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Impact of Metal Commodity Prices in Predicting the Future Rate of Inflation rate in Poland

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Abstract
The prices of metal commodities have long been influenced, especially by the lack of non-renewable resources and the widespread use of copper and aluminum in industry due to their properties. Metal commodities are irreplaceable for the sector of developed countries, and their scarcity during the COVID-19 period increases both their price and, subsequently, the price of products made of these metals. The paper deals with the trend of selected metal commodity prices on the global market in the context of the macroeconomic indicator trend of Poland's inflation rate. The paper aims to predict the inflation rate trend in Poland and determine which of the selected metal commodities is most closely linked to the economy. The research data were obtained from Investing.com (2024) and Eurostat (2024) and converted to time series. The price of metal commodities is given in US dollars per tonne, while the inflation rate is expressed as a percentage. The data on the development were processed using artificial intelligence and recurrent neural networks, including the Long Short Term Memory layer. In general, neural networks have great potential to predict this type of time series. The experiment involved prediction models built on artificial neural networks (NN) with the LSTM layer and 19-day lag. The research confirmed that the development of copper, zinc, and aluminum prices is closely interlinked with the Polish economy. Therefore, the inflation rate in Poland can be predicted with a high probability based on the development of the examined metal commodities prices.

Keywords
Copper price, aluminum price, zinc price, forecasting, neural networks, inflation rate, Poland, LSTM

Introduction

Inflation expectations represent the key inputs to monetary policy but are also one of the most difficult variables to measure. Inflation expectations are particularly difficult to determine in the low-inflation environment where large changes in important relative prices occur. The available measures of inflationary expectations vary largely for individual resources and cannot be used as a target but rather as a complementary element in monetary policy decisions (Alcidi et al., 2021; Sinicakova and Gavurova, 2017). Commodity price fluctuations affect developing economies. A hike in commodity prices means more capital is coming to economies (Baffes & Kabundi, 2023). The conflict between Russia and Ukraine and the COVID-19 pandemic have caused many economic crises on a global scale, raising the likelihood of hyperinflation and putting European nations at risk (Belas et al., 2018; Belas et al., 2022). European market faces issues when commodity prices are high. According to a survey from 2023, 53 million dollars worth of metal commodities were imported to Poland (Ha et al., 2022).

Inflation is the basic concept of economics. It cannot be too high or too low because it affects the functioning of the economy. This is why the authorities maintain the prices of goods and commodities (Jedruchniewicz, 2013; Sinicakova et al., 2017). The public gives more importance to policy announcements than to previous macroeconomic events. Because of this, the credibility of inflation targets in Poland has become strong, especially since the formal implementation of inflation targeting (Maliszewski, 2008). According to Szyszko (2015), shaping expectations of central banks' influence can achieve the main objective of monetary policy and guide public expectations; inflation forecasting is a great technique. Kopych & Shevchuk's (2024) findings and analysis prove that all countries have different inflation rates due to the influence of global metal commodity prices. International commodity price fluctuations affect inflation, and central banks focus on predicting inflation by studying the commodity price changes and their impact on other nations (Abbas & Lan, 2020; Tkacova and Gavurova, 2023; Bilan et al., 2017).

To determine the accuracy and influence of inflation forecasting is done by a process with four stages: the first stage is confirming the credibility of the central bank, the second stage is examining the precision of inflation forecast, the third is inflation forecast targeting (IFT) implementation put into qualitative analysis and the final stage is to find the interconnectedness of inflation forecasts, optimal policy methods, and inflation expectations (Szyszko & Tura, 2015). According to Mandalinci (2017), every forecasting method shows unequal results depending on the situation and nation. Inflation forecasting and central bank independence are negatively correlated. A stable environment with long-term growth is suitable for making better economic decisions, as it makes inflation predictions more accurate (Kliber et al., 2023). To understand the issues and impact of inflation, quantitative analysis is a powerful tool used to rectify those problems in Poland (Kelm & Pellegrini, 2023).

Also, inflation can occur due to increased money circulation in Poland, but its effect is comparatively small (Zivkov et al., 2020). Expectations of inflation are used by central banks as a tool to maintain price stability. That is, they analyze what people think about the future of inflation (Coibion et al., 2020), because public perceptions of future inflation and their trust in the central bank's ability under uncertainty (Ejdys et al., 2018) are critical factors of economic stability. High inflation often occurs in economies that are less harmful to production, so we use anti-inflation decisions (Charemza et al., 2015).

Our main aim of the research is to find the impact of the metal commodity price in predicting the future inflation rate in Poland. Polbin et al. (2018) state that metal commodity prices significantly affect macroeconomic indicators. So, we have to find the relationship between commodity prices and inflation, and this will lead to our first research question:

RQ1: What is the correlation between the development of selected metal commodity prices and the development of the inflation rate in Poland?

Out of all these metal commodities, we have to find which is mostly associated with the inflation rate so we can use the variable for future prediction.

RQ2: Which of the selected metal commodities is most closely linked with the macroeconomic indicator of the inflation rate, and what will Poland's future inflation rate be?

Literature Review

Inflation is a very important macroeconomic variable. Currently, it is considered the most harmful phenomenon in contemporary economies. The concept of inflation was developed by various economists and specialists who strived to formulate the most precise definition possible, explain the causes and factors determining this phenomenon, and its effect on the population and economic entities (Mindrican and Matei, 2021). Ciner (2011) analyzes the relationship using the frequencies between commodity prices and inflation, finding important long-term connections between inflation dynamics and commodity price shifts. Consumers, policy uncertainty, and Central bank communication strategies were pointed as key elements to study inflation forecast errors in seven European economies from 2016 to 2020 (Kliber et al., 2023).

Emerging economies like Nigeria and South Africa face a strong impact on their economy if the commodity price changes. It underscores the necessity of integrating commodity price fluctuations, considering their endogeneity and asymmetric effects, into inflation forecasting models to enhance predictive accuracy and policy relevance (Fasanya & Awodimila, 2020). Methodologies, including local projections and smooth transition autoregressive (STAR) models, have been used in studies such as the cross-country analysis on inflation dynamics and commodities price shocks, and these methodologies calculate the impact of metal commodity price shocks on consumer price indices (CPIs), indicating both immediate and long-term inflationary consequences (Sekine & Tsuruga, 2018). In terms of success rate and learning speed, LSTM performs better than real-time iterative learning, neural sequence chunking, Elman nets, back-propagation via time, and iterative cascade correlation (Hochreiter & Schmidhuber, 1997)

Gao et al. (2021) focused on analyzing the relationship between inflation and inflation uncertainty in China. Using a quantile causality test, they examined the existence of causality between these two variables. According to their results, there is a unidirectional causality from inflation to inflation uncertainty of a significantly asymmetric and time-varying nature. Inflation is very likely to cause inflation uncertainty in situations with higher inflation rates, especially in higher quantiles of the distribution. The COVID-19 pandemic has significantly impacted inflation and economic systems; therefore, it is necessary to have suitable tools and models for predicting inflation and response to this uncertainty. Moreover, observing inflation expectations and volatility is important, as they can be important indicators of future inflation trajectory and economic stability. Bobeica and Hartwig (2023) analyzed how the COVID-19 pandemic has influenced inflation modeling using VAR and suggested better forecasting methods to predict inflation during the pandemic. They found that during the pandemic, parameter estimates are influenced by several factors, which causes different and sometimes inaccurate inflation projections.

A time series is a sequence of data points in successive time order. Time series data are generated in many application scenarios, and the techniques used for their analysis have aroused considerable attention. Time series concatenation is a simple operation that retrieves all pairs of correlated subsequences from two given time series (Rong, Chen, and Silva, 2020). Y. Liu et al. (2019) presented the use of deep neural networks with recurrent structures, specifically LSTM (Long Short-Term Memory), to extract information from sequential data to predict trends in time series, especially in lime prices. The successful implementation of this model shows results that outperform conventional autoregressive models and are considerably more accurate than random estimation. The results were obtained on datasets related to stocks that have characteristics very similar to random walk sequences. The LSTM model showed high efficiency in analyzing and predicting time series.

T. Li et al. (2020) dealt with anomaly detection in time series using a prediction-based method. The aforementioned LSTM neural network was used for prediction, while a dynamic thresholding mechanism was applied for anomaly detection. The effectiveness of this method was verified on different public time series, thus confirming its ability to detect anomalies in time series with high accuracy. Ostroski et al. (2021) introduced a method for detecting and correcting anomalies in time series with a focus on disk usage data over several months. The method is based on calculating the differences between time series, identifying the transformed data mean value, and setting a threshold for anomaly detection. Engineering metals have a wide range of industrial applications due to their physical, chemical, or mechanical properties. These metals include copper, aluminum, lead, nickel, tin, zinc, steel, iron, etc. Metallurgy is considered a key sector of any national economy and an important sector of heavy industry, as it is strategically important for arms production and other industries and services. Its products are used mainly in construction, transport vehicles, infrastructure development, and many services and other industries (Wilczynski, 2020). Vochozka et al. (2021) deal with daily closing prices of copper using artificial intelligence and recurrent neural networks (LSTM) with great potential in predicting copper time series.

Several approaches to detecting and addressing time series anomalies have advantages and applications depending on a specific problem and dataset . Based on the research conducted on suitable methods applicable to predict and analyze the impact of metal commodities on the economies of individual countries, the LSTM method will be used to predict price time series and the production of the metal commodities under study. Data necessary for the analysis and prediction will be obtained using a content analysis.

Material and Methods

The analysis is focused on the macroeconomic variable (inflation rate) of Poland. Two types of sources were used to collect the data: macroeconomic variable was obtained from the Eurostat website, while data on metal commodities, specifically copper, zinc, and aluminum, were obtained from the investing.com website. The macroeconomic variable is taken separately for Poland. The data for the metal commodity price are available for the period 1st of July 2014 to 27 st June 2024.

An artificial neural network (NN) approach called Long Short-Term Memory (LSTM) is used to forecast the future trend of the macroeconomic variables. Several parameters are needed to create the Neural Network, specifically:

a) The Number of Elements in the Neural Network Model depends on the model's configuration and input data. The input data is of the matrix size $m\ x\ n$, in this case, it varies depending on the input data, i.e., $'19\ x\ 1', '19\ x\ 2', '19\ x\ 3'$, etc.
b) Diverse Activation functions (utilizing Elementwise Layer) will be employed to facilitate signal propagation among NN layers. The selection of activation functions will encompass the following options: Sine, Ramp (also recognized as ReLu – Rectified Linear Unit), and ArcTan.
c) Time series lag is a sequence of prior values that is used to anticipate future values. The latency will be judged to be 19 days.

The NN structure will be identical in all circumstances (except for the parameter changes). Figure 1 shows a schematic of the NN.

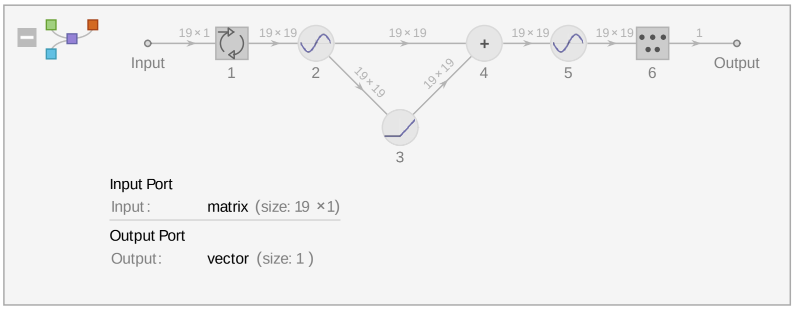

Fig. 1. Structure of NN with LSTM layer

The Neural Network consists of six main layers, excluding the input and output. The six layers between the input and output layers are hidden.

a) Input Layer: A matrix representing commodity pricing data is provided in the input layer. Different sizes of matrices will be investigated in the experiment (Based on the input data). Here, the matrix of size is "19 x 2". The value 'm' in the matrix represents the number of consecutive variables required to compute the following variable.
b) 1st Hidden Layer (LSTM Layer): The first hidden layer is an LSTM layer. It generates an output matrix of dimensions m x n,' where 'm' is the time series lag and 'n' is chosen empirically. Here, the matrix at the input layer 19 x 2 will generate a matrix 19 x 19 at the output). The 'n' value grows by one.
c) 2nd Hidden Layer (Elementwise Layer - Perceptron): This layer is built as an Elementwise Layer, which is a simple network that functions as a perceptron. These layers' activation functions will be chosen randomly from a specified list of activation functions.
d) 3rd Hidden Layer (Elementwise Layer): This layer is an Elementwise Layer with the same activation function selection criteria as the second hidden layer.
e) 4th Hidden Layer (Plus Layer): The fourth hidden layer, known as the "Plus" layer, accomplishes summing. It accepts input from the second and third hidden levels and transmits the output to the fifth hidden layer.
f) 5th Hidden Layer (Elementwise 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 (Linear Layer): The sixth hidden layer is a Linear Layer, which acts on a data matrix at the input (a 19 x 19 matrix is shown in the picture). It generates a vector with one element as output.
h) Output Layer: The output layer predicts the macroeconomic variable.

Long-Short Term Memory Layer $[n]$ represents a net that takes an input matrix representing a sequence of vectors and outputs a sequence of the same length. Each input sequence element is a vector of size k, and each output sequence element is a vector of size n. LSTM consists of four blocks: Input gate, output gate, forget gate, and memory gate.

$\{x1, x2, \ldots, xT\}$ is the input sequence, and the LSTM outputs a series of states $\{s1, s2, \ldots, sT\}$. The cell state is defined as follows:

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

where

c_t is a new variable state.
f_t forget gate.

c_{t-1}	the initial state of the variable.
i_t	input gate.
m_i	memory gate.

The input gate is defined as follows:

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

where

$$\sigma(z) = \frac{1}{(1 + exp(-z))} \quad (3)$$

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}	weight of the state in the input gate, matrix $n\ x\ n$.
S_{t-1}	the initial state.
b_i	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	output gate.
$Tanh$	Hyperbolic tangent.

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 the output gate, matrix $n\ x\ k$.
W_{os}	Weight of the state in output gate, matrix $n\ x\ n$.
b_o	Bias, vector size n.

When compared to, say, a Gated Recurrent Layer, the benefit 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 the weight of the state in the forget gate, matrix $n\ x\ n$.
b_f	Bias, vector size n.

The main processes of LSTM include memory gate, as follows:

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

where,

W_{mx}	Defines the input weight in memory gate, matrix $n\ x\ k$.
W_{ms}	Weight of the state in memory gate, matrix $n\ x\ n$.
b_m	Bias, vector size n.

Individual commodity prices were first coupled with one of the numerous macroeconomic factors to train a neural network. Next, the analysis was extended to incorporate numerous commodity prices in the training dataset. This comprehensive method aimed to find the most effective model in terms of accuracy in forecasting the selected variable. Pearson correlation coefficient was used to calculate the degree and direction of the linear relationship between real and predicted macroeconomic values to assess the model's performance.

Based on the above, the final objective was to choose the most resilient neural network design. After that, the selected model is used to predict future macroeconomic data with greater accuracy and reliability. This method of predicting macroeconomic trends is methodical and data-driven.

Results

This chapter presents a graphical and tabular illustration of the predicted development of inflation based on the time series of copper, aluminum, and zinc historical prices, including their combinations. Figure 2 shows the monthly trend of inflation in Poland and the copper price from 1 July 2014 to 27 June 2024.

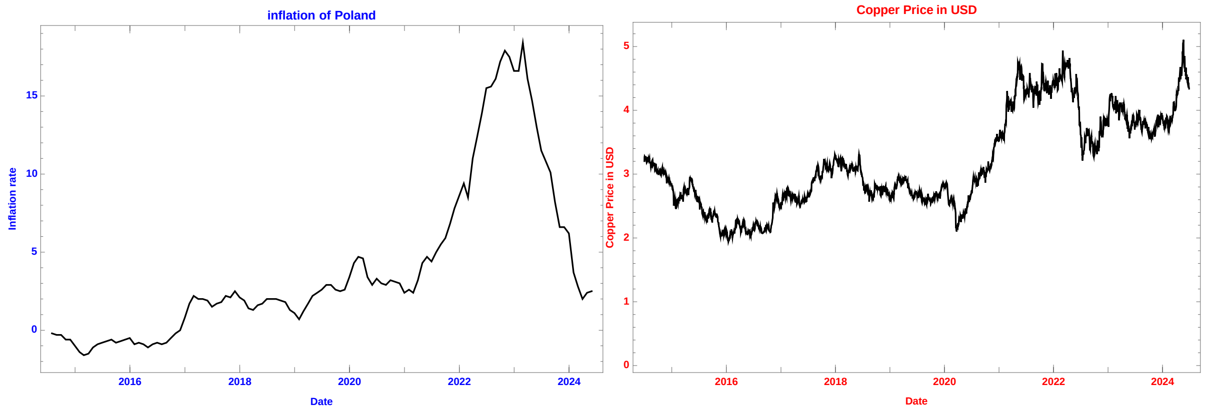

Fig. 2: Inflation trend in Poland and the Copper price in USD

Inflation predicted based on copper prices

The application of copper prices to predict inflation: The neural network analysis shows a strong correlation between copper prices and inflation with a 19-day lag. Among the five studied neural networks (as seen in Table 1), 3NN19 stands out for its exceptional accuracy and shows a correlation coefficient of 0.882924. High accuracy is achieved due to the unique activation function that combines Sin, Ramp, and Sin.

Tab.1: Basic setting of network parameters and performance

Network	Performance	Activation Function 1	Activation Function 2	Activation Function 3
1NN19	0.881205	Sin	ArcTan	Sin
2NN19	0.878543	Ramp	Sin	Ramp
3NN19	0.882924	Sin	Ramp	Sin
4NN19	0.881102	Sin	Sin	ArcTan
5NN19	0.864706	Ramp	ArcTan	ArcTan

Figure 3 compares real inflation in Poland with the predicted inflation generated by 5 neural networks, comparing the most accurate results predicted by the neural network and the real inflation.

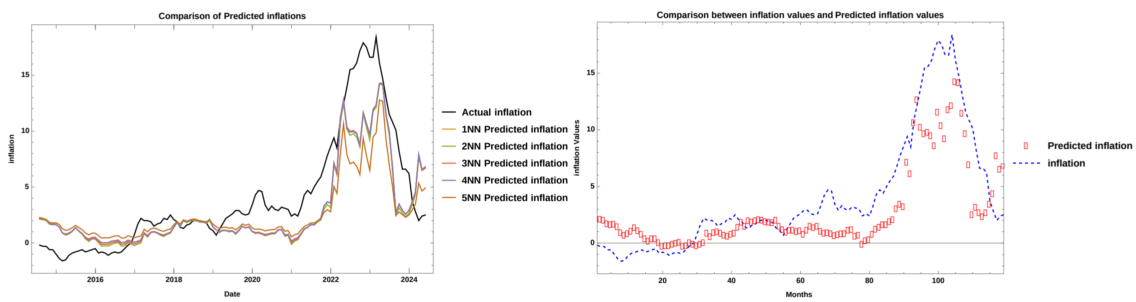

Fig. 3: Comparison of real and predicted inflation/comparison of real inflation with the most accurate predicted inflation

The conditional distribution of inflation and predicted inflation values are presented in Table 2, which shows minimum differences. The difference between minimum and maximum values has a higher change, which will impact future predictions.

Table 2: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-0.28943

Maximum	18.4000	14.20690
Mean	4.0000	2.76767
Variance	26.9256	13.14280
Standard Deviation	5.1889	3.62531
Quartile Deviation	2.1000	0.91950
Median Deviation	2.1300	0.69445
Mean Deviation	3.9159	2.69731

As seen in Figure 4, the predicted inflation in Poland for the following months is 6.82095 %, according to the values of copper prices. The predicted values indicate the growth in inflation compared to the preceding month and show the inflation trend in the next month, June 2024.

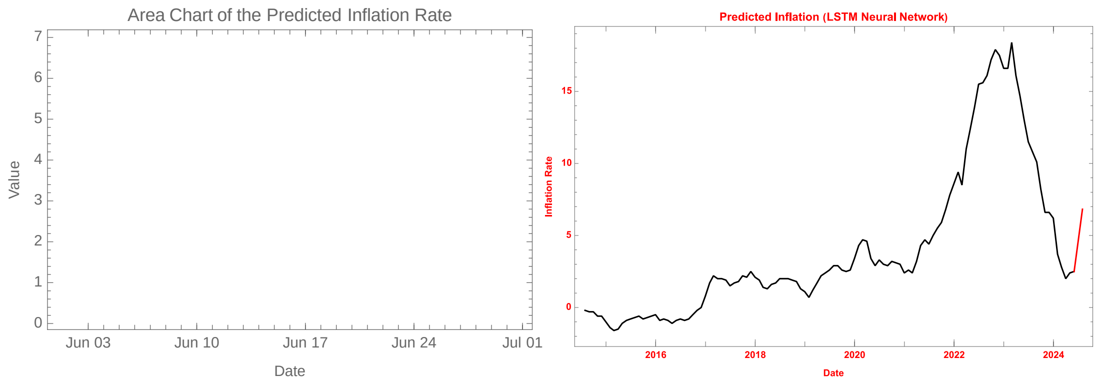

Fig. 4: Box plot of predicted inflation for the following month / Line chart for predicted inflation for the following month

Inflation predicted based on zinc prices

Figure 5 shows the daily zinc prices between 1 July 2014 and 27 June 2024.

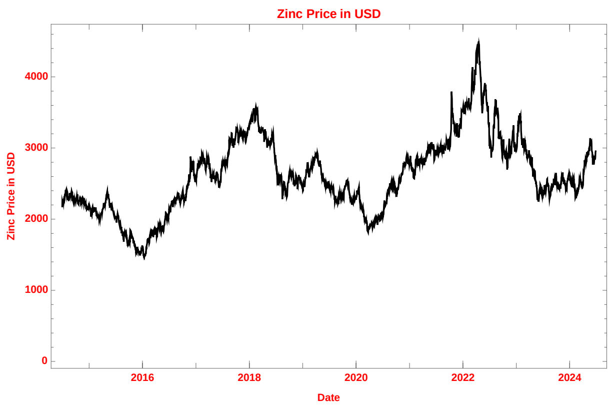

Fig. 5: Zinc price trend

Applying zinc prices to predict inflation: The neural network analysis shows a strong correlation between zinc prices and inflation with a lag of 19 trading days. Among the five studied neural networks (as seen in Table 3), 1NN19 stands out for its exceptional accuracy, with a correlation coefficient of 0.864306. The high accuracy is achieved due to the unique activation function combining Ramp, Sin, and Ramp.

Tab. 3: Basic settings of network performance and parameters

Network	Performance	Activation Function 1	Activation Function 2	Activation Function 3
1NN19	0.864306	Ramp	Sin	Ramp
2NN19	0.831091	ArcTan	Sin	Ramp
3NN19	0.800557	Sin	ArcTan	Ramp
4NN19	0.820154	Sin	ArcTan	Ramp
5NN19	0.815097	Ramp	ArcTan	ArcTan

Figure 6 shows the real inflation in Poland and the inflation values predicted by all five neural networks and compares the most accurate predicted values and real inflation.

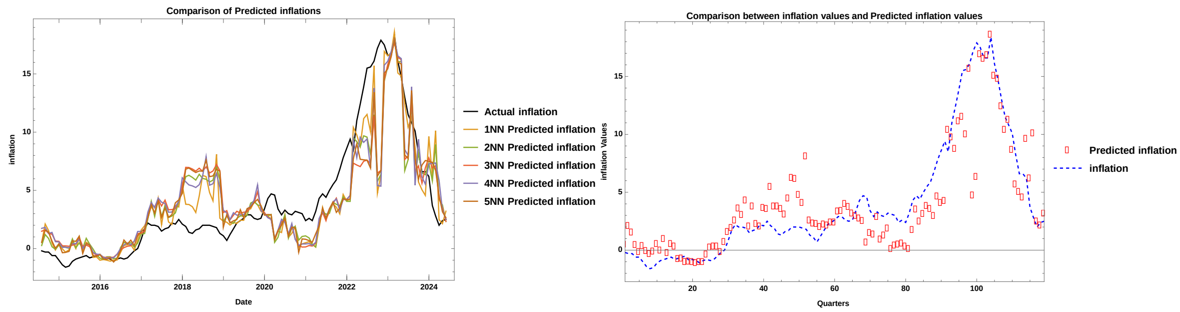

Fig. 6: Comparison of real and predicted inflation values / Comparison of real inflation with the most accurate predicted inflation values

The conditional distribution of real inflation and predicted inflation is presented in Table 4. As seen in the table, the conditional distribution of inflation and predicted inflation show minimal differences. The difference between the minimum and maximum values is nearly the same in both cases. This similarity points to a high degree of accuracy, thus confirming good predictive properties of the model and ensuring accurate values.

Tab. 4: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-1.08043
Maximum	18.4000	18.6131
Mean	4.0000	3.86278
Variance	26.9256	19.4642
Standard Deviation	5.1889	4.41182
Quartile Deviation	2.1000	2.0275
Median Deviation	2.1300	2.0354
Mean Deviation	3.9159	3.18207

Figure 7 shows that the inflation in Poland predicted for the following month is 3.01362 % when considering the zinc price. The prediction suggests a decline in inflation compared to the preceding month and shows the direction of the inflation in June 2024.

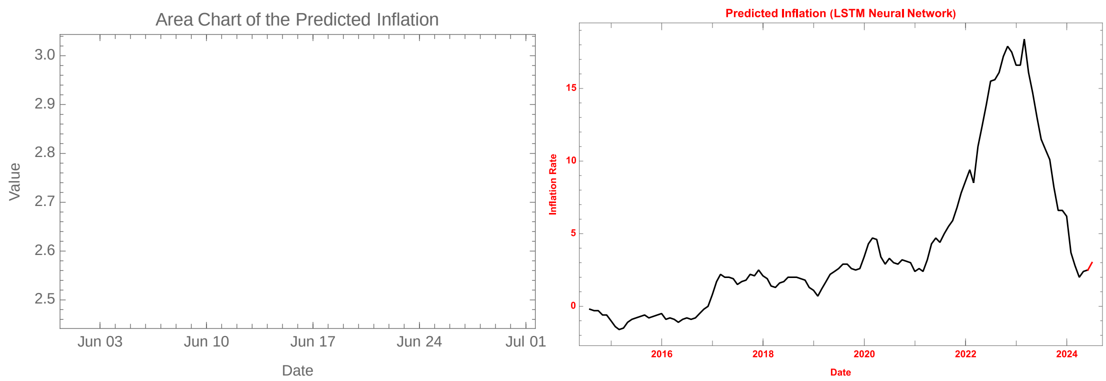

Fig. 7: Box plot of inflation predicted for the following month / Line graph of inflation predicted for the following month

Inflation predicted based on Aluminum prices

Figure 8 presents the daily prices of Aluminum between 1 July 2014 and 27 June 2024.

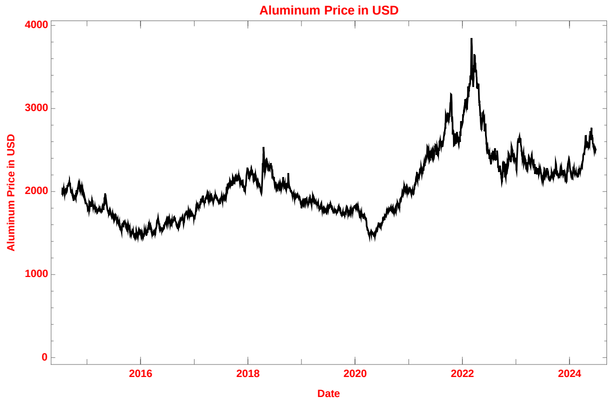

Fig. 8: Aluminum price trend

The application of aluminum prices for predicting inflation: The neural network analysis shows a strong correlation between aluminum prices and inflation with a lag of 19 trading days. Among the 5 neural networks under study (as seen in Table 5), 2NN19 shows the best accuracy and a correlation coefficient of 0.935586. The high accuracy is achieved due to the unique activation function that combines ArcTan, ArcTan, and Sin.

Tab.5: Basic settings of network performance and parameters

Network	Performance	Activation Function 1	Activation Function 2	Activation Function 3
1NN19	0.924479	Ramp	ArcTan	Sin
2NN19	0.935586	ArcTan	ArcTan	Sin
3NN19	0.933868	Ramp	Sin	Ramp
4NN19	0.921530	ArcTan	Ramp	Ramp
5NN19	0.927828	Ramp	Ramp	ArcTan

Figure 9 shows the real inflation in Poland and inflation predicted by all 5 neural networks, comparing the most accurately predicted and the real inflation values.

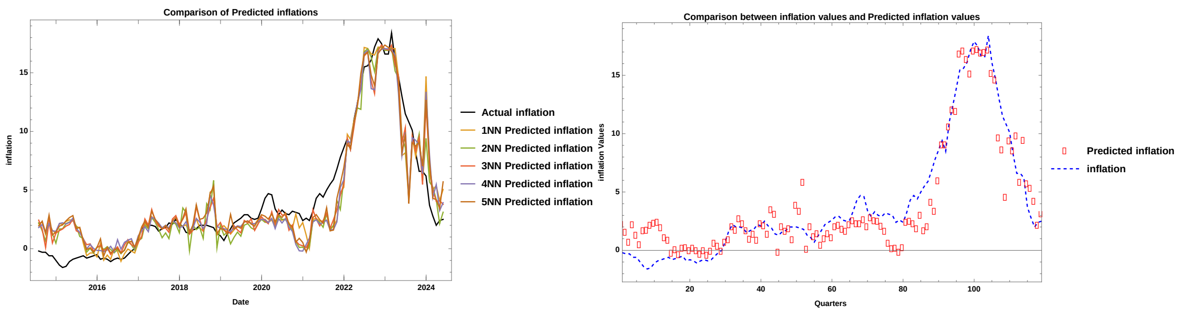

Fig. 9: Real and predicted inflation / Comparison real and most accurately predicted inflation values

The conditional distribution of real and predicted inflation is presented in Table 6. The conditional distribution of the real and predicted inflation shows some fluctuations. In the minimum values, there will be a huge difference, but the maximum values are nearly equal; similar variations can seen in the remaining statistical distributions in Table 6.

Tab. 6: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-0.426714
Maximum	18.4000	17.2088
Mean	4.0000	3.84999
Variance	26.9256	23.488
Standard Deviation	5.1889	4.84644
Quartile Deviation	2.1000	1.57251
Median Deviation	2.1300	1.25784
Mean Deviation	3.9159	3.59414

As seen in Figure 10, the predicted inflation in Poland for the following month is 5.03169 % when considering the aluminum prices. This prediction suggests a decline in inflation compared to the preceding month and shows the direction of inflation in June 2024.

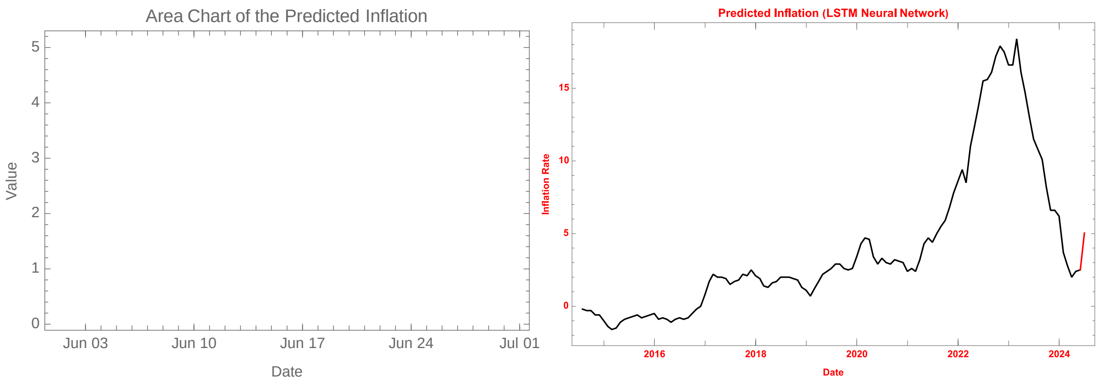

Fig. 10: Box plot of predicted inflation for the following month / Line graph of predicted inflation for the following month

Inflation predicted based on the copper and zinc prices

The application of copper and zinc prices to predict inflation: The neural network analysis shows a strong correlation between copper and zinc prices and inflation with a lag of 19 trading days. Among the 5 neural networks under study (see Table 7), 1NN19 shows extraordinary accuracy, with a correlation coefficient of 0.991817. High accuracy is achieved due to the unique activation function of combining ArcTan, ArcTan, and ArcTan.

Tab. 7: Basic settings of network performance and parameters

Network	Performance	Activation Function *1*	Activation Function *2*	Activation Function *3*
1NN19	0.991817	ArcTan	ArcTan	ArcTan
2NN19	0.975193	Ramp	ArcTan	Sin
3NN19	0.988257	ArcTan	Ramp	Sin
4NN19	0.982758	Sin	ArcTan	Ramp
5NN19	0.987006	Sin	Ramp	Sin

Figure 11 shows the real inflation in Poland and the prediction of inflation generated by all 5 neural networks, comparing the most accurately predicted inflation values and the real inflation. It's very clear that predicted inflation almost matches actual inflation with an accuracy of 99.18%.

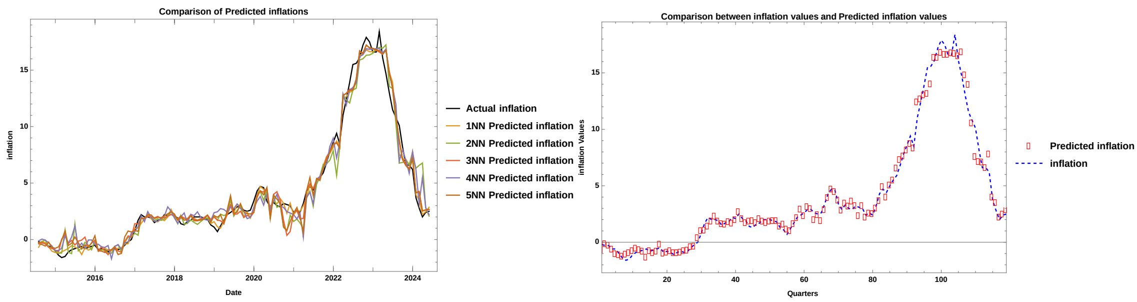

Fig. 11: Comparison of real and predicted inflation / Comparison of real and most accurately predicted inflation

The conditional distribution of real inflation and predicted inflation can be seen in Table 8. The conditional distribution shows minimal differences, with the difference between the minimum and maximum values being almost identical in both cases. The similarity suggests high accuracy, thus confirming the model's predictive capability and providing accurate values. As we can see there are differences in the minimum and maximum values, but in the case of Standard Deviation, it is almost equal.

Tab. 8: Conditional distribution of real and predicted inflation values

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-1.32945
Maximum	18.4000	16.8367
Mean	4.0000	3.97797

Variance	26.9256	26.2534
Standard Deviation	5.1889	5.12381
Quartile Deviation	2.1000	2.00446
Median Deviation	2.1300	2.38239
Mean Deviation	3.9159	3.87126

As seen in Figure 12, the predicted value of inflation in Poland in the following month is 2.6719 % for the copper and zinc prices. The predicted value suggests an increase in inflation compared to the preceding month and shows the direction of the inflation in June 2024.

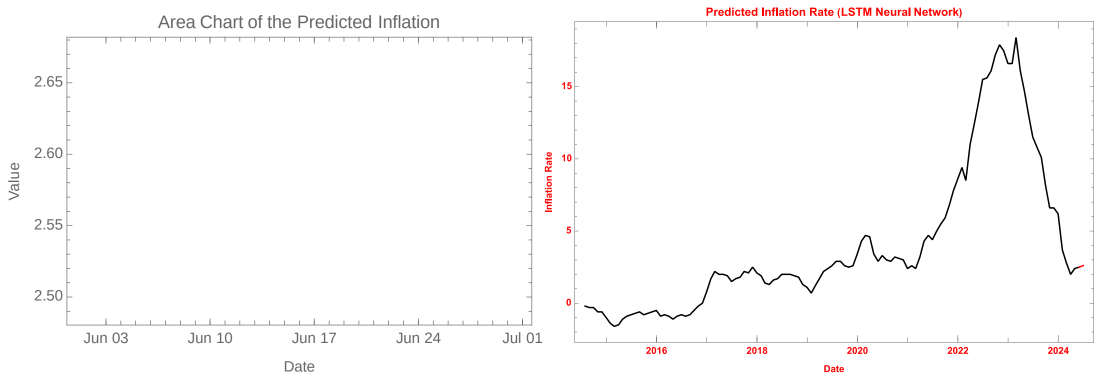

Fig. 12: Box plot of predicted inflation for the following month / Line graph of predicted inflation for the following month

Inflation predicted based on aluminum and copper prices

Applying the copper and aluminum prices to predict inflation: The neural network analysis shows a strong correlation between the copper and aluminum prices and inflation with a lag of 19 trading days. Among the five neural networks under study (see Table 9), 2NN19 shows excellent accuracy and a correlation coefficient of 0.954526. The high accuracy is achieved due to the unique activation function combining Sin, ArcTan, and Sin.

Tab. 9: Basic settings of network parameters and performance

Network	Performance	Activation Function 1	Activation Function 2	Activation Function 3
1NN19	0.944321	ArcTan	ArcTan	ArcTan
2NN19	0.954526	Sin	ArcTan	Sin
3NN19	0.947873	Sin	Sin	Sin
4NN19	0.936950	Sin	ArcTan	Ramp
5NN19	0.944333	Sin	ArcTan	Sin

Figure 13 shows the real inflation in Poland and the predicted inflation generated by all 5 neural networks, comparing the values predicted by neural networks and real inflation.

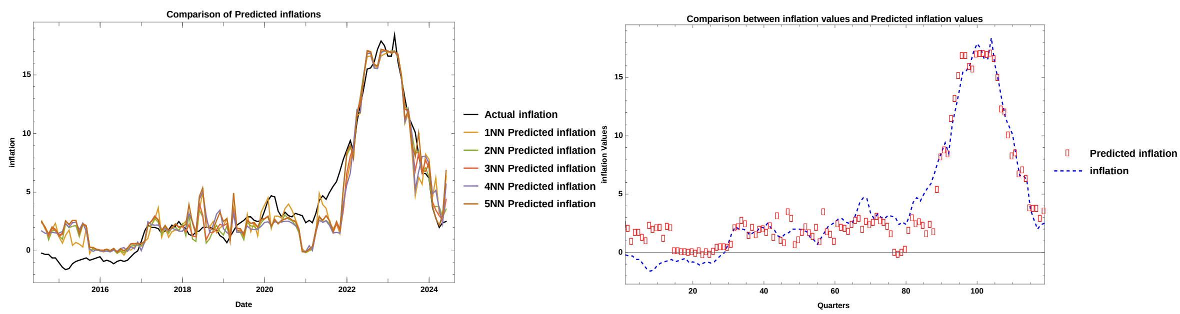

Fig. 13: Real and predicted inflation / Comparison of real inflation and most accurately predicted inflation values

The conditional distribution of real and predicted inflation can be seen in Table 10. Both distributions show minimum differences. The differences between minimum and maximum values are not even close, as we can see in the remaining statistical methods.

Tab. 10: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-0.206861
Maximum	18.4000	17.0718
Mean	4.0000	4.03578

Variance	26.9256	24.5676
Standard Deviation	5.1889	4.95657
Quartile Deviation	2.1000	1.15172
Median Deviation	2.1300	1.14893
Mean Deviation	3.9159	3.68003

As seen in Figure 14, the inflation in Poland predicted for the following month in terms of copper and aluminum prices is 4.19671 %. This prediction indicates a decline in inflation compared to the preceding month and indicates the direction of inflation in Jun 2024.

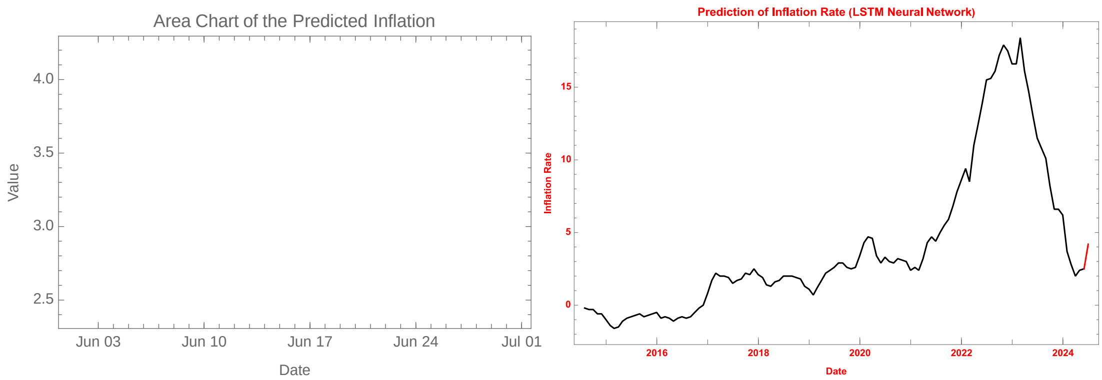

Fig. 14: Box plot of predicted inflation for the following month / Line graph of predicted inflation for the following month

Inflation based on the aluminum and zinc prices

The application of zinc and aluminum prices for predicting inflation. The neural network analysis shows a strong correlation between zinc and aluminum prices and inflation with a lag of 19 trading days. Among the 5 neural networks under study (as seen in Table 11), 5NN19 stands out with its accuracy and a correlation coefficient of 0.983614. The high accuracy is achieved due to the unique activation function combining Sin, Ramp, and ArcTan.

Tab. 11: Basic settings of network performance and parameters

Network	Performance	Activation Function *1*	Activation Function *2*	Activation Function *3*
1NN19	0.964181	Sin	ArcTan	Ramp
2NN19	0.982839	Ramp	Sin	Sin
3NN19	0.96434	Ramp	Sin	Ramp
4NN19	0.971993	Sin	ArcTan	Sin
5NN19	0.983614	Sin	Ramp	ArcTan

Figure 15 shows the real inflation in Poland and the predicted inflation generated by all 5 neural networks, comparing the most accurately predicted values of the inflation and the real inflation.

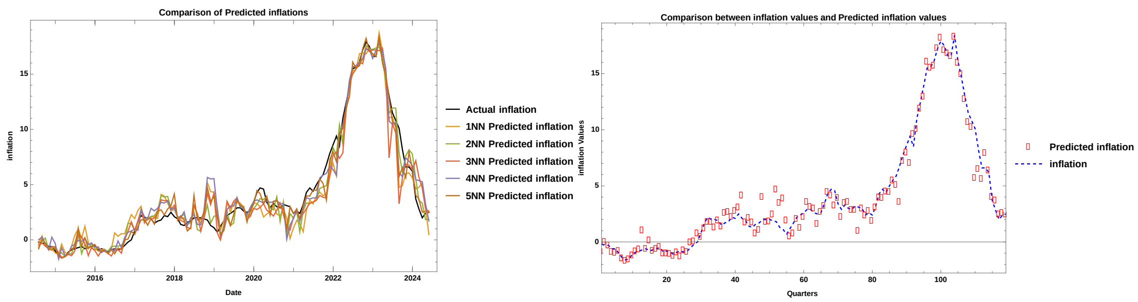

Fig. 15: Comparison of real and predicted inflation / Comparison of real and most accurately predicted values of inflation

The conditional distribution of real inflation and predicted inflation presented in Table 12 shows minimum differences, with the differences between the minimum and maximum values being almost identical for both cases. This similarity indicates high accuracy, which increases the model's predictive ability and ensures accurate predicted values.

Tab. 12: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-1.6557
Maximum	18.4000	18.3223
Mean	4.0000	3.96872
Variance	26.9256	25.6969
Standard Deviation	5.1889	5.06921
Quartile Deviation	2.1000	1.86811
Median Deviation	2.1300	1.86868
Mean Deviation	3.9159	3.66503

As seen in Figure 16, the inflation in Poland predicted for the following month based on zinc and aluminum prices is 1.64201 %. The prediction suggests a decline in inflation compared to the preceding month and shows the direction of inflation in the following month, June 2024.

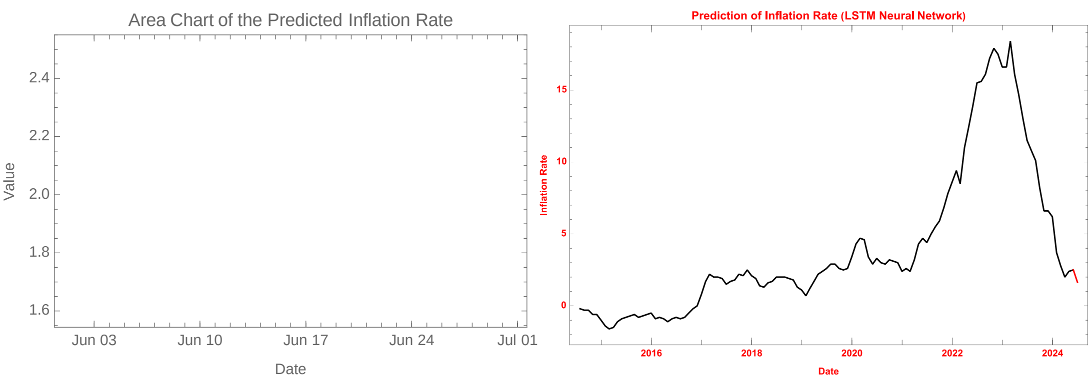

Fig. 16: Box plot of predicted inflation for the following month / Line graph of predicted inflation for the following month

Inflation predicted based on zinc, copper, and aluminum prices

The application of aluminum, zinc, and copper prices for predicting inflation: The neural network analysis shows a strong correlation between the aluminum, copper, and zinc prices with a lag of 19 trading days. Among the 5 analyzed neural networks (see Table 13), 2NN19 stands out with its high accuracy and a correlation coefficient of 0.99876. The high accuracy is achieved due to the unique activation function combining Ramp, Sin, and Sin.

Tab. 13: Basic settings of network parameters and performance

Network	Performance	Activation Function *1*	Activation Function *2*	Activation Function *3*
1NN19	0.997956	ArcTan	ArcTan	Ramp
2NN19	0.99876	Ramp	Sin	Sin
3NN19	0.99727	ArcTan	Ramp	Sin
4NN19	0.996278	Sin	ArcTan	ArcTan
5NN19	0.986972	Sin	Sin	Sin

Figure 17 shows the real inflation in Poland and predicted inflation generated by all 5 neural networks, comparing the most accurately predicted inflation values and real inflation.

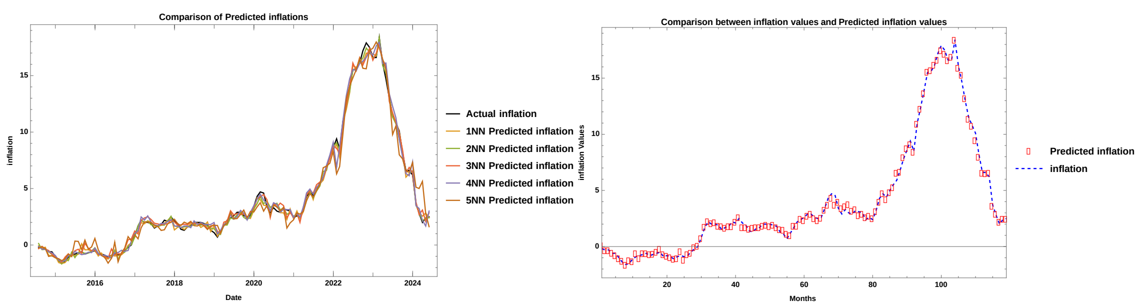

Fig. 17: Comparison of real and predicted inflation / Comparison of real inflation with the most accurately predicted inflation

The conditional distribution of real inflation and predicted inflation is presented in Table 14. The conditional distribution of real inflation and predicted inflation shows minimum differences, with the difference between the minimum and maximum values being nearly identical. This similarity indicates a high accuracy, which increases the predictive abilities of the model and ensures accurate values. This combination of metal commodities shows the highest accuracy of 99.87%.

Tab. 14: Conditional distribution of real and predicted inflation

Description	Inflation	Inflation-LSTM NN Prediction
Minimum	-1.6000	-1.67414
Maximum	18.4000	18.3672
Mean	4.0000	3.94573
Variance	26.9256	26.5363
Standard Deviation	5.1889	5.15134
Quartile Deviation	2.1000	2.00429
Median Deviation	2.1300	2.15315
Mean Deviation	3.9159	3.8649

As seen in Figure 18, the inflation in Poland predicted based on the prices of aluminum, zinc, and copper for the following month is 2.7342 %. This prediction suggests a decline in inflation compared to the preceding month and shows the direction of inflation in June 2024.

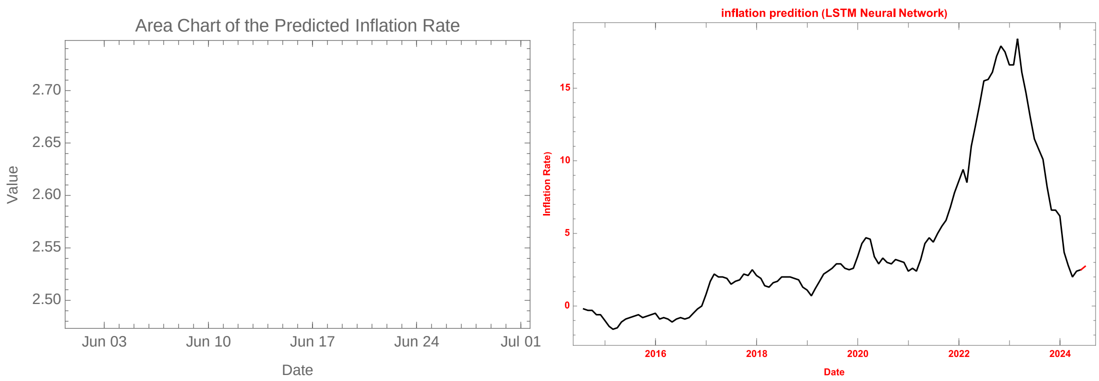

Fig. 18: Box plot of predicted inflation for the following month / Line graph of predicted inflation for the following month

By comparing the accuracy of the predicted inflation values based on combining metal commodities, it is possible to make the most accurate prediction for the following month. The accuracy of the predicted inflation values made based on metal commodities prices is presented in Table 15.

Tab. 15: Comparison of accuracy

Metal Commodity	Accuracy	Predicted Value
Zinc	0.864306	3.01362
Copper	0.882924	6.82095
Aluminum	0.935586	5.03169
Zinc & Copper	0.991817	2.67190
Zinc & Aluminum	0.983614	1.64201
Aluminum & Copper	0.954526	4.19670
Aluminum & Copper & Zinc	0.998760	2.73420

Table 15 provides an in-depth evaluation of the LSTM model's efficiency in predicting inflation based on the prices of various metal commodities and their combinations. The accuracy ranges from 86.43% to a staggering 99.87 %, representing the percentage of correct predictions of the model for each combination commodity. The predicted values representing the model's estimates range from 1.64% to 6.82%. Surprisingly, the combination of aluminum, copper, and zinc shows excellent accuracy, nearly 99.94 %, which explains that the combination of the metal commodity prices impacts the prediction of the inflation rate.

However, when we look at the highest accuracy, with 99 %, we can see that the combination of zinc and copper prices and the combination of all three commodities have a higher impact on the prediction of Poland's inflation. The predicted inflation for these two combinations is almost nearly equal. This shows that Poland's inflation will increase by approximately 0.2342% next month.

Discussion

RQ1: What is the correlation between the development of selected metal commodity prices and the development of the inflation rate in Poland?

The response to the first research question can be found in the section presenting the results, where the course of the zinc, copper, and aluminum time series is graphically represented; the tables present historical data on the distribution of the real and predicted inflation rate about individual metal commodity prices and their combinations. The time series from July 2014 to May 2024 was considered for the inflation rate. The results confirmed the assumption that neural networks with the LSTM layer and considered 19-day lag are most suitable for predicting the development of future selected metal commodity prices.

The combination of aluminum, zinc, and copper prices turned out to be the most accurate way to predict the inflation rate in Poland. For the inflation rate, NN provides results in the form of a correlation coefficient with a lag of 19 trading days. From the five neural networks specified above, 2NN19 (see Table 13) provides the most accurate results (0.99876). In terms of the activation function, a combination of Ramp, Sin, and Sin was used.

The results indicate that the price development of the selected metal commodities is strongly correlated with the development of the inflation rate in Poland. This statement is based on the finding that the time series used combined with neural networks showed very high prediction accuracy. The values of the predicted inflation rate in Poland range between 1.64% and 6.82%, with a combination of aluminum, copper, and zinc showing the highest accuracy. The predicted inflation rate for Poland for June 2024 is 2.6719%, increasing as compared to the previous month. In conclusion, it can be stated that despite the considerable volatility of the predicted values of the inflation rate in Poland, the prediction of selected commodity prices can be very reliably linked with the development of the Polish economy using the given macroeconomic indicator (inflation rate).

RQ2: Which of the selected metal commodities is most closely linked with the macroeconomic indicator of the inflation rate in Poland?

The largest part of the research deals with predicting the inflation rate in Poland based on the development of aluminum, zinc, and copper prices using neural networks. The obtained data are presented in tables and then graphically illustrated. In the case of Poland, the highest accuracy from individually selected metal commodities and their linking with the inflation rate predicted using the neural network 5NN with a 19-day lag was found in the case of each metal commodity the reliability or the relationship between the predicted and actual values of the inflations have lower values, Zinc, Copper and Aluminium have 86.43%, 88.29%, 93.55% respectively. Each commodity has a positive relationship, but aluminum has a greater impact on inflation values. When we combine the two metals, the accuracy and all commodities increase.

The highest accuracy (0.998760) was achieved in the case of 2NN19 (see Table 13), predicting the inflation rate for Poland for June 2024 at the level of 2.7342% based on combining Aluminum, zinc, and copper. The combination of Zinc and Copper shows the second-best accuracy (0.991817) in the case of 1NN19 (see Table 7), which predicts the inflation rate for Poland to be 2.6719%. These two predicted inflations have more similarities, like the inflation in Poland for the next month, which is going to increase as compared to the previous month.

The observation of Poland's inflation rate over the last few months showed a decreasing inflation. For this reason, the authors consider the combination of aluminum, copper, and zinc to be the most reliable, showing the most realistic values of the inflation rate, assuming a stabilization in the global markets.

Summarising the previous findings, combining all the metal commodities examined showed the highest accuracy. In conclusion, it can be confirmed that the development of the inflation rate in Poland can be very accurately predicted based on aluminum, zinc, and copper prices in the global market.

Conclusions

The objective of the paper was to link the development of predicted prices of selected metal commodities (zinc, copper, and aluminum) with the development of a macroeconomic indicator in Poland, specifically Poland's inflation rate. After a turbulent development, the Polish economy has shown a decline in the inflation rate over the last few months. The highest accuracy of 99.87% was achieved in the case of combining aluminum, copper, and zinc, with a predicted inflation rate of 2.73 %, which is predicted to increase in June 2024. The predicted values, representing the model's estimates, range from 1.64% to 6.82%. The prediction of the inflation rate development in Poland made using LSTM neural networks showed very high accuracy in certain combinations of the selected metal commodities. However, the predicted values show a very wide range due to the considerable volatility of the inflation rate in recent years caused by the COVID-19 pandemic and the war in Ukraine.

The observation of Poland's inflation rate over the last few months showed a decreasing inflation. For this reason, the authors consider the combination of aluminum, copper, and zinc to be the most reliable, showing the most realistic values of the inflation rate, assuming a stabilization in the global markets. The research goal was achieved, which is also confirmed by the results of the application part, indicating the relation of the prices of selected metal commodities (copper, zinc, and aluminum), including their combinations, to the selected macroeconomic indicator of the inflation rate of Poland. The research also predicts the nearest possible development of this macroeconomic indicator.

These findings are also confirmed by Wilczynski (2020), who states that the selected engineering metals have a wide range of industrial applications due to their physical, chemical, or mechanical properties. Metallurgy is considered a key industry of any country's economy, and it is an important sector of heavy industry, as it is strategically important for arms production and other industries and services. More accurate results could be obtained if more detailed data with a longer time series were used in a more open economy. In evaluating the Polish economy, the authors consider the use of the data sufficient within the European market. Potential further research could focus on larger territories and longer time series.

References

Abbas, S. K., & Lan, H. (2020). Commodity price pass-through and inflation regimes. ENERGY ECONOMICS, 92, 104977. https://doi.org/10.1016/j.eneco.2020.104977

Alcidi, C., Gros, D., & Shamsfakhr, F. (2021). Inflation Expectations: Models and Measures. POLITICA ECONOMICA, 37(3), 389–406.

Baffes, J., & Kabundi, A. (2023). Commodity price shocks: Order within chaos? Resources Policy, 83, 103640. https://doi.org/10.1016/j.resourpol.2023.103640

Belas, J., Gavurova, B., Dvorsky, J., Cepel, M., & Durana, P. (2022). The impact of the COVID-19 pandemic on selected areas of a management system in SMEs. ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA, 35(1), 3754–3777. https://doi.org/10.1080/1331677x.2021.2004187

Belas, J., Ivanova, E., Rozsa, Z., & Schonfeld, J. (2018). Innovations in SME Segment: Important Factors and Differences in The Approach by Size and Age of the Company. TRANSFORMATIONS IN BUSINESS & ECONOMICS, *17*(3), 55-71.

Bilan, Y., Gavurova, B., Stanislaw, G., Tkacova, A. (2017). The Composite Coincident Indicator (CCI) for Business Cycles. ACTA POLYTECHNICA HUNGARICA, 14(7), 71–90. https://doi.org/10.12700/aph.14.7.2017.7.5

Bobeica, E., & Hartwig, B. (2023). The COVID-19 shock and challenges for inflation modelling. INTERNATIONAL JOURNAL OF FORECASTING, 39(1), 519–539. https://doi.org/10.1016/j.ijforecast.2022.01.002

Ciner, C. (2011). Commodity prices and inflation: Testing in the frequency domain. Research in International Business and Finance, 25(3), 229–237. https://doi.org/10.1016/j.ribaf.2011.02.001

Coibion, O., Gorodnichenko, Y., Kumar, S., & Pedemonte, M. (2020). Inflation expectations as a policy tool? JOURNAL OF INTERNATIONAL ECONOMICS, 124, 103297. https://doi.org/10.1016/j.jinteco.2020.103297

Ejdys, J., Ginevicius, R., Rozsa, Z., & Janoskova, K. (2019). The Role of Perceived Risk and Security Level in Building Trust in E-government Solutions. E+M EKONOMIE A MANAGEMENT, *22*(3), 220-235. doi:10.15240/tul/001/2019-3-014

Fasanya, I. O., & Awodimila, C. P. (2020). Are commodity prices good predictors of inflation? The African perspective. RESOURCES POLICY, 69, 101802. https://doi.org/10.1016/j.resourpol.2020.101802

Gao, X., Ren, Y., & Li, X. (2021). Time Variation or Asymmetry? The Inflation and Inflation Uncertainty Nexus: A Case of China. SINGAPORE ECONOMIC REVIEW, 66(03), 881–903. https://doi.org/10.1142/S0217590819500760

Ha, J., Kose, M. A., & Ohnsorge, F. (2022). Global Stagflation (SSRN Scholarly Paper 4131943). https://doi.org/10.2139/ssrn.4131943

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. NEURAL COMPUTATION, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Charemza, W., Makarova, S., & Shah, I. (2015). Making the most of high inflation. APPLIED ECONOMICS, 47(34–35), 3723–3739. https://doi.org/10.1080/00036846.2015.1021462

Jedruchniewicz, A. (2013). Fulfillment of the Inflation Target in Poland. OECONOMIA COPERNICANA, 4(3), 5–21. https://doi.org/10.12775/OeC.2013.020

Kelm, R., & Pellegrini, I. S. (2023). Imported Inflation and the Wage-Price Nexus in Poland. GOSPODARKA NARODOWA-THE POLISH JOURNAL OF ECONOMICS, 315(3), 48–70. https://doi.org/10.33119/GN/169436

Kliber, A., Szyszko, M., Prochniak, M., & Rutkowska, A. (2023). Impact of uncertainty on inflation forecast errors in Central and Eastern European countries. EURASIAN ECONOMIC REVIEW, 13(3–4), 535–574. https://doi.org/10.1007/s40822-023-00237-9

Kliber, A., Szyszko, M., Próchniak, M., & Rutkowska, A. (2023). Impact of uncertainty on inflation forecast errors in Central and Eastern European countries. Eurasian Economic Review, 13(3), 535–574. https://doi.org/10.1007/s40822-023-00237-9

Kopych, R., & Shevchuk, V. (2024). Time-Varying Impact of Commodity Prices on Output Growth and Inflation in the Eastern European Countries. COMMODITIES, 3(1), Article 1. https://doi.org/10.3390/commodities3010002

Liu, Y., Su, Z., Li, H., & Zhang, Y. (2019). An LSTM based classification method for time series trend forecasting. PROCEEDINGS OF THE 2019 14TH IEEE CONFERENCE ON INDUSTRIAL ELECTRONICS AND APPLICATIONS (ICIEA 2019), 402–406. https://www.webofscience.com/wos/woscc/full-record/WOS:000555952600074

Maliszewski, W. (2008). Credibility of Inflation Targets in Poland. COMPARATIVE ECONOMIC STUDIES, 50(3), 494–510. https://doi.org/10.1057/ces.2008.25

Mandalinci, Z. (2017). Forecasting inflation in emerging markets: An evaluation of alternative models. INTERNATIONAL JOURNAL OF FORECASTING, 33(4), 1082–1104. https://doi.org/10.1016/j.ijforecast.2017.06.005

Mindrican, I. M., & Matei, E.-F. (2021). The Evolution of Inflation in the Context of the COVID-19 Pandemic. In A. M. Dima (Ed.), RESILIENCE AND ECONOMIC INTELLIGENCE THROUGH DIGITALIZATION AND BIG DATA ANALYTICS (s. 432–440). Sciendo. https://doi.org/10.2478/9788366675704-043

Ostroski, D., Slovenec, K., Brajdic, I., & Mikuc, M. (2021). Anomaly Correction in Time Series Data for Improved Forecasting. In M. Antonic & J. Babic (Ed.), PROCEEDINGS OF THE 16TH INTERNATIONAL CONFERENCE ON TELECOMMUNICATIONS (CONTEL 2021) (s. 85–88). IEEE. https://www.webofscience.com/wos/woscc/full-record/WOS:000698760300017

Polbin, A. V., Andreyev, M. Y., & Zubarev, A. V. (2018). How Commodity Prices Influence the Members of the Eurasian Economic Union. Economy of Region, 14(2), 623–637. https://doi.org/10.17059/2018-2-23

Sekine, A., & Tsuruga, T. (2018). Effects of commodity price shocks on inflation: A cross-country analysis. Oxford Economic Papers, 70(4), 1108–1135. https://doi.org/10.1093/oep/gpy015

Sinicakova, M., Gavurova, B. (2017). Single Monetary Policy versus Macroeconomic Fundamentals in Slovakia. EKONOMICKY CASOPIS, 65(2), 158–172.

Sinicakova, M., Sulikova, V., Gavurova, B. (2017). Twin deficits threat in the European Union. E&M EKONOMIE A MANAGEMENT, 20(1), 144–156. doi: 10.15240/tul/001/2017-1-010

Szyszko, M. (2015). Inflation Forecasts Versus Shaping Inflation Expectations. Comparative Analysis. Comparative Economic Research. CENTRAL AND EASTERN EUROPE, 18(4), Article 4. https://doi.org/10.1515/cer-2015-0033

Szyszko, M., & Tura, K. (2015). Can Inflation Forecast and Monetary Policy Path be Really Useful? The Case of the Czech Republic. EQUILIBRIUM-QUARTERLY JOURNAL OF ECONOMICS AND ECONOMIC POLICY, 10(3), 9–26. https://doi.org/10.12775/EQUIL.2015.022

Tkacova, A., & Gavurova, B. (2023). Economic sentiment indicators and their prediction capabilities in business cycles of EU countries. OECONOMIA COPERNICANA, 14(3), 977–1008. https://doi.org/10.24136/oc.2023.029

Vochozka, M., Kalinova, E., Gao, P., Smolikova, L. (2021). Development of copper price from July 1959 and predicted development till the end of year 2022. ACTA MONTANISTICA SLOVACA, 26(2), 262-280. https://doi.org/10.46544/AMS.v26i2.07

Wilczynski, P. L. (2020). Metallurgic industry in Europe in the years 1990-2020. PRACE KOMISJI GEOGRAFII PRZEMYSLU POLSKIEGO TOWARZYSTWA GEOGRAFICZNEGO-STUDIES OF THE INDUSTRIAL GEOGRAPHY COMMISSION OF THE POLISH GEOGRAPHICAL SOCIETY, 34(4), 171–183. https://doi.org/10.24917/20801653.344.11

Zivkov, D., Kovacevic, J., & Loncar, S. (2020). Is Inflation a Monetary Phenomenon in the East European Economies? - Multifrequency Bayesian Quantile Inference. EKONOMICKY CASOPIS, 68(8), 787–810. https://doi.org/10.31577/ekoncas.2020.08.02