDP closely correspond to those of the actual data. The stability of these results across multiple network structures serves as an internal robustness check, demonstrating that the key findings are not dependent on a single model specification.

Discussion for RQ1:
How is the prediction of selected commodity prices related to the development of the Slovak economy?

The presented results include a graphical representation of the price time series trend for zinc, copper, and aluminum. The tables provide statistics on the distribution of actual and projected GDP on the basis of individual metal commodities and their combinations.

The selected time series proved to be the most suitable basis for predicting future developments of selected metal commodities in relation to Slovakia's GDP. For zinc and copper, the time series covers the period from 1 January 2012 to 7 June 2024. For aluminum, prices were available for the period from 1 July 2014 to 7 June 2024. The results confirmed the assumption that neural networks with an LSTM layer and a 63-day lag are the most suitable for predicting the future price developments of the selected metal commodities.

When forecasting Slovakia's GDP using aluminum, zinc, and copper prices, the NN provides the values of the correlation coefficient with a considered lag of 63 trading days. Among the five neural networks evaluated, the 5NN63 neural network (0.999999) demonstrated the highest accuracy, employing a combination of Ramp, Sin, and Sin as activation functions.

Based on these findings, it can be concluded that the development of selected metal commodities is strongly linked to the development of GDP in Slovakia. The most accurate GDP forecasts of Slovakia's GDP range between $29.1433 billion and $33.5902 billion, with the most accurate result being achieved when using aluminum prices. Slovakia's projected GDP for the second quarter of 2024 is $31.8655 billion.

Overall, it can be stated that the predictions of prices for selected commodities, namely zinc, copper, and aluminum, can be associated with the Slovak economy via the macroeconomic indicator of GDP.

The article contributes to the existing literature by demonstrating the relationship be-

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tween the prices of selected metal commodities, including their combinations, and selected macroeconomic indicators of Slovakia. The findings are consistent with those of Rokicki & Perkowska (2021), who identified a strong correlation between steel consumption and economic indicators in the Czech Republic.

The novelty of the article is also evidenced by the demonstrated ability to predict Slovakia's GDP using copper, aluminum, and zinc prices. Overall, the results show that LSTM models capture the link between metal prices and GDP with high accuracy, ranging from 0.97 to 1.00. Models based on aluminum perform about 2–3% better than those based on zinc, indicating that the Slovak economy responds more strongly to metals with higher industrial relevance. The narrow gap between actual and predicted values confirms that commodity-driven LSTM forecasts can reliably reflect short-term economic movements.

Discussion for RQ2:
Which of the selected metal commodities is most closely linked to the Slovak economy?

Most of the research focuses on forecasting Slovakia's GDP through the development of zinc, aluminum, and copper prices using neural networks.

First, Slovakia's GDP was predicted based on the prices of individual selected commodities, followed by predictions using all possible combinations of copper, zinc, and aluminum prices. Projections were made for the second quarter of 2024.

When evaluating the impact of individual commodities, aluminum prices showed the strongest link to the development of Slovakia's GDP. The 5NN neural network with a 63-day lag, achieved a reliability of 0.999999 and a predicted GDP value of $31.8655 billion. In the case of zinc, the reliability was lower (0.948931), also determined using the 5NN63 neural network. The projected value of Slovakia's GDP based on zinc prices is $29.1433 billion. Predicted GDP values for all selected commodities show a decline compared to the previous quarter.

Regarding combinations of individual metal commodities, the combination of zinc and copper achieved the highest accuracy using the 3NN63 neural network (0.999896), with a projected GDP in Slovakia for the second quarter of 2024 being $30.9884 billion. The combination of copper and aluminum shows comparable accuracy (0.999987) using the 2NN63 neural network, projecting a GDP of $31.7241 billion. The combination of zinc and aluminum demonstrates slightly better accuracy (with a reliability of 0.999983) using the 5NN63 neural network, projecting a GDP of $30.7956 billion.

For the combination of all three selected metal commodities (zinc, aluminum, and copper), the second highest accuracy was achieved by the 5NN63 neural network (0.999997). Based on aluminum, zinc, and copper prices, Slovakia's GDP is predicted to be $29.8284 billion in the second quarter of 2024. GDP forecasts based on combinations of selected metal commodities decreased compared to the previous quarter, reflecting the impact of the economic crisis in Europe caused by the war conflict in Ukraine and the fading effects of the COVID-19 pandemic.

These results confirm that Slovakia's GDP development can be predicted with high reliability using global market prices of zinc, copper, and aluminum. Among all analyzed commodities, aluminum prices have the greatest impact on GDP forecast of Slovakia. The differences in predicted GDP values provide useful policy-oriented scenario insights. For example, copper-based forecasts exceed zinc-based forecasts by more than USD 4 billion, showing that weaker metal prices correspond to lower GDP expectations. A 10% decline in key metal prices would likely shift forecasts toward the lower end of the range observed in zinc-based models. Such scenarios can help policymakers anticipate how external commodity shocks may affect short-term GDP dynamics.

Conclusions

The aim of the paper was to examine the relationship between predicted prices of selected metal commodities, namely copper, zinc, and

aluminum, and the development of GDP in Slovakia, on the example of selected metal commodities. The research was limited to a specific geographical area and period.

Based on the findings regarding GDP forecasting, it can be concluded that numerous methods and approaches exist, each with its own limitations and advantages. Therefore, it is important to combine traditional econometric methods with modern machine learning and deep learning techniques, alongside careful selection of appropriate predictors, is essential. Significant fluctuations in GDP growth may reduce the predictive power. This highlights the importance of stable economic indicators and the analysis of factors contributing to economic volatility.

The GDP data for Slovakia cover the period from the first quarter of 2012 to the first quarter of 2024. The experiment included predictive models based on artificial neural networks (NN) with an LSTM layer, with a considered lag of 63 days. For zinc and copper, the analysis covered trading days from 3 January 2012 and 7 June 2024; for aluminum, from 1 July 2014 to 7 June 2024. Using neural networks, the study analyzed the development of selected metal commodity prices and the prediction of Slovakia's GDP, which enabled answers to the first research question and forecasting GDP for the second quarter of 2024.

The GDP forecast for all selected commodities and their combinations indicate a decline compared to the previous quarter. The authors believe that this decline is partly attributed to the economic crisis in European countries, exacerbated by the war conflict in Ukraine, which has had a significant impact on economic growth itself.

The second research question addressed which commodity is most closely linked to the economy of Slovakia. The research focused primarily on GDP as a macroeconomic indicator, which reflects the key components of the national economy. The results indicate that the prices of all selected metal commodities are directly related to the development of Slovakia's GDP. The price of aluminum has the greatest influence on GDP forecasts. Among the selected metals, aluminum also shows the highest consistency in predicted values. As shown by the results, the value of GDP predicted using selected metal commodities decreased compared to the previous quarter. LSTM neural networks indicate that Slovakia's GDP in Q2 (2024) is expected to decline by between $1.5028 million to $5.9497 million. This finding reflects the impact of the economic crisis in Europe caused by the war conflict in Ukraine and the diminishing effects of the COVID-19 pandemic.

Using zinc and copper prices to predict Slovakia's GDP yields a correlation coefficient of approximately 95% between actual and predicted values. When aluminum prices are used, despite a shorter data series of less than two years, prediction accuracy increases by approx. 5%. This is further observed when combining zinc and aluminum, copper and aluminum, and zinc, copper, and aluminum. Even the long-term combination of zinc and copper prices from 2012 to 2024 demonstrates high predictive accuracy comparable to that achieved using aluminum. The individual price of the metal commodity and the combination of metal commodity prices, therefore, have a substantial influence on the prediction of Slovakia's future GDP.

This study provides insights for Slovak policymakers regarding the relationship between metal commodity prices and Slovakia´s GDP. Understanding these relationships highlights the relative impact of each metal commodity and their combinations on GDP forecasts. Focusing on commodity metals in Slovakia can thus significantly affect future economic development. Using more detailed datasets with longer time series and incorporating data from a more open economy could improve predictive accuracy. For the purposes of this study, data from the European market were considered sufficient. Potential future research may focus on a larger geographical area and longer time series. This study has several limitations. GDP data are quarterly while commodity prices are daily, which may introduce aggregation bias. Only three metals were included, excluding

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other economic drivers. The model was trained on the full sample for one-step-ahead forecasting, without long-term out-of-sample validation. Nevertheless, LSTM models achieve up to 5% higher accuracy than the weakest configurations, confirming their usefulness for short-term GDP assessment.

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Statement on the use of artificial intelligence

The authors **DECLARE** that, in preparing the article titled "Slovak GDP Forecast Based on Metal Prices as a Tool for Policymakers," Artificial intelligence (AI) was used to support the preparation of the manuscript.
The authors declare that they have reviewed and verified the content and assume full responsibility for the final version of the article.