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Evaluation and prediction of polyolefin price development

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Abstract

Over the past three years, many unprecedented events have happened which have significantly influenced the whole world. This paper deals with several topical issues, such as the impact of the coronavirus pandemic on Brent's oil prices, on the price of plastics, specifically polyolefins, i.e., polyethene and polypropylene, price trends of petroleum products, in different crisis periods from 2006 to the present and predicts the price trend of petroleum products (polyolefins) using artificial intelligence. In the application part of the research, the following research methods were used: time series regression using neural networks and correlation and regression analysis. Neural networks confirmed a significant effect of the coronavirus pandemic on Brent's oil price. Correlation analysis showed a long-term comparable trend in the development of Brent oil and polyolefin prices, which is a confirmation of the significant impact of COVID-19 on the price of polyethene and polypropylene. The greatest benefit of this research for the application sphere is the prediction of the price development of polyolefins. All generated variants of the ANS neural network module predict a decreasing trend of polypropylene and polyethene prices until the end of 2023. The conducted research on the prices of polyolefins is a unique study with practical benefits for companies producing the most in-demand material in the world – plastic. Analysing and predicting the price development of the commodities under study can be useful for entities in their strategic assessment and subsequent investment decisions. A limitation of the research is the ongoing war conflict in Ukraine, as the oil market is sensitive to political conflicts and becomes difficult to control and predict.

Keywords

Oil, polyolefin, prediction, price trend, neural networks, COVID-19, war in Ukraine

Introduction

The coronavirus disease COVID-19 began to spread from China to the rest of the world at the beginning of 2020 (Luo et al., 2021) and affected all areas of our lives within a few weeks (Svabova et al., 2021; Kramarova et al., 2022). The coronavirus crisis significantly hindered the global economy and started the process of deglobalisation; industrial production was disrupted, demand was reduced, and the economic slowdown led to commodity imbalance (Privara, 2022; Zhao et al., 2023). We can state that economic instability was a major consequence of the pandemic. The impact of the pandemic was very noticeable. The effect of the war conflict between Russia and Ukraine may be even more noticeable (Fiszeder & Małecka, 2022). Despite this, we remain a rich and consumer civilisation, and overconsumption rapidly reduces the planet's limited resources (Megevand et al., 2022). The behaviour of contemporary society leads to considerations about which resources we will leave to future generations. Researchers dealing with the relationship between a successful business and sustainable corporate behaviour have concluded that sustainability measures bring stable investments, improve the company's image, and increase the whole company's value (Kasych & Vochozka, 2018; Matuszewska-Pierzynka, 2021; Valls Martínez et al., 2022). One of the areas that may significantly influence sustainable development is the petrochemical industry. The raw material base of the petrochemical industry is oil. Oil is being processed increasingly, but the resources are limited (Sun et al., 2022).

Oil has a dominant position in the market, not only as a source of energy but also as an important raw material for producing many industrial products, such as pesticides, fertilisers, and solvents. Its daily consumption equals approximately 93 million barrels (Vochozka et al., 2020). Oil is an essential resource in the production of plastics. An important attribute of plastics related to sustainability is their recyclability. Polyolefins represent plastics that are relatively environmentally friendly. Polyolefins, in particular polyethene and polypropylene, account for more than 50 % of the volume of manufactured polymers. The properties that distinguish polyolefins from other commodity plastics include low price and low toxicity, and they meet the requirements of sustainable development and green polymer chemistry (Sauter et al., 2017). The astronomical increase in the use of plastics for industrial applications started in 1920 (Babafemi et al., 2018). Plastics refer to a large group of materials that are based on macromolecular polymers (Wang et al., 2020).

In the context of the economic instability caused by the coronavirus pandemic, businesses are facing an energy crisis and, due to international political disputes, also uncertainty in oil supplies. These factors influence supply, demand, and commodity prices. This paper aims to determine the impact of the coronavirus pandemic on Brent's oil price and the prices of oil products - polyolefins, to compare the price trends of oil and polymers in various crisis periods from the year 2006 to the present and predicts the price development of polyolefins. Polyolefins account for more than 50 % of the global demand for plastics. Predicting the price trends of this material in the world oil market is useful for industries using plastics in their production. The objective will be achieved by answering the following four research questions.

The first research question deals with the negative impacts of the coronavirus pandemic on the balance of commodities, especially oil, as currently one of the most important and scarcest commodities.

RQ1: Did the coronavirus pandemic cause the oil price fluctuations?

Given the fact that oil is the basic input raw material for the production of polyolefins, it can be assumed that their price is affected by the pandemic to a similar extent as the price of oil. The correctness of this assumption is verified using the second research question.

RQ2: Does the price trend of polyolefins copy the trend of the oil prices?

About the coronavirus pandemic, the Organization for Economic Cooperation and Development warns of a global economic recession (Algamdi et al., 2021). The coronavirus pandemic started in the year 2020 (Luo et al., 2021). In February 2022, the crisis related to the coronavirus pandemic was deepened by the war conflict in Ukraine. The previous economic recession affecting the whole world began in 2006 (Wallace et al., 2022). The third research question aims to determine whether these economic crises have a similar development.

RQ3: Are the price trends of polyolefins in the periods of great recession, the coronavirus pandemic, and the war conflict in Ukraine comparable?

Polyolefins account for more than half of the global demand for plastics. Determining possible future prices of this commodity is particularly useful for industries for which plastics represent an essential material. The last research question examines whether it is possible to predict future development.

RQ4: Is it possible to predict the future price development of polyolefins based on available information?

Literature Review

For effective decision-making and subsequent solutions in the COVID-19 pandemic caused by a new pathogen, it is necessary to continuously collect, consolidate, and evaluate data and evidence concerning the disease. One of the basic tasks of the WHO (World Health Organization) is to shape the research agenda and provide valuable information about COVID-19 (Azim et al., 2022; Liu et al., 2021).

The long-lasting COVID-19 pandemic has affected all areas of society, including industry, economy, education, and culture (Min et al., 2022; Gavurova et al., 2022a; Idris et al., 2022). The spread of the highly contagious coronavirus has significantly affected the global economy in two dimensions. The first dimension is health, which is characterised by many dead and infected persons, accentuated by persistent mutations of the virus. The second dimension is the disrupted economy and its further development (Katsampoxakis et al., 2022; Kelemen et al., 2022).

The regression analysis confirmed the negative effect of the health situation, especially the number of persons with COVID-19 and the number of deaths associated with COVID-19, on economic growth (Ghecham, 2022; Landmesser, 2021; Svatosova, 2022). The correlation analysis used in the study "The effects of COVID-19 on the interrelationship among the oil prices, stock prices, and exchange rates in selected oil exporting economies" proved that stock prices of almost all countries exporting oil decreased significantly; the oil price shocks caused negative exchange rate responses and the sharp decline in the oil prices caused currency devaluation in the oil-producing economies under study (Kumeka et al., 2022; Kuzmenko et al. 2023).

Using regression analysis, the effect of the COVID-19 pandemic on the GDP of European countries was demonstrated (Zamfir & Iordache, 2022; Gavurova et al., 2023). After repealing restrictions introduced to stop the spread of the pandemic, European governments applied various tools to stimulate consumption and restore economic growth. However, these measures only slowed down the sharp decline in GDP temporarily. In the long term, the lockdowns, tax relief, and increased state social support represent an unsustainable situation leading to an economic crisis (Mourão & Popescu, 2023; Janková, 2023). Eurostat data from 27 EU countries were processed using multiple linear regression, which confirmed the significant negative effect of COVID-19 on GDP growth, public debt growth, and the government deficit (Adina & Dumitru-Cristian, 2022). The development of GDP in the Eurozone was assessed using MIDAS regression analysis in the period when the first significant decline in GDP was observed in the Eurozone during the COVID-19 pandemic at the end of March 2020. The decrease was a consequence of the WHO announcement on 11 March 2020, when the epidemic was declared a pandemic. This was followed by lockdowns, and stock prices declined significantly (Ferrara et al., 2022). MIDAS regression analysis also confirms a significant effect on the Chinese economy, whose share of world GDP accounted for 16 % in 2019 (Gunay et al., 2021). According to the results of the regression analysis, the real impact of the COVID-19 pandemic on the GDP in the USA in the second quarter of 2020 was -31.2 % compared to the preceding quarter (Zamfir & Iordache, 2022).

Granger's causality confirmed a strong impact of the COVID-19 pandemic on all markets, including gold and oil prices. The fluctuations in oil prices significantly influenced oil producers, as well as carriers, travel agencies, and manufacturing companies. The application of quantile regression showed the sensitivity of the Iranian stock market to the oil prices, unlike the global gold prices, which do not significantly affect stock returns (Zeinedini et al., 2022). The quantile regression model confirmed the ability to identify an asymmetric relationship between financial and economic variables. Granger causality using the vector autoregressive (VAR) model identified the COVID-19 pandemic as a factor causing changes in oil prices both directly and indirectly (Tuna & Tuna, 2022).

Consumer expenditure around the world has fallen dramatically due to the restrictions taken, including travel restrictions, closure of schools, suspending full operation of plants, or social isolation. A Fuzzy Logic Time Series model combined with RMSE and MAE methods showed that pandemic-related deaths influence the volatility of the oil prices in the range of 8% - 22%; the sharpest drop in the oil prices (25 %) was recorded in the period of the war between Russia and Saudi Arabia (Öztunç Kaymak & Kaymak, 2022). Panel Vector Autoregression PVAR found a 4.3% drop in the global economy caused by the COVID-19 pandemic, which is comparable to the Great Recession and two world wars. The pandemic thus caused panic among investors, leading to a collapse in oil prices (Atif et al., 2021), which fell by nearly 66 % between 24 February and 21 April 2020. The results of the applied Kalman filter confirmed that the stock markets of energy-dependent economies are sensitive to asymmetric price shocks of oil, and large oil importers are more vulnerable to oil shock prices than smaller countries (Refai et al., 2022).

The decrease in oil prices during the pandemic is also addressed in the study by Dey & Das (2022), which used a new air mobility index based on quantile regression modelling. The authors argue that both the travel trend and air mobility significantly influence oil prices. It was confirmed that the lower the mobility, the lower the oil price (Dey & Das, 2022). The Autoregressive Distributed Lag model was used to determine a considerable effect of high economic uncertainty, the expected volatility of stock markets, and speculations in the oil market on oil prices. The autoregressive model also identified a critical factor leading to the oil market's collapse: the Russia-Saudi Arabia oil price war (Le et al., 2021). Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) was used to assess the efficiency of China's new energy market regarding domestic crude oil, international crude oil, gold, the global new energy market, and the US new energy market. Among other things, it was found that the efficiency of China's new energy market is more dependent on domestic crude oil than global crude oil (Fu et al., 2022).

Another study used wavelet coherence and Gaussian graphical model (GGM) to point to a strong medium and long-term causal effect of the COVID-19 pandemic on the oil prices, stock market indices, and economic uncertainty for both oil-importing and oil-exporting countries (Khalfaoui et al., 2022). Atif et al. (2021) used Granger causality and Panel Vector Autoregression (PVAR) to confirm the fall in the oil prices resulting from the COVID-19 pandemic and the fact that both oil-exporting and oil-importing countries were affected similarly, but changes in the oil prices had a greater impact on countries exporting this commodity. The major oil importers (the USA, Great Britain, France, Germany, Canada, and China) faced a slowdown of their economies in key sectors during the COVID-19 pandemic (Kumeka et al., 2022).

The Pearson correlation coefficient and Bayesian NN regressor determined COVID-19 as a driver of commodity price instability, where the results obtained indicate that the prices of gold are more stable and less sensitive than oil Fields (Samee et al., 2022). Non-linear autoregressive distributed lag demonstrated the negative effect of the COVID-19-related crisis on bitcoins, oil, gold, and foreign exchange markets (Tanin et al., 2022). Using Granger causality, Yan et al. (2022) confirmed that the Russian market was more affected by the COVID-19-induced changes in oil prices than the Canadian and US markets. Regression analysis and neural networks demonstrated the dependence of the EUR/USD exchange rate on the oil price (Vochozka et al., 2020).

Oil prices have many characteristics, including randomness, sudden structural changes, intrinsic nonlinearity, volatility, and chaotic nature (Sun et al., 2022). In addition to the COVID-19 pandemic, many other variables affect oil prices, and their prediction is now a very complicated task. There are many methods used to predict oil prices. Generally, data prediction models can be divided into three basic categories. The first category includes traditional econometric models, the second category is models based on artificial intelligence, and the third category consists of hybrid models integrating two or more individual models (Niu et al., 2021).

In traditional models, intuition is often backed by the experience and knowledge of experts. Analysts and economists use data transformation and regression, including the autoregressive moving average models, such as ARMA, ARIMA, or vector autoregressive VAR with varying input values to predict oil costs (Gupta & Nigam, 2020; Gavurova et al., 2022b). Traditional models also include generalised autoregressive conditional heteroskedasticity GARCH, RW, and error correction models ECM. Traditional econometric models require data linearity, which is a limitation for making predictions using non-linear and non-stationary toil price data (Niu et al., 2021; Tkacova & Gavurova, 2023).

The models based on artificial intelligence include Artificial Neural Networks (ANN) or Support Vector Machines (SVM) (Öztunç Kaymak & Kaymak, 2022). SVM was developed by Vladimir Vapnik for the application of non-linear classification or regression problems. Widely used artificial intelligence algorithms include Least Squares Support Vector Regression, Generalised Regression Neural Network GRNN, and genetic algorithm neural network GANN (Niu et al., 2021).

The study entitled "Forecasting Crude The Oil Prices with WT-FNN Model" uses a three-layer FNN neural network based on backpropagation of error algorithms for data processing. It is a combination of a stochastic time-efficient function and an FNN model. Bartoš et al. (2022) proved that neural network 1NN30L with an LSTM layer and 30-day lag is the most suitable network for predicting future prices of copper. Based on the prediction, copper prices will decrease in 2021, and the trend will be stable in the next period.

Gupta & Nigam (2020) recommend predicting oil prices using artificial neural network ANN as a modern, innovative, and reliable tool. The authors see the advantages of using neural networks in generalising inputs and inferring relationships without the need to create strong links. Artificial neural networks represent a system that attempts to imitate the architecture of the biological neural networks of the human body with a high number of nodes (neurons) and connections. The purpose of neural networks is to construct an output model based on an input model. ANN model is based on two key phases: the training and test phases. In the training phase, inputs are received by neurons through their input connections. In the test phase, the system's performance is tested using a part of the input data, and the predicted and actual data are compared. The main benefit of the ANN model is its ability to solve sophisticated problems (Maleki et al., 2020). An even better tool for predicting oil prices is artificial neural networks with an integrated LSTM.

Vochozka et al. (2020) used a neural network consisting of 11 layers (1 input layer, 1 output layer, and 9 hidden layers). The input layer of neurons is a matrix providing information about the previous oil prices. For prediction, 400 neural networks were generated for each of the three datasets of the input oil prices, i.e., a total of 1,200 neural networks, which were compared using the Pearson correlation coefficient. The study showed that all selected neural networks can be successfully used to predict the future development of Brent oil prices.

Another method, BOP-BL, uses a framework based on the Bi-LSTM network and the BOP dataset for predicting Brent oil prices. The BOP dataset provides a time series of daily oil prices, including the date and price. The Bi-LSTM module filters and further processes the information from the BOP dataset. Empirical analysis in the study Brent Oil Prediction Using Bi-LSTM Network confirms the high efficiency of sequence-based models such as Bi-LSTM or LSTM (Vo et al., 2020).

Prediction of oil prices is a very complex problem due to the nonlinearity and chaos. The method using ANN neural network combined with support vector machine SVM, based on fuzzy logic and fuzzy time series, can capture and evaluate chaotic and non-linear behaviour of daily prices of oil and thus prepare investors and speculators for fluctuations in the oil prices (Öztunç Kaymak & Kaymak, 2022).

The LSTARGARCHLSTM hybrid modelling technique derived from the LSTARGARCH model and the LSTM method represents a considerable improvement in time series forecasting and aims to capture and evaluate the chaotic and non-linear evolution of oil prices. This forecasting method applies the GARCH and ARCH models on oil prices in two regimes where the regime transitions are governed by a smooth LSTAR-type transition (Bildirici et al., 2020).

Niu et al. (2021) introduced VMD-KELM as a hybrid forecasting model based on VMD (variational mode decomposition and kernel extreme learning machine (KEML). The application of the model consists of three main processes: specifically, data decomposition using the VMD method, individual forecasting using the KELM algorithm, and the integration of results using linear aggregation. The advantage of KELM is that it provides a quality predictive ability, is less time-consuming, and is less sensitive to parameters. Compared to other models, the VMD-KELM model shows high reliability not only in oil price forecasting but also in predicting volatility. It has been found that business strategies based on a new system of DSS (Decision Support System) can reduce and eliminate losses incurred during market downturns, even during the COVID-19 pandemic (Tudor & Sova, 2022).

The DSS is based on the proven ARMA or GARCH models. DSS uses computational intelligence to integrate a dynamically optimised forecasting process for algorithmic trading with Brent and WTI oil in the markets. DSS includes seven main phases. The local projection method used to estimate impulse response functions confirmed that a significant decline usually follows a pandemic shock in production and trade. The impact of a pandemic on the current account is different in developed economies, where it improves the balance, and in developing economies, where it worsens the current account balance. The business effects of COVID-19 are qualitatively comparable to the impacts of previous shocks (Jalles & Karras, 2023).

Material and Methods

The research uses ICIS data for the period January 2006 - February 2023 with a weekly interval. ICIS provides price information services used in trading with chemical and energy products. ICIS stands for Independent Commodity Intelligence. Information provided by ICIS helps in making strategic decisions and can mitigate the risks associated with market development (INDEPENDENT CHEMICAL & ENERGY MARKET INTELLIGENCE, 2022). Following the research questions, the data will be processed using the research methods specified below.

The answer to RQ1 will be found using neural networks, the ANS module, and time series regression analysis. This prediction method is one of the advanced methods of artificial intelligence. The same method has been used to answer a similar question by many experts, such as Kumeka et al. (2022), Katsampoxakis et al. (2022), and Zamfir & Iordache (2022). The research analyses the data on Crude Oil ICE Brent between 2006 and the outbreak of COVID-19, i.e., 31 December 2019, given in USD/bbl in the ICIS reports. The analysis is carried out on the principle of a prediction made using the analytic system TIBCO Statistica 14.0.015. Historical data on Brent oil prices represent an input layer or matrix. The output of the regression analysis is the prediction of Brent oil prices for the period during the COVID-19 pandemic.

The specific setup of the analysis is as follows: When selecting variables, the historical price of Brent oil is selected as the output and the Date as an input. The neural network's performance depends on the degree of generalisation into unseen data used during the training. To achieve a better network performance, the data is divided into three groups (datasets) for training networks, testing the performance of the networks during the training and validating the ability to predict new values. For data processing, the random sampling method is used. The data distribution is as follows: 70 % training dataset, 15 % test dataset, and 15 % validation dataset. The number of random samples is 1,000. The number of time steps used for inputs is 1; the number of forward steps is also 1. The output is the models of multilayer perceptron network MLP. To ensure the proper functionality of MLP, it is necessary to set activation functions for hidden neurons and output neurons. In our case, the activation functions for both groups of neurons are Identity, which ensures the output of neurons in the interval of $(-\infty, \infty)$, Logistic, which uses sigmoid, S-shape curve, with the output in the interval of (0, 1), Hyperbolic tangent with the output interval of (-1, 1), Negative exponential function with the output interval of $(0, \infty)$, Sine with the interval of the output values of (-1, 1). The result of the prediction is compared with the actual price. The period of COVID-19 is the time interval from 1 January 2020 – to 23 February 2022. For clarification of the interval, the first infected and dead persons infected with COVID-19 were recorded by the WHO on 3 January 2020. Although the COVID-19 pandemic officially ended in May 2023, this research must clearly distinguish between the pandemic's effect and the war conflict's effect on oil prices. Therefore, the time interval ends on 23 February 2022. Since 24 February 2022, the Russian-Ukrainian war has significantly influenced the price of oil and other commodities.

The answer to RQ2 will be found using correlation analysis, which will be used to determine the relationship of two different price time series - polyolefins and oil. The data used are weekly price information, specifically from the ICIS reports and Polyethylene (Europe) and Polypropylene (Europe) reports. Data used for research are mentioned in the report under the terms Polyethylene, HDPE, DOMESTIC PRICES, PE HDPE Injection, FD EU, Price Range, minimum value in EUR/t; Polypropylene, a minimum value of PP Homopolymers Injection FD EU in EUR/t in the section PP DOMESTIC PRICES; Crude Oil ICE Brent. The oil price needs to be converted from USD/bbl to EUR/t to be unified with the compared price unit of polyolefins. To convert the units, it is necessary to convert USD/bbl to EUR/bbl first, which requires knowledge of the historical exchange rates of EUR/USD. The data source is the European Central Bank web portal (*EXR.D.USD.EUR.SP00.A | ECB Data Portal*, n.d.).

The data selection covers the period from 1 January 2006 to the Transformation Period-to-Period change. Daily data are downloaded in the format CSV – character separated, then converted into xls format, and paired with weekly data using the function SVYHLEDAT. In the second stage of converting price units of Brent oil from EUR/bbl to EUR/t, it is necessary to know the conversion coefficient of barrel vs ton, which can be found in the Rigzone calculator (Zamfir & Iordache, 2022). For the correctness of the conversion, it is necessary to select Fluid Conversions and convert Barrel (Petroleum)(bbl) into Tonne of Oil Equivalent(toe). The result is as follows: 1 Barrel = 0.1363636 Tonne of Oil. The resulting price in EUR/t is determined as a quotient of the oil price in EUR/bbl and the determined coefficient.

The COVID-19 pandemic was a cause of the global economic crisis. This economic crisis was deepened by the war conflict in Ukraine. The previous global economic crisis was caused by the Great Recession, which started in 2006. RQ3 aims to determine whether the trend of the polyolefin price development is similar in individual crises. The answer is found using a regression analysis of polyolefin price time series and data obtained from the ICIS reports, specifically Polyethylene (Europe) and Polypropylene (Europe) reports. The data used for the research is mentioned in the reports under the terms Polyethylene, HDPE, DOMESTIC PRICES, PE HDPE Injection, FD EU, Price Range, a minimum value in EUR/t, and Polypropylene (Europe), minimum value PP Homopolymers Injection FD EU in EUR/t in the section PP DOMESTIC PRICES. The assessed time intervals of the development of PE and PP prices are as follows: 1 July 2006 – 31 August 2008, related to the Great Recession, the beginning of which is considered to be the outbreak of the US subprime mortgage crisis.

It is a period of approximately the same length as in the case of the period considered in connection with the crisis during the COVID-19 pandemic. This shortened period is used to determine the development trend, although the end of the Great Recession is officially the year 2015. The second time interval is from 1 January 2020 to 23 February 2022, which is related to the COVID-19 pandemic, with the first infected person being recorded by the WHO on 3 January 2020. The third interval to be considered is 24 February 2022 – 17 February 2023, related to the war in Ukraine.

RQ4 will be answered using the model of neural networks. The data containing polyolefin prices are non-stationary and non-linear. The most suitable method of processing them into a price prediction appears to be artificial intelligence, specifically the ANS neural network module. The neural network's task is to model the relationship between the input and output values using a suitable mathematical function. ANS will be used to generate, train, and test neural networks for predicting future values.

The selected network best represents the relationship between the input and output variables, i.e., polyolefin prices. The neural network's performance is measured according to the degree of the generalisation of unseen data, i.e., how well it can predict data that were not used in the training. The outputs of the ANS analysis are multilayer perceptron neural networks and MLP. The prediction is based on the polyolefin price time series between January 2006 and February 2023. There will be evaluated the price of PE (ICIS report Polyethylene, HDPE, DOMESTIC PRICES, PE HDPE Injection FD EU, Price Range, minimum value in EUR/t) and PP (ICIS report Polypropylene, DOMESTIC PRICES, PP Homopolymers Injection FD EU, Price Range, minimum value in EUR/t). A total of 1,000 neural networks will be generated, out of which 5 with the highest correlation coefficient, i.e., with the highest potential to make accurate predictions, will be selected. The parameters in the analytic system TIBCO Statistica 14.0.015 are set as follows: HDPE INJ and PP HOMO as Continuous targets, Date in the field Continuous input, Random sample sizes: Train: 70 %, Test: 15 %, Validation: 15 %, Seed for sampling: 1000, Number of time steps used as inputs: 1, Number of steps ahead to predict: 1, Activation functions: Identity, Logistic, Tanh, Exponential, Sine for Hidden and Output neurons. The generation of a total of 1,000 MLP networks for training will be required, with a minimum of 2 and a maximum of 8 neurons. The required number of generated and retained networks is 5.

Results

Coronavirus pandemic and oil price fluctuations. Based on the historical data on Brent oil prices in the period 1 January 2006 – 31 December 2019, 1,000 neural networks were generated using the ANS model and the regression analysis of time series, out of which five networks with the most suitable parameters for predicting Brent oil prices in the period of the COVID-19 pandemic, i.e., from 1 January 2020 – 23 February 2022. After the training stage, the five generated MLP networks are presented in the table of results. The first selected model showed negative values on the output and was thus not included in the research analysis. The selected networks best represent the relationship between the input and output variables; the selected models achieve the maximum correlation between the input and output of the neural network. The correlation coefficients of the generated models are shown in Table 1, where they are divided into three groups, namely the networks for training, testing, and validation of the ability to predict new values.

Table 1: Correlation coefficients of MLP models for prediction of Brent oil prices

Brent oil prices – Prediction	Generated MLP models			
Correlation coefficients	2. MLP 1-8-1	3. MLP 1-7-1	4. MLP 1-7-1	5. MLP 1-8-1
Train	0.9727	0.9729	0.9737	0.9723
Test	0.9705	0.9732	0.9760	0.9750
Validation	0.9714	0.9719	0.9698	0.9723

Source: Author

To generate a prediction table (Spreadsheet) for each network selected in the training, it is necessary to indicate the type of information necessary for display. The following options were selected in this case: Inputs – which displays input variables, Targets – target variables, Output – output variables, Residuals – residual values, Absolute residuals – absolute values of residuals, Square residuals – squares of the residual values, Standard residuals – standardised residuals. The numeric designation of the MLP models 1-8-1 and 1-7-1 indicates the number of neurons in individual layers, specifically input-hidden-output. Specifically, the MLP 1-8-1 model is a multilayer perceptron network with the following number of neurons: one input neuron, eight hidden neurons, and one output neuron. At this stage of the research, the number of output neurons (1) is of interest to us. It is the anticipated Brent oil price in USD/barrel predicted for a specific date. The output of each MLP model is the predicted Brent oil price for the period 1 January 2020 – 23 February 2022 in weekly intervals. The output is four variants of the development of the Brent oil price in the given period.

The statistical characteristics of the selected MLP models for the predicted Brent oil prices in the COVID-19 period are shown in Table 2.

Table 2: The actual values and the predicted variants of the development of Brent oil prices in the period of COVID-19, stat. char.

Brent oil price Prediction USD/bbl	Generated MLP models for the period 1 January 2020–23 February 2022				Actual
Statistical characteristics	2. MLP 1-8-1	3. MLP 1-7-1	4. MLP 1-7-1	5. MLP 1-8-1	Values
Number of data	112	112	112	112	112
Arithmetic mean	63	67	64	133	59
Median	63	67	64	143	62
Minimum	60	65	64	70	16
Maximum	66	67	64	143	98
Standard deviation	2	1	0	21	19

Source: Author

The predicted variants of the development of Brent oil prices are graphically illustrated in Figure 1, together with the actual development (Reality) and the relationship to the preceding period.

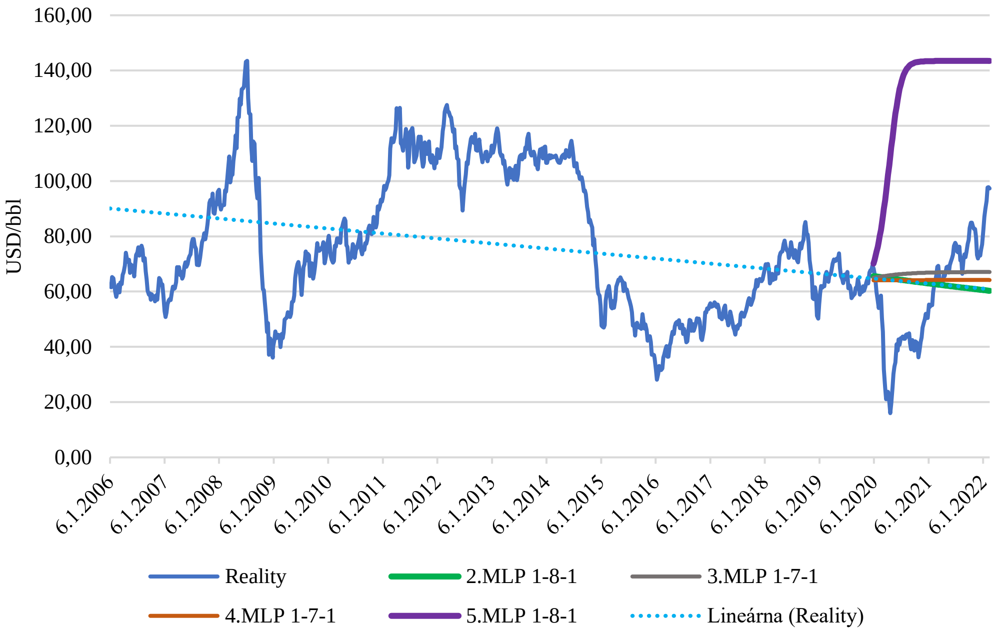

Figure 1: Actual and predicted development of Brent oil prices in the period of COVID-19

Polyolefin price development, Oil price development. The following section determines the dependence of polyolefin prices and Brent oil prices. The price units of EUR/t (Brent oil), PE HDPE Injection, and PP Homopolymers Injection were unified to achieve the correct result. Figure 2 shows the price development of all three commodities.

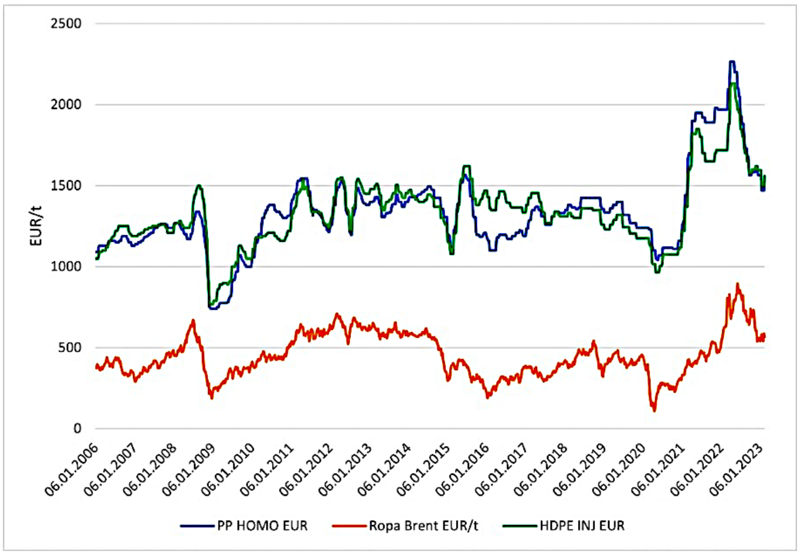

Figure 2: Price development of Brent oil, PE HDPE Injection, and PP Homopolymer Injection

Table 3 shows the statistical values concerning the development of the prices of the examined commodities for the period 1 January 2006 – 17 February 2023.

Table 3: Development of prices of the examined commodities in EUR/t for the period 1 January 2006 – 17 February 2023

Statistical characteristics	Brent Oil	PE HDPE Injection	PP Homo Injection
Number of data	897	897	897
Arithmetic mean	450	1334	1333
Median	424	1330	1315
Minimum	109	770	740
Maximum	894	2130	2265
Standard deviation	136	220	258

Source: Author

The prices of Brent oil and polyolefins were compared using correlation analysis. The results are shown in Table 4.

Table 4: Correlation analysis of Brent oil and polyolefins

Correlation analysis	Brent oil and PE HDPE Injection	Brent oil and PP Homopolymer Injection
Correlation coefficient	0.60914342	0.626962

Source: Author

Comparison of polyolefin price trends in the periods of the Great Recession, coronavirus pandemic, and war conflict in Ukraine. The price development is determined using regression analysis of selected time intervals of polyolefin prices. The periods under review are the periods of economic crises, specifically the following ones:

1 July 2006 – 31 August 2008 Great Recession
1 January 2020 – 23 February 2022 COVID-19
24 February 2022 – 17 February 2023 War conflict in Ukraine.

Statistical characteristics of PE by individual periods are presented in Table 5.

Table 5: PE price in EUR/t in the periods of crises – statistical characteristics

PE price in EUR/t	Period		
Statistical characteristics	1 July 2006–31 August 2008	1 January 2020–23 February 2022	24 February 2022–17 February 2023
Number of data	113	112	52
Arithmetic mean	1253	1385	1766
Median	1250	1220	1700
Minimum	1190	965	1500
Maximum	1500	1850	2130
Standard deviation	65	316	204

Source: Author

The next section presents graphical illustrations of the development of PE prices. Figure 3 shows the development of polyethene prices during the period of the Great Recession.

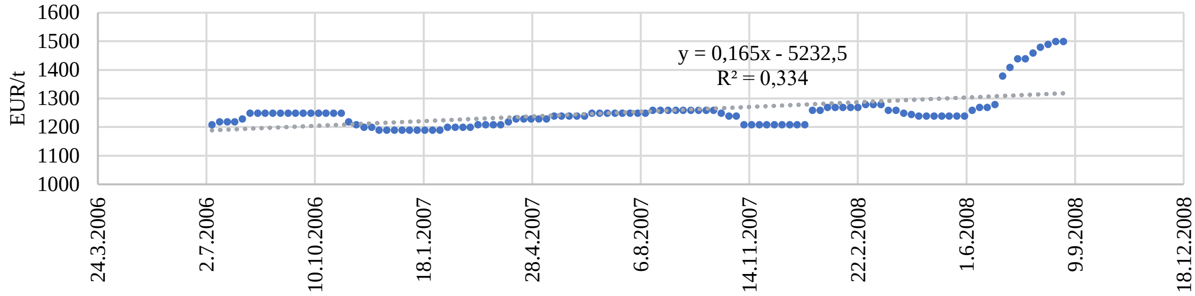

Figure 3: Development of PE with a trendline in the period of the Great Recession

Another period in which the price trend development was monitored was the COVID-19 pandemic. The graphical illustration of the monitored data for polyethene can be seen in Figure 4.

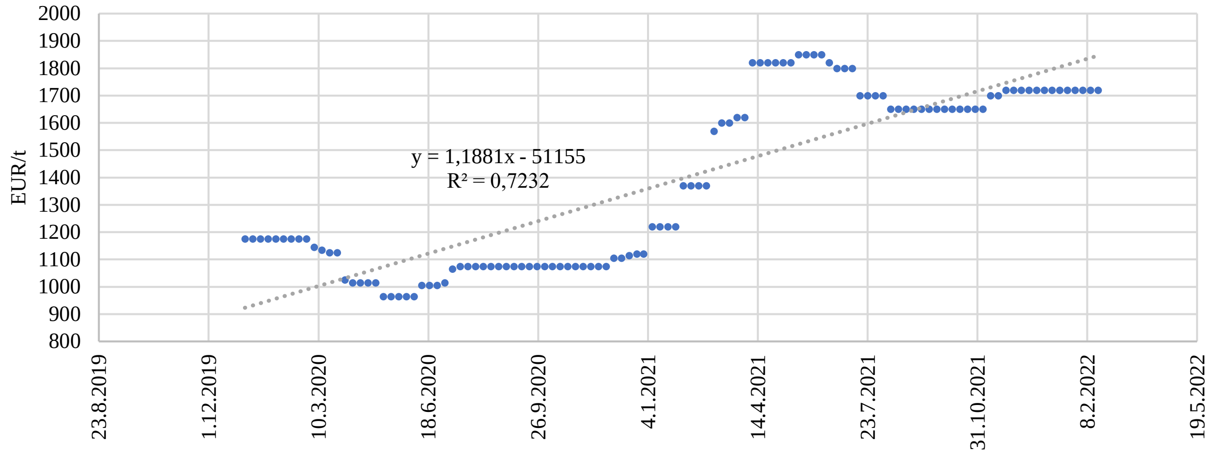

Figure 4: PE development with a trendline in the period of the COVID-19 pandemic

The war in Ukraine was the last event that had a significant impact on the global economic situation and thus the development of oil and polyolefin prices. The trend of polyethene price development from the beginning of the war conflict is presented in Figure 5.

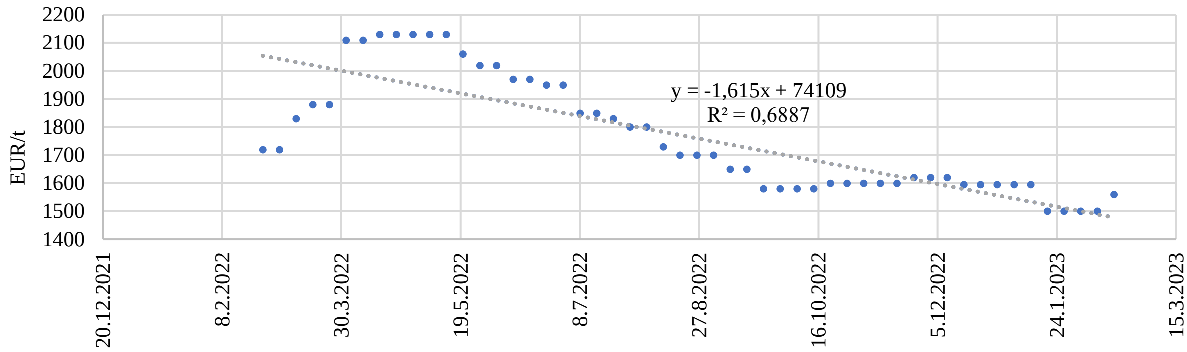

Figure 5: PE development with a trendline in the period of war conflict in Ukraine

A similar survey and subsequent analysis of the price trend during crises was also conducted for polypropylene.
The statistical characteristics of PP by individual periods are presented in Table 6.

Table 6: PP price in EUR/t in the periods of crises – statistical characteristics

PP prices in EUR/t Statistical characteristics	Periods 1 July 2006–31 August 2008	 1 January 2020–23 February 2022	 24 February 2022–17 February 2023
Number of data	113	112	52
Arithmetic mean	1211	1505	1827
Median	1200	1285	1730
Minimum	1130	1040	1470
Maximum	1340	1980	2265
Standard deviation	53	380	276

Source: Author

The next section presents the graphical illustrations of the development of PP prices in the selected periods. Again, the first period analysed is the period of the Great Recession. Figure 6 shows the polypropylene price trend in the time interval from 1 July 2006 to 31 August 2008.

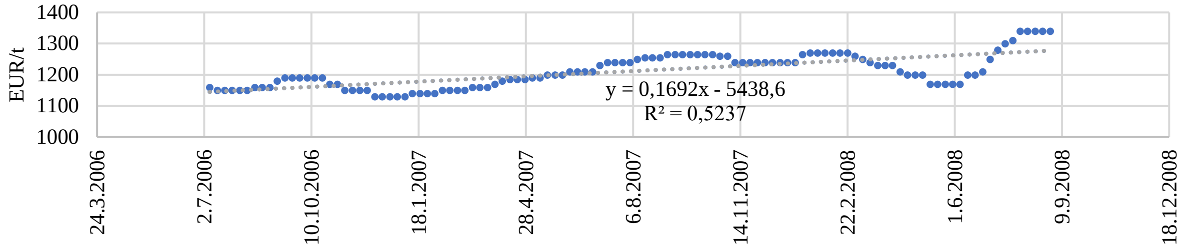

Figure 6: PP development with a trendline in the period of the Great Recession

The trend of polypropylene price development during the COVID-19 pandemic is presented in Figure 7.

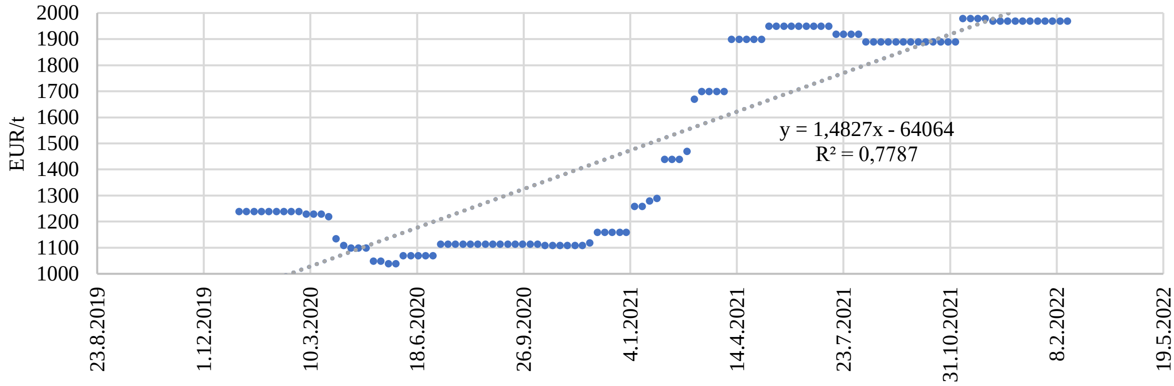

Figure 7: Development of PP with a trendline in the period of the COVID-19 pandemic

More than one year after the beginning of the war conflict in Ukraine, it is possible to determine the price development of polypropylene, the trend of which is presented in Figure 8.

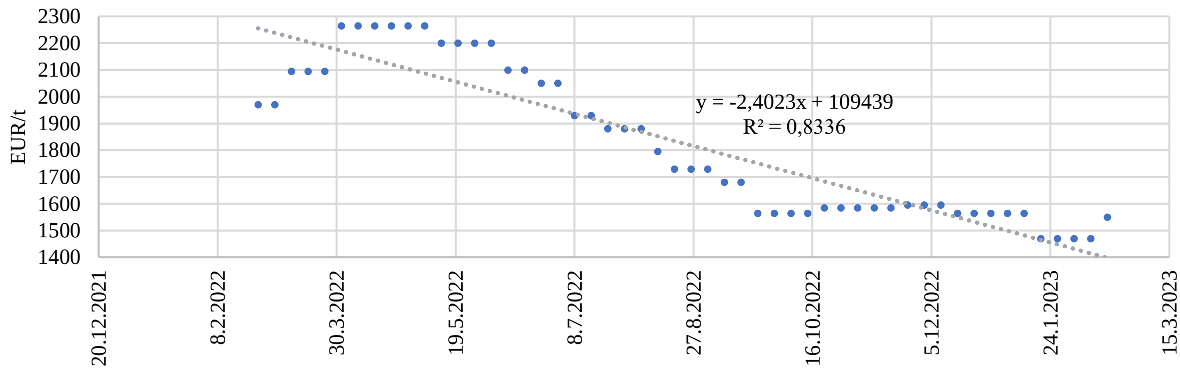

Figure 8: Development of PP with a trendline in the period of the war conflict in Ukraine

Prediction of future polyolefin price development. The ANS module and time series regression analysis were used to generate 1,000 neural networks, out of which five networks with the most suitable parameters for the prediction of polyolefin prices were selected. The prices of polyolefins in the period from January 2006 to February 2023 were analysed. The starting date for prediction was 24 February 2023, i.e., one week after the last known value, and the ending date was the end of the year 2024. The five best-generated networks for predicting the polyethene prices were retained and shown in Table 7 with their correlation coefficients by the types of networks for which the networks were generated and evaluated. The correlation coefficient value expresses the relationship between the input and output variables, i.e., the networks achieving the highest correlation values have great potential for generating the most likely future values.

Table 7: Correlation coefficient of MLP models for predicting PE prices

PE prices – Prediction	Generated MLP models				
Correlation coefficient	1. MLP 1-6-1	2. MLP 1-7-1	3. MLP 1-6-1	4. MLP 1-8-1	5. MLP 1-8-1
Train	0.9128	0.9125	0.9159	0.9149	0.9162
Test	0.9171	0.9187	0.9176	0.9229	0.9232
Validation	0.9320	0.9176	0.9332	0.9267	0.9319

Source: Author

Two out of five generated networks for predicting polyethene prices achieve the highest correlation coefficient values in individual groups (Train, Test, Validation). Model 3 MLP 1-6-1 shows the highest correlation coefficient value for the Validation networks and model 5. MLP 1-8-1 was most successful in the Train and Test groups of networks. The generated MLP models were used to predict the future values of polyethene prices in the period 24 February 2023 – 31 December 2024. The statistical characteristics of the selected MLP models, including the output activation functions, are presented in Table 8.

Table 8: Variants of PE price development – statistical characteristics

PE price in EUR/t – Prediction	Generated MLP models for the period 24 February 2023–31 December 2024				
Statistical characteristics	1. MLP 1-6-1	2. MLP 1-7-1	3. MLP 1-6-1	4. MLP 1-8-1	5. MLP 1-8-1
Number of data	97	97	97	97	97
Arithmetic mean	1448	1380	1683	1045	1392
Median	1453	1403	1680	1036	1383
Minimum	1245	1028	1662	586	1204
Maximum	1630	1643	1713	1542	1625
Standard deviation	112	179	15	295	134
Output activation function	Identity	Tanh	Sine	Tanh	Tanh

Source: Author

The results related to the historical values of polyethene prices are graphically illustrated in Figure 9.

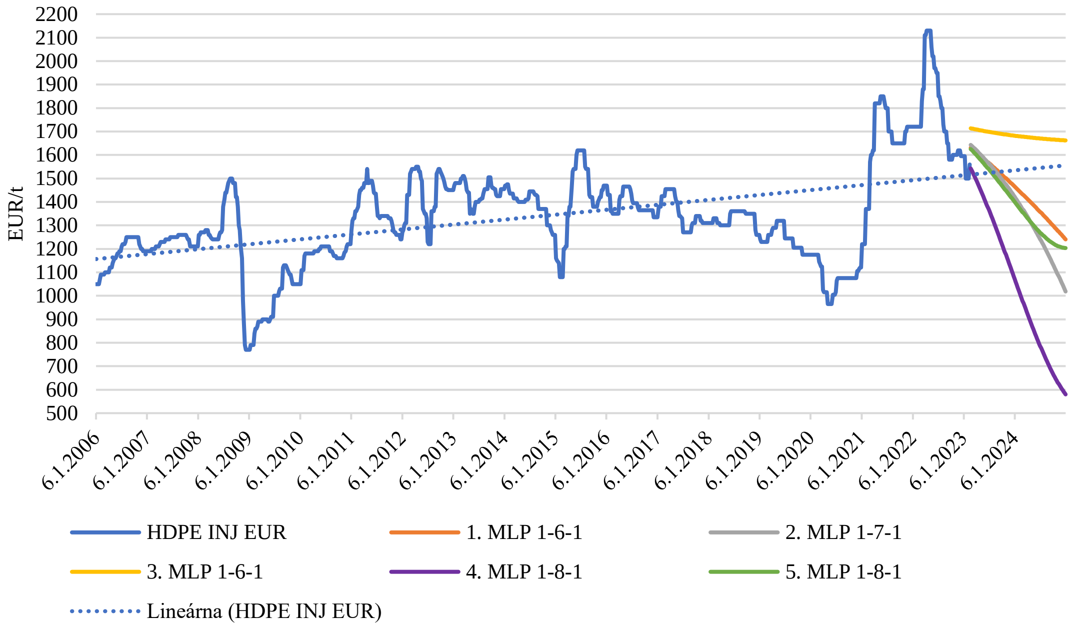

Figure 9: Actual and predicted development of PE prices

The most suitable networks for predicting polyethene prices, i.e., the networks with the highest correlation coefficient, are presented in Table 9.

Table 9: Correlation coefficient of MLP models for predicting PP prices

PP prices – Prediction	Generated MLP models				
Correlation coefficient	1. MLP 1-6-1	2. MLP 1-8-1	3. MLP 1-7-1	4. MLP 1-8-1	5. MLP 1-8-1
Train	0.9441	0.9394	0.9438	0.9460	0.9484
Test	0.9451	0.9389	0.9378	0.9414	0.9479
Validation	0.9590	0.9611	0.9577	0.9586	0.9579

Source: Author

All generated models were used to predict the future polypropylene prices from 24 February 2023 to 31 December 2024. The predicted values follow the time series of the historical data on the prices recorded in weekly intervals. Table 10 contains statistical information on the future polypropylene prices by individual MLP models.

Table 10: Variants of PP price development – statistical characteristics

PP prices in EUR/t – Prediction	Generated MLP models for the period 24 February 2023–31 December 2024				
Statistical characteristics	1. MLP 1-6-1	2. MLP 1-8-1	3. MLP 1-7-1	4. MLP 1-8-1	5. MLP 1-8-1
Number of data	97	97	97	97	97
Arithmetic mean	1280	1119	833	973	1187
Median	1260	1075	749	909	1149
Minimum	1201	879	740	806	1080
Maximum	1452	1516	1329	1395	1453
Standard deviation	72	188	153	164	103
Output activation function	Logistic	Logistic	Logistic	Logistic	Logistic

Source: Author

The curves representing the development of polypropylene prices can be seen in Figure 10. The five-coloured curves represent five MLP models with the predicted PP prices in the time interval 6 January 2006 – 17 February 2023, which follow the historical prices of the analysed commodity.

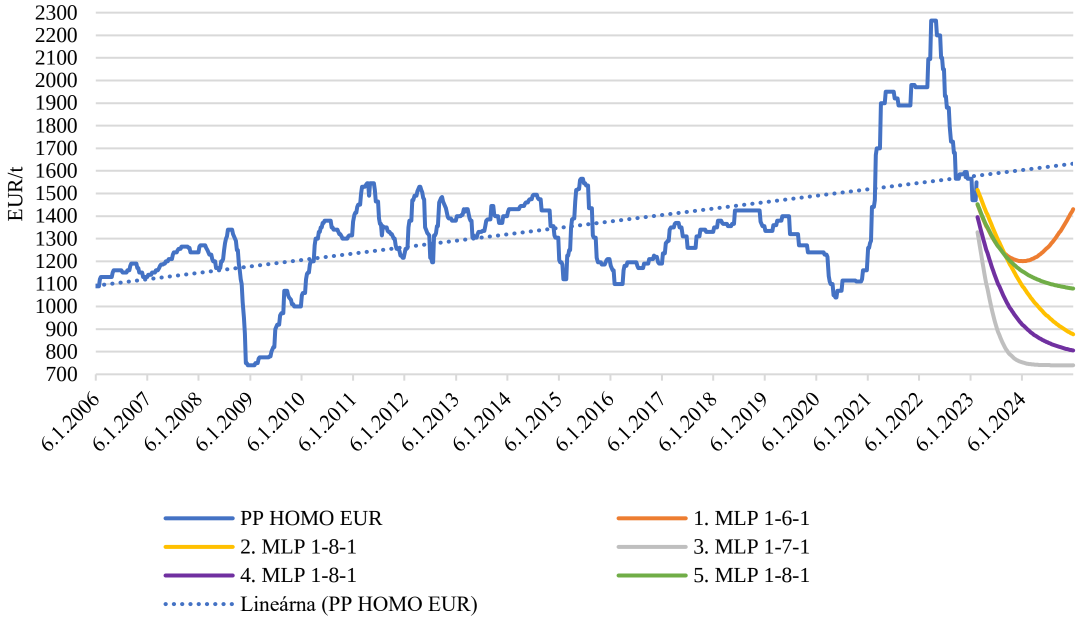

Figure 10: Actual and predicted development of PP prices

The upward trend of the polypropylene price development was recorded only in the case of 1. MLP 1-6-1.

Discussion

RQ1: Did the coronavirus pandemic cause the oil price fluctuations?

Historical data on Brent oil prices processed using time series regression within the ANS module of neural networks were the basis for creating models of possible future development of Brent oil prices. A total of four variants of the predicted Brent oil price development were selected. The comparison of these generated predictions with the actual development of Brent oil prices in the period of the COVID-19 pandemic provided the answer to RQ1. The results provided by the selected predictive models correlate with the input information with the coefficient in the interval 0.9698 – 0.9760 (Table 1). For the period of the COVID-19 pandemic, the period from 1 January 2020 to 23 February 2022 was selected. The compared time series contains 112 weekly values. The highest correlation coefficient of the networks able to predict new values was recorded in the case of the last model, 5. MLP 1-8-1. The comparison of the statistical characteristics of this model and the actual values (Table 2) showed similarity only in the values of Standard deviation. In the case of model 5 MLP 1-8-1, the value of the standard deviation was 21, while the actual value was 19. In both cases, the deviation indicates a higher degree of dissimilarity of individual 112 values in the time series.

Other statistical values of the model 5. MLP and the actual values differ significantly. When looking for other similarities between the actual statistical values and the generated MLP models, we can see some similarities in terms of the Median and Arithmetic mean of model 2. MLP 1-8-1. However, when comparing the actual price development trend and the trend of Model 2. MLP 1-8-1, we can see an opposite direction in the period of the COVID-19 pandemic, as the actual price development shows a downward trend, while the trend of model 2. MLP 1-8-1 is decreasing. The remaining models, which have not been mentioned yet, specifically 3. MLP 1-7-1 and 4. MLP 1-7-1 shows an upward trend, but the increase is very slight compared to the actual values. In terms of the statistical values, the most significant difference between the predicted and actual values can be seen in the case of Minimum. None of the generated variants showed values close to the actual minimum value of 16 USD/bbl. The lowest price of Brent oil (60 USD/bbl) was predicted by the model 2. MLP 1-8-1. The development of Brent oil price predicted by all generated MLP variants was very different from the actual development. The above findings confirm the impact of the COVID-19 pandemic on the price of Brent oil. RQ2 can thus be answered as follows: Yes, the coronavirus pandemic caused considerable fluctuations in oil prices. This finding is in line with the results by Öztunç Kaymak & Kaymak (2022), Jalles & Karras (2023), Bildirici et al. (2020), Tudor & Sova (2022), Tuna & Tuna (2022), Dey & Das (2022), Le et al. (2021), Atif et al. (2021), Tanin et al. (2022). The research conducted within RQ1 was the basis for answering RQ2.

RQ2: Does the price trend of polyolefins copy the trend of the oil prices?

The answer to RQ1 confirmed the impact of the COVID-19 pandemic on Brent oil prices. RQ2 aims to determine its possible effect on the price of oil products and polyolefins. In this section, the research builds on the historical data of Brent oil prices obtained in the context of RQ1 and converted to EUR/t. It uses correlation analysis to compare them with the historical prices of polyolefins. The period under review, 1 January 2006 – 17 February 2023, contains 897 weekly prices of Brent oil, polyethylene HDPE Injection, and polypropylene Homopolymers Injection. The comparison of the arithmetic mean of the examined commodities in the given period (Table 3) shows that the price of oil accounts for approximately 1/3 of the polyolefin price, specifically 33.76 % in the case of polyethene and 33.76 % in the case of polypropylene. The assumption is that the remaining 2/3 of the price is given by the prices of other raw materials, the so-called additives in the form of UV stabilisers, catalysts, and colourings, which are part of the production process. The polyolefin prices also reflect the prices of energies, production costs, transport costs, labour costs, and distributors' margins, as well as the cost of investments related to sustainable development and the circular economy. The minimum price of Brent oil (109 EUR/t; 16 USD/bbl) was recorded in April 2020.

A significant decline and historical minimum of the oil price are mentioned by Atif et al. (2021), Jalles & Karras (2023), Bildirici et al. (2020), and Tudor & Sova (2022). The minimum price of PE (770 EUR/t) was recorded in December 2008; the same situation was in the case of PP, the minimum price of which was 740 EUR/t. The maximum values for all commodities were recorded in the second quarter of 2022. The cause was the beginning of the war conflict in Ukraine and the related uncertainty concerning the oil supply. The maximum prices of individual commodities were 894 EUR/t (129 USD/bbl) in the case of Brent oil, 2,130 EUR/t in the case of PE, and 2,265 EUR/t for PP. The comparison of the mutual relationship of the Brent oil and polyethene price time series provided a correlation coefficient of 0.61 (Table 4), while the comparison of the Brent oil and polypropylene prices provided a correlation coefficient of 0.63. Figure 2 shows that the development of polyethene and polypropylene prices copies the oil price development in the long run. The price fluctuations occur approximately in the same periods, in the case of polyethylene and polypropylene with a small delay as a response to the movement of oil prices. A small difference in the development of polyolefin and oil prices can be seen in the fluctuations, as the fluctuations in the case of oil are represented by sharp curves, whereas the curves of polyolefins are rather rounded.

RQ3: Are the price trends of polyolefins in the periods of the Great Recession, the coronavirus pandemic, and the war conflict in Ukraine comparable?

When looking for the answer to RQ3, identical or similar features of the price development of polyethene and polypropylene in different periods of crises were analysed. The research was conducted using the regression analysis of polyolefin time series, i.e., PE HDPE Injection and PP Homopolymers Injection. The compared periods were the period of the Great Recession, the COVID-19 pandemic, and the war conflict in Ukraine.

When comparing the development of polyethene time series in defined crisis intervals, we can see a slightly increasing trend during the first 113 weeks of the Great Recession. The time series shows only one significant extreme two years after the beginning of the period when the polyethene price grew by 220 EUR/t within two months. The difference between the minimum and maximum in the period of the Great Recession is 310 EUR/t. The equation of the graph is expressed as follows: $y = 0.165x – 5232.5$. In the case of the COVID-19 pandemic, price fluctuations are significant from the beginning of the crisis period, with the difference between the minimum and maximum within 112 weeks being 885 EUR/t. At the beginning of this period, the polyethene price was 1,175 EUR/t, while the last recorded value before the beginning of the war was 1,720 EUR/t. The trendline in the pandemic period is growing and can be expressed by the following equation: $y = 1.1881x – 51155$. The time series of the PE price is shorter in the case of the last considered period (war in Ukraine), consisting of 52 weekly data. Here, the authors point to the combined influence of the war conflict in Ukraine and the ongoing COVID-19 pandemic. In this case, the price development trend is downward, and the trendline is expressed by the equation $y = -1.615x + 74109$. The difference between the minimum and maximum price is 630 EUR/t. The first price value is identical to the last price value during the pandemic (without the influence of the war in Ukraine), specifically 1,720 EUR/t. The last value recorded on 17 February 2023 was 1,560 EUR/t. Since January 2020, there has been a crisis period, which started with the COVID-19 pandemic, and since February 2022, the crisis has been deepened by the negative effect of the war conflict. It can thus be assumed that the last period without crisis was December 2019. The last recorded value of the polyethylene price was 1,175 EUR/t, recorded in December 2019. The last known, i.e., the most recent value, is thus 1,560 EUR/t.

The polypropylene price time series shows a slightly upward trend during the Great Recession. The trendline is expressed by the following equation: $y = 0.1692x – 5438.6$. A major fluctuation of the time series can be seen after two years from the beginning of the crisis. The difference between the minimum and maximum price is 210 EUR/t. In the period of the pandemic, the volatility of the PP price is high. The trendline is significantly upward and is expressed by the equation $y = 1.4827x – 64064$. The initial price in this period is 1,240 EUR/t, while the final price is 1,970 EUR/t. The difference between the minimum and maximum is 940 EUR/t. The trend of the polypropylene price development in the period of the war conflict decreases sharply, with the trendline being expressed by the equation $y = -2.4023 + 109439$. The difference between the minimum and maximum is 795 EUR/t. At the beginning of the war conflict, the price was 1,970 EUR/t, while the last recorded price was 1,550 EUR/t. The last recorded price of PP before the outbreak of the pandemic, i.e., before the last considered crisis period, was 1,240 EUR/t. The difference between the last two recorded values is 310 EUR/t.

Based on the data obtained, it can be stated that the development of the polypropylene and polyethene price trend is identical. However, comparing the polyolefin prices time series by individual periods shows that the trend is specific for each of the considered periods. The period of the Great Recession is characterised by low price volatility, with more significant growth being recorded two years after the beginning of the crisis period. During the COVID-19 pandemic, a record fall in the price was observed within 4 months from its beginning, which was followed by a record price growth of 885 EUR/t 13 months later (in the case of polyethene). The trendline showed an upward trend during the Great Recession and the COVID-19 pandemic. The period of the war conflict is characterised by a downward trend of the trendline and the record growth in the price after its beginning. RQ3 can thus be answered as follows: The price trends of polyolefins in the Great Recession, the coronavirus pandemic, and the war conflict in Ukraine are different and specific for each considered period.

RQ4: Is it possible to predict the future price development of polyolefins based on available information?

The most suitable method for processing non-linear and non-stationary data concerning the oil and polyolefin prices was the time series regression method using neural networks. Based on the historical data on polyolefin prices, the ANS module generated five MLP models of the future polyethene and polypropylene prices for the period February 2023 – December 2024, i.e., 97 weekly data. Figure 9 graphically illustrates the actual development of the polyethene prices followed by five MLP variants (in different colours) of future prices. The trendline of the input, i.e., historical data, shows an upward trend, while all five generated variants of the future polyethene prices show a decrease. Table 7 shows the values of correlation coefficients generated by the MLP models predicting the polyethene prices divided into the training, testing, and validation groups. The most successful model achieving the maximum correlation between the input and output variables for Validation neural networks turned out to be 3. MLP 1-6-1 (for polyethylene), with a correlation coefficient of 0.9332. Model 5. MLP 1-8-1 achieved the highest correlation for the Training (0.9162) and Testing (0.9232) networks. Model 3. MLP 1-6-1 shows the slightest decrease of all generated variants of the polyethene price development, with the equation of the trendline being $y = -0.0744x + 5056.6$. Table 8 shows the basic statistical characteristics of all generated variants of the future polyethene price development. For all models, the maximum value of the development curve is at the beginning, i.e., 24 February 2023, and the minimum value is at the end of the period, i.e., in December 2024. The maximum value for the model 3. MLP 1-6-1 is 1,713 EUR/t. The predicted minimum value is 1,662 EUR/t at the end of the year 2024. The predicted price of polyethene at the end of the year 2023 is 1,682 EUR/t. The arithmetic mean for this model is 1,683 EUR/t. Model 5. MLP 1-8-1 predicts a more significant decrease than the model 3. MLP 1-6-1, with its trendline being expressed with the equation $y = -0.6768x + 32065$. The development curve shows the highest value of 1,625 EUR/t at the beginning, and the minimum price of polyethene is 1,204 EUR/t at the end of the predicted period. For the end of 2023, this model predicts the polyethenes' price to be 1,405 EUR/t. The calculated value of the arithmetic mean is 1,392 EUR/t.

The development trend of the polypropylene price up to now and the predicted development are presented in Figure 10. The trendline of the input data indicates an upward trend. The generated variants of the future development of polypropylene prices show a downward trend in four cases; in one case, it is a slightly upward trend. Based on the highest value of the correlation coefficient presented in Table 9, it is possible to select the most successful models for predicting polypropylene prices. In the case of the Validation group of networks, the most suitable generated model is 2. MLP 1-8-1 has a correlation coefficient of 0.9611; for the train group of networks, it is 5. MLP 1-8-1 has a correlation coefficient of 0.9484, and for the test group of networks, it is 5 again. MLP 1-8-1, with a correlation coefficient of 0.9479. The trendline of 2. MLP 1-6-1 is visibly decreasing and is expressed with the equation $y = -0.9317x + 43340$. From the statistical values in Table 10, it can be seen that the model 2. MLP 1-6-1 reaches the maximum at the beginning of the prediction period, i.e., on 24 February 2023, specifically the value of 1,516 EUR/t; the minimum value of 879 EUR/t is achieved at the end of the curve, i.e., on 31 December 2024; the arithmetic mean is 1,119 EUR/t. The polypropylene price predicted by this model at the end of 2023 is 1,102 EUR/t. Model 5. MLP 1-8-1 shows the slightest decreasing trend of all generated MLP models predicting a decreasing trend; the trendline equation is $y = -0.4861x + 23214$. The maximum of 1,453 EUR/t for this model is achieved at the beginning of the period, and the minimum of 1,080 EUR/t at the end of the period; the arithmetic mean is 1,187 EUR/t. For the end of 2023, the model 5. MLP 1-8-1 predicts the polypropylene price to be 1,160 EUR/t. The only generated model predicting the growing price of polypropylene is 1. MLP 1-6-1. The maximum value of 1,452 EUR/t is recorded at the beginning of the curve, the minimum is 1,201 EUR/t at the end of the year 2023, and at the beginning of the year 2024, the arithmetic mean is 1,280 EUR/t. The predicted price of polypropylene at the end of the period, i.e., in December 2024, is 1,422 EUR/t. The price prediction was made for the time interval February 2023 – December 2024, i.e., a total of 23 months. Let's consider the year 2023 as a shorter-term prediction. The predicted price of polypropylene for the end of the year 2023 made by the three most successful MLP models is as follows: 1,102 EUR/t, 1,160 EUR/t, and 1,201 EUR/t. Here, it should be mentioned again the price of polypropylene at the turn of 2019 and 2020, a period before the outbreak of the COVID-19 pandemic and the subsequent crises caused by the pandemic and the war in Ukraine, was 1,240 EUR/t.

The answer to RQ4 is thus as follows: Yes, neural networks can be used for predicting the future development of polyolefin prices. The results related to this part of the research lead to a clear conclusion: a downward trend of the polyethene and polypropylene prices until at least the end of 2023. Ten out of ten generated MLP models predict a decrease in the price until December 2023. Nine out of ten generated models predict a downward trend in the development of polyolefin prices for the year 2024. One model predicts an upward trend of the polypropylene price from January 2024.

Conclusions

Oil is the fundamental raw material for 99 % of all polyolefins produced and accounts for 31 % of global energy consumption. With its 10% share in global trade, it can be considered the most important commodity and the most influential global resource. Oil price fluctuations or even supply shortages thus have a considerable effect on the global economy in the form of economic shocks. Conversely, according to the findings presented in this paper, non-standard and unprecedented situations that cause uncertainty concerning the future development of the global economy, such as a viral disease pandemic or a war conflict, can be expected to affect the price of oil.

With the application of neural networks and historical Brent oil prices, the significant impact of COVID-19 on the development of Brent oil prices was confirmed. In April 2020, Brent oil price achieved its historical minimum, specifically 16 USD/bbl. The lowest price predicted by artificial intelligence for the defined period was 60 USD/bbl, an unprecedentedly rapid fall in oil prices. The research results state that the coronavirus pandemic caused significant fluctuations in oil prices.

Oil is the basic input material for the production of plastic, the most important representatives of which are polyolefins. Since the effect of the pandemic on oil prices has been demonstrated, there was a logical assumption that COVID-19 would also affect petroleum products and polyolefins. This assumption was demonstrated using historical Brent oil prices from 2006, which were compared with the prices of polyethene and polypropylene using correlation analysis. The analysis confirmed the existence of a similar trend in the development of Brent oil and polyolefin prices in the monitored period from January 2006 to February 2023. The value of the correlation coefficient of the polyethene price about the price of Brent oil was determined at 0.61. In the case of the polypropylene price, the correlation with the Brent oil price is expressed by the coefficient 0.63. The trend in the polyolefin price development follows the trend of Brent oil prices in the long term. All three commodities, i.e., Brent oil, polyethene, and polypropylene, recorded their historical minimum (Brent oil 894 EUR/t, i.e., 129 USD/bbl, PE 2,130 EUR/t, PP 2,265 EUR/t) approximately at the same time, specifically in the second quarter of 2022, i.e., a few weeks after the outbreak of the war conflict in Ukraine.

To better prepare for possible future unexpected events, periods in which economic stability was disrupted and the economy weakened were analysed. The findings can also be applied to the development of oil prices because RQ2 confirmed the consistency in oil and polyolefin price developments from 2006 to the present. A detailed examination of the polyolefin time series showed that the development was specific for each of the monitored periods. The events considered were the Great Recession, the COVID-19 pandemic, and the war conflict in Ukraine. About the conducted research, it can be stated that the economic disruption in the period of the Great Recession caused by the mortgage crisis did not have as significant an effect on the polyolefin prices as the coronavirus pandemic or the war conflict involving a major oil exporter.

To predict the future development of the polyolefin price, the authors applied a scientific method of artificial intelligence, specifically time series regression, using neural networks. In the short term, i.e., until the end of the year 2023, a downward trend of the polyolefin price is predicted by all selected MLP models. The last price of polyethene predicted by the most successful model for the end of December 2023 is 1,405 EUR/t; for polypropylene, it is 1,160 EUR/t. In the long-term horizon, i.e., for the end of 2024, the predicted price is 1,204 EUR/t for polyethene and 1,080 EUR/t for polypropylene. Nine out of ten generated models predict a downward trend in the development of polyolefin prices for the year 2024. One model predicts an increasing price trend for polypropylene from January 2024.

In the context of predicting the polyolefin price, the facts related to the main raw material necessary for their production should be mentioned. The oil market is sensitive to political conflicts and is difficult to control in such a situation. Oil is imported into the European Union mostly from politically unstable regions and countries prone to terrorism, conflicts, and wars. This means that there is a high risk of oil supply shortages, which can lead to considerable fluctuations in oil prices and, consequently, fluctuations in the price of polyolefins. To eliminate the risks associated with oil supply shortages and fluctuations in oil prices and polyolefins, people should try to move away from this resource by investing in technologies processing alternative and renewable resources. Businesses investing in sustainable development would thus be protected against oil shocks, which will bring stability to their business and contribute to protecting the planet and its resources for future generations.

References

Adina, D., & Dumitru-Cristian, O. (2022). The Effectiveness of Fiscal-Budgetary Measures to Counteract the COVID-19 Crisis. Evidence from EU Countries. Economics - The Open-Access, Open-Assessment Journal, 16(1), 137–151.

Algamdi, A., Brika, S. K. M., Musa, A., & Chergui, K. (2021). COVID-19 Deaths Cases Impact on Oil Prices: Probable Scenarios on Saudi Arabia Economy. Frontiers in Public Health, 9. https://www.frontiersin.org/articles/10.3389/fpubh.2021.620875

Atif, M., Rabbani, M., Bawazir, H., Hawaldar, I., Daouia, C., Karim, S., & AlAbbas, A. (2021). Oil price changes and stock returns: Fresh evidence from oil exporting and oil importing countries. Cogent Economics & Finance, 10. https://doi.org/10.1080/23322039.2021.2018163

Azim, T., Bhushan, A., Del Rio Vilas, V. J., Srivastava, R., Wijesinghe, P. R., Ofrin, R., Chauhan, S., & Krishnan, A. (2022). Public health research priorities for WHO on COVID-19 in the South-East Asia Region: Results of a prioritization survey. Health Research Policy and Systems, 20(1), 96. https://doi.org/10.1186/s12961-022-00862-x

Babafemi, A. J., Šavija, B., Paul, S. C., & Anggraini, V. (2018). Engineering Properties of Concrete with Waste Recycled Plastic: A Review. Sustainability, 10(11), Article 11. https://doi.org/10.3390/su10113875

Bartoš, V., Vochozka, M., & Šanderová, V. (2022). Copper and Aluminium as Economically Imperfect Substitutes, Production and Price Development. Acta Montanistica Slovaca, 27, 462–478. https://doi.org/10.46544/AMS.v27i2.14

Bildirici, M., Guler Bayazit, N., & Ucan, Y. (2020). Analyzing Crude Oil Prices under the Impact of COVID-19 by Using LSTARGARCHLSTM. Energies, 13(11), Article 11. https://doi.org/10.3390/en13112980

Dey, A. K., & Das, K. P. (2022). How do mobility restrictions and social distancing during COVID-19 affect oil price? Journal of Statistical Theory and Practice, 16(2), 22. https://doi.org/10.1007/s42519-022-00247-x

EXR.D.USD.EUR.SP00.A | ECB Data Portal. (n.d.). Retrieved 21 October, 2023, from https://data.ecb.europa.eu/data/datasets/EXR/EXR.D.USD.EUR.SP00.A

ECB | Evropská centrální banka [online]. [cit. 05. 03. 2023]. Available from: http://ECB reference exchange rate, US dollar/Euro, 2:15 pm (C.E.T.) - Quick View - ECB Statistical Data Warehouse (europa.eu)

Ferrara, L., Mogliani, M., & Sahuc, J.-G. (2022). High-frequency monitoring of growth at risk. International Journal of Forecasting, 38(2), 582–595.

Fiszeder, P., & Małecka, M. (2022). Forecasting volatility during the outbreak of Russian invasion of Ukraine: application to commodities, stock indices, currencies, and cryptocurrencies. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *17*(4), 939–967. https://doi.org/10.24136/eq.2022.032.

Fu, Z., Niu, H., & Wang, W. (2022). Market Efficiency and Cross-Correlations of Chinese New Energy Market with Other Assets: Evidence from Multifractality Analysis. Computational Economics, 1–25. https://doi.org/10.1007/s10614-022-10301-2

Gavurova, B., Kelemen, M., Polishchuk, V. (2022a). Expert model of risk assessment for the selected components of smart city concept: From safe time to pandemics as COVID-19. Socio-Economic Planning Sciences, 82, 101253. https://doi.org/10.1016/j.seps.2022.101253

Gavurova, B., Jencova, S., Bačík, R., Miskufova, M., & Letkovský, S. (2022b). Artificial intelligence in predicting the bankruptcy of non-financial corporations. Oeconomia Copernicana, 13(4), 1215–1251. https://doi.org/10.24136/oc.2022.035

Gavurova, B., Skare, M., Belas, J., Rigelsky, M., & Ivankova, V. (2023). The relationship between destination image and destination safety during technological and social changes COVID-19 pandemic. Technological forecasting and social change, 191, 122488. https://doi.org/10.1016/j.techfore.2023.122488

Ghecham, M. A. (2022). The Impact of COVID-19 on Economic Growth of Countries: What Role Has Income Inequality in It? Economies, 10(7), Article 7. https://doi.org/10.3390/economies10070158

Gunay, S., Can, G., & Ocak, M. (2021). Forecast of China's Economic Growth During the COVID-19 Pandemic: A MIDAS Regression Analysis (SSRN Scholarly Paper 3823882). https://papers.ssrn.com/abstract=3823882

Gupta, N., & Nigam, S. (2020). Crude Oil Price Prediction using Artificial Neural Network. Procedia Computer Science, 170, 642–647. https://doi.org/10.1016/j.procs.2020.03.136

Idris, Z. Z., Ismail, N. W., & Ibrahim, S. (2022). Comparative Advantage and Competitiveness of COVID-19-Related Medical Products Exporters. Journal of Competitiveness, 14(1), 61–79. https://doi.org/10.7441/joc.2022.01.04

Jalles, J. T., & Karras, G. (2023). Pandemics and Trade in the 21st Century: Evidence from five Pre-Covid Pandemics. Open Economies Review, 34(4), 895–918. https://doi.org/10.1007/s11079-022-09687-1

Janková, Z. (2023). Hybrid wavelet adaptive neuro-fuzzy tool supporting competitiveness and efficiency of predicting the stock markets of the Visegrad Four countries. Journal of Competitiveness, 15(1),56-72. https://doi.org/10.7441/joc.2023.01.04

Kasych, A., & Vochozka, M. (2018). Methodical support of the enterprise sustainable development management. Marketing and Management of Innovations, 371–381. https://doi.org/10.21272/mmi.2018.1-29

Katsampoxakis, I., Christopoulos, A., Kalantonis, P., & Nastas, V. (2022). Crude Oil Price Shocks and European Stock Markets during the COVID-19 Period. Energies, 15(11), Article 11. https://doi.org/10.3390/en15114090

Kelemen, M., Gavurova, B., & Polishchuk, V. (2022). A Complex Hybrid Model for Evaluating Projects to Improve the Sustainability and Health of Regions and Cities. International Journal of Environmental Research and Public Health, 19(13), 8217. https://doi.org/10.3390/ijerph19138217

Khalfaoui, R., Solarin, S. A., Al-Qadasi, A., & Ben Jabeur, S. (2022). Dynamic causality interplay from COVID-19 pandemic to oil price, stock market, and economic policy uncertainty: Evidence from oil-importing and oil-exporting countries. Annals of Operations Research, 313(1), 105–143. https://doi.org/10.1007/s10479-021-04446-w.

Kramarova, K., Švábová, L., & Gabrikova, B. (2022). Impacts of the Covid-19 crisis on unemployment in Slovakia: A statistically created counterfactual approach using the time series analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *17*(2), 343–389. https://doi.org/10.24136/eq.2022.012.

Kumeka, T. T., Uzoma-Nwosu, D. C., & David-Wayas, M. O. (2022). The effects of COVID-19 on the interrelationship among oil prices, stock prices and exchange rates in selected oil exporting economies. Resources Policy, 77, 102744. https://doi.org/10.1016/j.resourpol.2022.102744

Kuzmenko, O., Bilan, Y., Bondarenko, E., Gavurova, B., & Yarovenko, H. (2023). Dynamic stability of the financial monitoring system: Intellectual analysis. PloS one, 18(1), e0276533. https://doi.org/10.1371/journal.pone.0276533

Landmesser, J. (2021). The use of the dynamic time warping (DTW) method to describe the COVID-19 dynamics in Poland. *Oeconomia Copernicana*, *12*(3), 539–556. https://doi.org/10.24136/oc.2021.018.

Le, T.-H., Le, A. T., & Le, H.-C. (2021). The historic oil price fluctuation during the Covid-19 pandemic: What are the causes? Research in International Business and Finance, 58(C). https://ideas.repec.org//a/eee/riibaf/v58y2021ics0275531921001100.html

Liu, N., Xu, Z., & Skare, M. (2021). The research on COVID-19 and economy from 2019 to 2020: analysis from the perspective of bibliometrics. *Oeconomia Copernicana*, *12*(2), 217–268. https://doi.org/10.24136/oc.2021.009.

Luo, M., Qin, S., Tan, B., Cai, M., Yue, Y., & Xiong, Q. (2021). Population Mobility and the Transmission Risk of the COVID-19 in Wuhan, China. ISPRS International Journal of Geo-Information, 10(6), Article 6. https://doi.org/10.3390/ijgi10060395

Maleki, A., Safdari Shadloo, M., & Rahmat, A. (2020). Application of Artificial Neural Networks for Producing an Estimation of High-Density Polyethylene. Polymers, 12(10), Article 10. https://doi.org/10.3390/polym12102319

Matuszewska-Pierzynka, A. (2021). Relationship between corporate sustainability performance and corporate financial performance: evidence from U.S. companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 16*(4), 885–906. https://doi.org/10.24136/eq.2021.033.

Megevand, B., Cao, W.-J., Di Maio, F., & Rem, P. (2022). Circularity in Practice: Review of Main Current Approaches and Strategic Propositions for an Efficient Circular Economy of Materials. Sustainability, 14(2), Article 2. https://doi.org/10.3390/su14020962

Min, H., Kim, J., Moon, K., Lee, S., Kim, J., & Ko, Y. (2022). Development and validation of COVID-19 Impact Scale. BMC Psychology, 10(1), 88. https://doi.org/10.1186/s40359-022-00793-w

Mourão, P.J.R. & Popescu, I.A. (2023). Investment, growth and competitiveness: The multiplier-accelerator in the 21st century. Journal of Competitiveness, 15(3), 60-78. https://doi.org/10.7441/joc.2023.03.04

Niu, H., Zhao, Y., Niu, H., & Zhao, Y. (2021). Crude oil prices and volatility prediction by a hybrid model based on kernel extreme learning machine. Mathematical Biosciences and Engineering, 18(6), Article mbe-18-06-402. https://doi.org/10.3934/mbe.2021402

Öztunç Kaymak, Ö., & Kaymak, Y. (2022). Prediction of crude oil prices in COVID-19 outbreak using real data. Chaos, Solitons, and Fractals, 158, 111990. https://doi.org/10.1016/j.chaos.2022.111990

Privara, A. . (2022). Economic growth and labour market in the European Union: lessons from COVID-19. *Oeconomia Copernicana*, *13*(2), 355–377. https://doi.org/10.24136/oc.2022.011.

Refai, H. A., Zeitun, R., & Eissa, M. A.-A. (2022). Impact of global health crisis and oil price shocks on stock markets in the GCC. Finance Research Letters, 45, 102130. https://doi.org/10.1016/j.frl.2021.102130

Samee, N. A., Atteia, G., Alkanhel, R., Alhussan, A. A., & AlEisa, H. N. (2022). Hybrid Feature Reduction Using PCC-Stacked Autoencoders for Gold/Oil Prices Forecasting under COVID-19 Pandemic. Electronics, 11(7), Article 7. https://doi.org/10.3390/electronics11070991

Sauter, D. W., Taoufik, M., & Boisson, C. (2017). Polyolefins, a Success Story. Polymers, 9(6), Article 6. https://doi.org/10.3390/polym9060185

Svabova, L., Tesarova, E. N., Durica, M., & Strakova, L. (2021). Evaluation of the impacts of the COVID-19 pandemic on the development of the unemployment rate in Slovakia: counterfactual before-after comparison. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(2), 261–284. https://doi.org/10.24136/eq.2021.010.

Svatosova, V. (2022). Changes in Online Shopping Behavior in the Czech Republic During the COVID-19 Crisis. Journal of Competitiveness, 14(1), 155–175. https://doi.org/10.7441/joc.2022.01.09

Sun, X., Hao, J., & Li, J. (2022). Multi-objective optimization of crude oil-supply portfolio based on interval prediction data. Annals of Operations Research, 309(2), 611–639.

Tanin, T. I., Sarker, A., Brooks, R., & Do, H. X. (2022). Does oil impact gold during COVID-19 and three other recent crises? Energy Economics, 108, 105938. https://doi.org/10.1016/j.eneco.2022.105938

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

Tudor, C., & Sova, R. (2022). Flexible Decision Support System for Algorithmic Trading: Empirical Application on Crude Oil Markets. IEEE Access, PP, 1–1. https://doi.org/10.1109/ACCESS.2022.3143767

Tuna, G., & Tuna, V. E. (2022). Are effects of COVID-19 pandemic on financial markets permanent or temporary? Evidence from gold, oil and stock markets. Resources Policy, 76, 102637. https://doi.org/10.1016/j.resourpol.2022.102637

Valls Martínez, M. del C., Soriano Román, R., & Mart´ín-Cervantes, P. A. (2022). Should risk-averse investors target the portfolios of socially responsible companies?. *Oeconomia Copernicana*, *13*(2), 439–474. https://doi.org/10.24136/oc.2022.014.

Vo, A., Nguyen, T., & Le, T. (2020). Brent Oil Price Prediction Using Bi-LSTM Network. Intelligent Automation & Soft Computing, 26(6), 1307–1317. https://doi.org/10.32604/iasc.2020.013189

Vochozka, M., Horák, J., Krulický, T., & Pardal, P. (2020). Predicting future Brent oil price on global markets. Acta Montanistica Slovaca, 25, 375–392. https://doi.org/10.46544/AMS.v25i3.10

Wallace, M., Li, A., & Hyde, A. (2022). The Great Recession Index: A Place-based Indicator for Countries, States, and Metropolitan Areas. Social Indicators Research, 160(1), 401–426. https://doi.org/10.1007/s11205-021-02799-0

Wang, G.-X., Huang, D., Ji, J.-H., Völker, C., & Wurm, F. R. (2020). Seawater-Degradable Polymers-Fighting the Marine Plastic Pollution. Advanced Science (Weinheim, Baden-Wurttemberg, Germany), 8(1), 2001121. https://doi.org/10.1002/advs.202001121

WHO | World Health Organization. Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data [online]. [cit. 05.03.2023] Available from: https://covid19.who.int/WHO-COVID-19-global-table-data.csv

WHO | World Health Organization. WHO-convened Global Study of Origins of SARS-CoV-2: China Part. [online]. 30. 3. 2021. Copyright © [cit. 18.09.2022]. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/origins-of-the-virus

Yan, R., Cao, F., & Gao, K. (2022). Determining the COVID-19 effects on spillover between oil market and stock exchange: A global perspective analysis. Environmental Science and Pollution Research International, 29(44), 66109–66124. https://doi.org/10.1007/s11356-022-19607-y

Zamfir, I.-C., & Iordache, A.-M. M. (2022). The influences of covid-19 pandemic on macroeconomic indexes for European countries. Applied Economics, 54(39), 4519–4531.

Zeinedini, S., Karimi, M. S., & Khanzadi, A. (2022). Impact of global oil and gold prices on the Iran stock market returns during the Covid-19 pandemic using the quantile regression approach. Resources Policy, 76(C). https://ideas.repec.org//a/eee/jrpoli/v76y2022ics0301420722000526.html

Zhao, L., Rasoulinezhad, E., Sarker, T., & Taghizadeh-Hesary, F. (2023). Effects of COVID-19 on Global Financial Markets: Evidence from Qualitative Research for Developed and Developing Economies. The European Journal of Development Research, 35(1), 148–166. https://doi.org/10.1057/s41287-021-00494-x