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## DETERMINATION OF IRON PROCUREMENT STRATEGY FOR MANUFACTURING COMPANIES

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**Abstract.** The objective of this paper is to evaluate the price development of iron (steel rebar and hot rolled coil steel) on commodity exchanges, to determine the dependence of the price of iron on prices of other major commodities (crude oil and natural gas), to forecast its future development and to propose a particular iron procurement strategy for manufacturing companies in the South Bohemian Region until the end of 2028. The content analysis method was selected to evaluate the price development. It was also used to assess the dependence of iron prices on other major commodities, which was considered using the correlation analysis method. The artificial neural network method, multilayer perceptron networks, was selected and used to forecast future price development. All calculations are performed using Statistica software (version 13). Linear regression is conducted using different functions, with 1,000 neural structures being generated each time, out of which 5 structures showing the best characteristics are selected. These are retained to forecast future prices for the 2023-2028 period in three experiments. Results are presented in tables and graphs processed in Microsoft Excel. Based on the selected variants of future steel price forecasting, a specific iron procurement strategy can be recommended for manufacturing companies in the South Bohemian Region until the end of 2028.

**Keywords:** price of steel; time series; future price forecasting; artificial neural networks; regression analysis

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**JEL Classifications:** C45, C22, Q02

**Additional disciplines:** construction engineering, strategic management, strategic planning

### 1. Introduction

Together with energy, iron and steel are the most critical raw materials needed to develop economies around the world (Rokicki, 2019). Historically, crude iron ore was traded based on long-term contracts. However, this changed in 2006 when the negotiation model between large producers and large consumers changed, and subsequently, trades were made on the spot market based on prices set mainly by independent benchmarking companies, which, however, have later seen frequent fluctuations in the price of crude iron ore (Kim et al., 2022; Behun et al., 2018). The main explanation for the collapse of the benchmarking system turned out to be the strengthening importance of the Chinese market (Olczyk et al., 2022). The current iron ore pricing system is based on several indices developed by benchmarking companies according to specific systematic procedures, which is also reported by

Wårell (2018). Iron ore is an essential mineral as it is used to produce steel. In 2020, iron ore became the 13th most traded product worldwide, with the value of these trades amounting to USD 141 billion. The largest exporters in 2020 were Australia (56 %, USD 80 billion) and Brazil (19 %, USD 26 billion), while the largest importers were mainly China (70 %, USD 99 billion), followed by Japan (6 %, USD 8 billion) and South Korea (4 %, USD 6 billion), which shows that the diversification of sellers and buyers is limited (OEC-Iron Ore, 2022).

Iron ore prices have been fluctuating widely since 2000, and there is a general belief that these price shifts may translate into inflation (Ahn et al., 2017). For instance, the price of iron ore increased extremely from USD 12/tonne in 2000 to USD 154/tonne in 2008, i.e. more than a 12fold increase, whilst the price of iron ore generally declined between 2011 and 2016. Chinese inflation has followed a similar trend to the international price of iron ore (Chen & Yang, 2021). The rise in the price of iron ore results from a combination of unprecedented macroeconomic expansion and intensive use of the commodity, especially from China. Given such circumstances, iron ore price changes are characterized by higher volatility, which directly affects the movement of the Australian dollar (AUD) exchange rate and indirectly affects Australia's economic prospects (Gomwe & Li, 2020).

Then, steel products are indispensable for machinery, construction of entire infrastructures and housing, and also essential for the automotive and engineering industries (Tkacova & Gavurova, 2023). With the significant development of machinery manufacturing, infrastructure construction, housing, and the automotive industry development, approximately 80 % of China's steel production is consumed by these enumerated industries (Ma, 2021). In the middle of 2021, various headlines were again piling up about skyrocketing prices of steel as well as depleted inventories of companies and long lead times for these steel products. All of this in turn can be unsettling for designers, builders, and steel workers at the end of the value chain of these steel structures. The construction cost of an entire steel building is complicated to determine mainly due to the volatile prices of materials and hence seems fraught with risk (Fischer, 2021).

The World Steel Association (WSA) defines steel as the most critical engineering and construction material in the world. The steel industry's contribution to social development and the far-reaching use of steel in its many forms in our daily lives determine its importance to our prosperity and well-being. The steel industry is often considered an indicator of economic progress, and several previous studies have focused on the close relationship between various aspects of the steel industry and the economy, particularly through GDP dynamics (Cerasa & Buscaglia, 2019). Given the wide use of steel products, their price changes play a crucial role in the development of related industries and even in the stable functioning of national economies (Qi et al., 2020; Simionescu & Gavurova, 2023).

Baláž & Bayer (2019) stated that the domestic industry is losing its former positions and is being pushed out of domestic and international markets. Development in the international steel market over the past year confirmed that the market is likely to experience significant changes as a result of safeguard measures, most of which will threaten the international competitiveness of the European steel industry with negative impacts on its overall economic growth (Simionescu et al. 2021, 2022; Bilan et al. 2017). Hančlová et al. (2020) pointed out that the iron and steel industry has had a very strong tradition in the Czech Republic since the nineteenth century and is extremely important for the Czech economy. According to data from the Czech Statistical Office, the share of sales of finished iron and steel products in GDP has been between 4 % and 5 % in recent years.

In 2020, there were, on average, 65 iron manufacturing companies in the South Bohemian Region (CZ-NACE 25, 28, 29, 30, and 33), which represents a 7 % share of the total number of such entities in the Czech Republic, with the companies generating sales of CZK 92 billion, which represents 54 % of the total sales of the industrial sector in the South Bohemian Region (CZSO.cz, 2021).

This paper aims to evaluate the development of iron prices on commodity exchanges, the impact of these prices on manufacturing companies in the South Bohemian Region, and to propose a strategy for procuring iron until the end

of 2028. The prices of iron ore, as well as many other raw materials and commodities, have been fluctuating significantly for several periods. Iron ore prices react quickly to the supply and demand situation in the world market (Chen & Yang, 2022). Iron ore has been the most expensive in the world in the last decade. Steel is the primary material that determines the price of other commodities and materials (Echo24.cz, 2021).

This issue leads to the formulation of the following research question (RQ1).

RQ1: What is the historical price development of iron in the 2010-2022 period?

Kim et al. (2022) reported that several academic studies have been conducted to understand the relationship between the price of iron ore and other economic indices or prices of other commodities as well. Ma & Wang (2019) examined the relationships between prices of crude oil, natural gas, thermal coal, and iron ore along with the Australian dollar and the exchange rate of the Chinese RMB.

About the above research conducted, the following research questions (RQ2, RQ3a) can be formulated:

RQ2: What is the relationship between the price of iron and other major commodities?

RQ3a: What price of iron can be estimated taking into account available price forecasts for other commodities in future years (2023-2028)?

If the relationship between the price of iron and other major commodities is not found, it will be necessary to formulate the following research question (RQ3b):

RQ3b: Given the historical price development of iron, what price can be estimated for future years (2023-2028)? It is expected that steel production will again grow faster than consumption, resulting in renewed pressure on the price of steel. This adds to the fact that the historically high price of iron ore reduces the margins of companies unable to pass on cost increases to their clients (Credendo.com, 2021). Forecasting the iron ore price development is very important, considering that it significantly impacts company production costs and profitability (Lee et al., 2019).

These significant price changes and impacts on company production costs lead to the following research question (RQ4) formulation:

RQ4: What iron procurement strategy can be proposed for manufacturing companies in the South Bohemian Region until the end of 2028?

## **2. Literature Review**

Iron is one of the most widely used metals in manufacturing worldwide. The development of demand and supply mainly determines the global price of iron ore. There are also many parameters (e.g. price of steel, steel production, price of crude oil, price of gold, interest rate, inflation rate, production of iron and price of aluminium) that affect the global price of iron (Li et al., 2020). Iron ore is an important and essential source of steel production, hence forecasting its price is strategically important, particularly for risk management in companies and related production projects (Tuo & Zhang, 2020; Gavurova et al. 2017). There are several methods for price forecasting, with some of the most appropriate methods being those that examine time series variables in a non-linear and dynamic way closer to reality, i.e. iron price fluctuations (Lv et al, 2022; Kolková, & Ključnikov, 2021; Kolkova & Rozehnal, 2022). A time series includes statistical data on various quantitative indicators of economic and social phenomena in a time sequence, and methods based on time series analysis comprise various estimation techniques (Landmesser, 2021; Fiszeder & Małecka, 2022), where the most important technique is the exponential smoothing estimation method

(Kahraman & Akay, 2022). Ten years time series analysis was used by Jeremić et al. (2022) in their research on agricultural development in Serbia, examining the relationship between crude oil and gold and the price of iron, concluding that changes in the price of steel cause a gradual increase in the price of agricultural machinery, which significantly increases the cost of agricultural production. Vochozka et al. (2021) collected research data from daily closing historical prices of copper converted into a time series, with the data then being processed with the use of artificial intelligence, recurrent neural networks including a Long short-term memory layer, as neural networks have great potential to forecast this type of time series. Carrasco et al., 2015 decided to look into the price of copper by analyzing the time series of prices of copper over the last 30 years and studying chaotic systems.

Su et al. (2017) examined whether there are multiple bubbles in the price development of iron ore by using the Dickey-Fuller test, considering this method suitable for the practical implementation of time series and recognition of the initiation and termination of multiple bubbles. The empirical results of their research indicated that there were four bubbles from January 1980 to December 2016 and that prices of iron ore differed from their intrinsic values based on market fundamentals to such an extent that they mainly explained the first three bubbles by excessive demand from China and attributed the last bubble mainly to the negative impact of the 2008 global financial crisis. An analysis of prices of iron was conducted by Wårell (2018) using time-series data related to the development of monthly prices between January 2003 and June 2017 and performing statistical tests of structural breaks as well as reduced-form price regressions of the most important factors for prices of iron over the given period. The overall results suggest that the price régime change does not have a significant impact on the prices of iron when the period is extended; rather, it was the end of the commodity boom in 2014. However, GDP growth in China had the strongest impact on the prices and still appears to be the most influential factor determining international prices of iron ore. A time series of steel price indices covering ten years from 15 June 2011 to 15 April 2021 was applied by Mir et al. (2021) for forecasting with the use of non-linear auto-regressive neural networks as a forecasting model. These simulations have proved to be relatively simple, generating forecasts of high accuracy and stability. To forecast commodity prices, Lasheras et al. (2022) used the methodology of using input value information from a time series of prices in previous months, while the research method itself is based on decomposing the time series into its trend, seasonal and random components, and using trend information as independent variables in a multivariate adaptive spline regression model.

Ma & Wang (2019) focused on examining dependency structures between prices of crude oil, natural gas, thermal coal, and iron ore, Australian dollar and Chinese RMB exchange rates based on dependencies analyzed and compared using copula models, resulting in the finding that the increase in commodity prices coincided with the rise in the Australian dollar and the decrease in the Chinese RMB. Kim et al. (2022) examined the relationship between monthly prices of iron ore and 12 other monthly commodity prices or indices in both bivariate and multivariate perspectives using the Augmented Dickey-Fuller (ADF) test and concluding that the price of iron ore has a bidirectional effect on the prices of oil, copper and Australian coal and vice versa, i.e. the price of iron ore is dependent on the price of other commodities. Looking into the long-run dependence and causality between prices of crude oil and precious metals (gold, silver, platinum, palladium, steel, and titanium), Shafiullah et al., 2021 used time series properties using new econometric techniques by testing each pair of variables for long-run equilibrium (cointegration) and Granger causality. The relationship between the main commodities was measured by Nicola et al., 2016 using correlation coefficients and studying the degree and time development of unconditional and conditional correlations by estimating and testing uniform spacing, multivariate dynamic conditional correlation models, and stepwise regression procedures. The relationship between foreign trade with iron in the European Union countries and the overall economic situation was researched by Rokicki (2019) with the use of the following methods: descriptive, graphical, and Pearson's linear correlation coefficient. To analyze the correlation between exchange rates and commodities, Tsiakas & Zhang (2021) selected an analysis based on a dynamic conditional correlation model with mixed data sampling, where this model separates high-frequency from low-frequency volatility and correlation dynamics and allows to relate long-run volatility and correlation.

Since steel is also included as a significant cost of construction projects, it is important to forecast its price accurately; to do so, Zhang (2015) first conducted a time series analysis of steel prices and used the autoregressive moving average (ARMA) model for the future price, with the forecast results being considered accurate and reliable based on the tests conducted. To develop three models that use artificial neural networks for forecasting future prices of steel rebar in the context of the Egyptian construction industry 6 months ahead, Shiha et al. (2020) used Microsoft Excel, NeuralTools software, and Python programming language in Spyder software to apply historical data on prices of steel and cement as well as macroeconomic indicators in Egypt from May 2008 to June 2018, where these proposed models can be potentially useful tools for forecasting and quantifying price fluctuations. In their price forecasting of hot rolled steel in Spain, Alcalde et al. (2023) applied artificial non-linear neural networks to several different input time series to identify whether any of the neural models outperformed the other models in forecasting steel prices. Lee et al. (2019) used a forecasting method based on multivariate time series analysis, with the forecasting target in their study being the price of iron ore, which was the largest contributor to the price of raw materials for steel products. They found that the proposed method was more than 2.3 times more accurate than past average values. Xu & Zhang (2022) regard the auto-regressive integrated moving average (ARIMA) model, vector auto-regressive (VAR) model, and vector error correction model (VECM) as the most popular and powerful approaches to solving numerous price forecasting problems. The ARIMA (or "autoregressive integrated moving average") model based on time series analysis provides a basic theory and good solution focusing on the steel price issue. It was used by Liu et al. (2015) to analyze and forecast the first ten periods of the Chinese thread steel price index, with the result showing that the short-term (four-phase) forecast is very effective and the ARIMA model is suitable for price forecasting. Concerning future steel price forecasting based on a time series of prices collected by anonymous weekly surveys among Italian steel operators, Zola & Carpita (2016) also used the ARIMA regression method. To forecast copper spot prices (from the New York Commodity Exchange), García-Gonzalo et al. (2022) used machine learning methods and support vector regression in conjunction with different modeling schemes (recursive, direct, and hybrid multi-step), and by using these techniques, they constructed three different time series analyses and compared their performance, showing that the hybrid direct-recursive model obtained the best results.

The vector error correction (VEC) model was identified by Faghieh & Kashani (2018) as reliable in forecasting short-term and long-term prices of asphalt, steel, and cement. Li et al. (2020) developed and presented a new model, namely the group method of data handling (GMDH), for price forecasting of iron ore. The study results showed that the GMDH forecasting model is significantly better than other forecasting models and that the GMDH technique can forecast the price of iron ore with a higher degree of accuracy than other techniques analyzed. Cetin et al. (2019) developed a steel price forecasting method using the long short-term memory (LSTM) network model, which is an adapted model of recurrent neural network architecture, and obtained the best forecasting result from the forward five-day forecasting model with high correlation coefficient R. For their forecast of iron sale price, Jian Ming et al. (2016) looked into different data analysis methods and used artificial neural networks and automatic regression moving average as forecasting models. They concluded that the combined forecasting model is effective and feasible, and the results of this forecast can provide effective support for companies in their strategic decision-making.

### **3. Methodological approach**

#### **3.1 Data**

The primary data sources for RQ1, RQ2, and RQ3a will be data obtained from TradingEconomics.com (2023) and Investing.com (2023), containing current and historical data from commodity, equity, and currency markets. Specifically, the related data involve the price development of two types of steel (steel rebar and hot rolled coil steel) and two major commodities, i.e. crude oil and natural gas, selected with RQ2. The time interval for each commodity monitored will be set on a month-by-month basis for the 2010-2022 period. Prices of steel are in USD per tonne or CNY per tonne, with the CNY currency converted to USD using the exchange rate from Investing.com

(2023), prices of crude oil are in USD/barrel, and prices of natural gas are in USD/million British thermal units. The data source for RQ3a will be data on crude oil and natural gas forecast prices published on the European Central Bank website ([ecb.europa.eu](http://ecb.europa.eu), 2023) in the European Central Bank Macroeconomic Forecast as of 15 December 2022.

### 3.2 Methods

In terms of addressing RQ1, the historical time series of prices of two types of steel will be analyzed, specifically by observing these values at certain time intervals (months and years). Subsequently, using the content analysis method, the historical price development of iron will be assessed, and the results will be presented, among other things, in a graph prepared in Microsoft Excel, where a linear trend line will be inserted, from which it can be deduced whether the price is increasing or decreasing.

To answer RQ2, correlation analysis, specifically the Pearson correlation coefficient method, will be used to determine possible dependence on the price of steel and selected major commodities (crude oil and natural gas). By calculating the Pearson correlation coefficient  $r$ , it will be determined whether there is a dependence between the price of steel and main commodities (i.e. prices of electricity, crude oil, and natural gas). If  $r = 0$ , there is no linear correlation between the variables. If the resulting  $r < 0$ , a negative relationship can be observed, whereas if the resulting  $r > 0$ , the correlation is positive. Therefore, the coefficient of  $r$  must be  $< 1$  and  $> -1$ .

The formula for calculating the Pearson correlation coefficient  $r$  is as follows:

$$r = \frac{\sum_i(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i(x_i - \bar{x})^2} \sqrt{\sum_i(y_i - \bar{y})^2}} \quad (1)$$

where  $x$  and  $y$  are the mean values of the selection of AVERAGE (matrix1) and AVERAGE (matrix2).

The data will be processed using Microsoft Excel, whilst the CORREL statistical function will be used to calculate the coefficient  $r$ .

The strength will be interpreted by dividing the resulting coefficient  $r$  into the following three groups according to its correlation value: low (weak), medium, and very strong correlation. There will be a low (weak) correlation if the resulting  $r$  value ranges from 0.001 to 0.3 and from -0.001 to -0.3. A medium correlation will be represented by the resulting  $r$  value ranging from 0.3 to 0.9 and from -0.3 to -0.9. A very strong correlation will be the resulting  $r$  value between 0.9 and 1 and between -0.9 and -1.

If a very strong correlation between the price of steel and another commodity is established about RQ2, a particular forecast of the price of steel to answer RQ3a will be set concerning the future price of this commodity. However, provided that a very strong correlation between the price of steel and another commodity is not established about RQ2, the following procedure will ensure the answer to RQ3b.

The obtained data on prices of steel (steel price time series) will be processed in Microsoft Excel to import the data into the Statistica software (version 13) by Tibco Software Inc. A particular forecast of the future prices of steel will be determined using multilayer perceptron neural networks available in this software.

In the first stage, regression analyses will be performed for both types of steel using neural structures. The procedure will be the same, as neural networks will be generated for each type of steel, using so-called MLP – multilayer perceptron networks. An independent variable will always be the period, whereas a dependent variable will be the

price of each type of steel. The distribution of the steel price time series will be classified into three datasets, i.e. the training, the testing, and the validation. The first dataset will contain 70 % of the input information and will be used to train the neural structures, whilst the other 15 % of the input data will be used to test validation of the reliability of the found neural structures, or the found model. The time series delay will be 1 or 12.

There will be a total of 3 experiments (i.e. Experiment 1, Experiment 2, Experiment 3), and the software setup will be as follows:

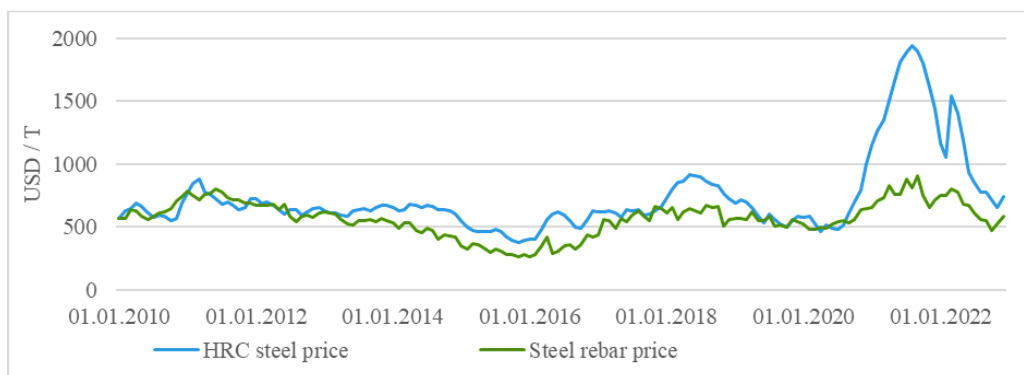
- 1) The content of the hidden layer for MLP networks will always be formed in the first experiment and the second experiment: at least 2 neurons and a maximum of 8 neurons, or at least 3 neurons and a maximum of 11 neurons for the third experiment. A total of 1,000 neural networks will always be generated, and the five neural networks showing the best resulting characteristics will always be selected for the next forecast.
- 2) Activation functions: about the multilayer perceptron network of all experiments, the following activation functions will be valid in the hidden and output layer of neurons: Identity (linear), Logistics (logistics), Tanh (hyperbolic tangent), Exponential (exponential) and Sine (sine).
- 3) Other settings will be left as per the ANS (automated neural network) settings.

Regarding the first and second experiments, the monthly period will be selected as the independent variable, which will also apply to the third experiment, where the period will be further broken down into months, dates, and days of the week. Related results will then be processed and presented in tables and graphs prepared in Microsoft Excel. To forecast future prices for both types of steel, individual neural networks will be imported back into the Statistica software, with the future price time series being modeled over five years, namely 2023-2028 (by month). These forecasts will be made for all 3 experiments (always for all of the 5 neural networks with the best characteristics), hence there will be a total of 6 forecasts. The time series delay will be 12. Only time series showing meaningful forecast development will be selected for the presentation of the results, e.g. projections with negative or extreme values will not be presented. The selected results will also be subsequently processed and presented in tables and graphs prepared in Microsoft Excel.

#### 4. Results and Discussion

##### RQ1: What is the historical price development of iron in the 2010-2022 period?

Figure 1 shows the development of the historical prices of steel rebar and hot rolled coil steel between 2010 and 2022.



**Figure 1.** Historical price development of hot rolled coil steel and steel rebar

*Source:* Authors, based on data from TradingEconomics.com (2023)

In 2010, the price of both types of steel was at USD 570/t and gradually increased in the following years, reaching its peak in March 2011, after which the price gradually declined until February 2016, which, according to Csas.cz

(2020), was mainly related to the high growth of steel production in China in the previous years and the gradual decrease in demand. After 2016, the price started to rise again until around mid-2018, after which it started to fall again, with the price of both commodities hovering around USD 500/t during the year. Steep growth again followed, particularly for hot rolled coil steel, with an extremely high value in September 2021 trading at USD 1 900/t, which was almost four times the 2010 price. The price of steel rebar also rose significantly in the same month (up to USD 905/t), being less than double the original price in 2010. According to Credendo.com (2021), the main reason for this could be seen in limited growth in steel production on the one hand and significantly increased Chinese demand on the other, while the rise in prices of steel was also supported by an increase in the price of iron ore during this period. It then began to decline again but then rose sharply in early 2022, which was linked to the beginning of the Russian invasion of Ukraine and the fact that Russia and Ukraine account for 60 % of global iron ore exports and for some iron and steel products their share of global exports reaches 40 % (Csas.cz, 2022). From 2022 onwards, the price started to decline again to approximately average values of the other discussed commodities over the period under review.

**RQ2: What is the relationship between the price of iron and other major commodities?**

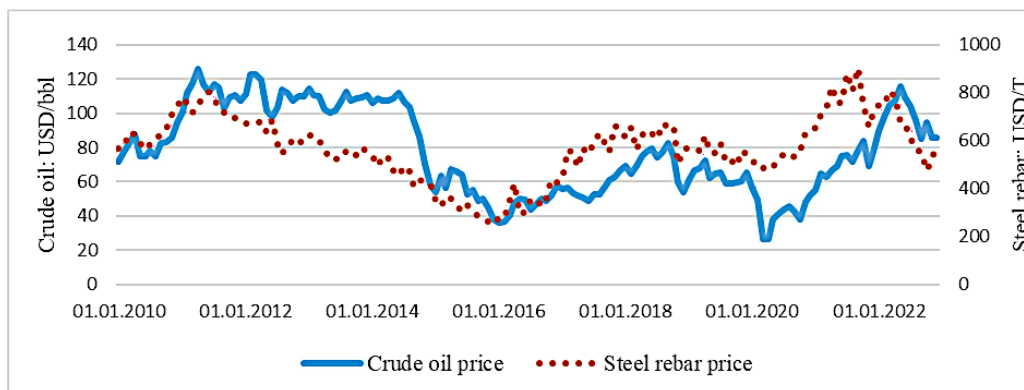
The correlation of historical prices was followed to determine the relationship between the prices of iron, or hot rolled coil steel and steel rebar, and two other important commodities (crude oil and natural gas). The correlation results of these prices showed a weak to moderate correlation of crude oil and natural gas with hot rolled coil steel and steel rebar prices. A summary of the correlation results is presented in Table 1 below. The strongest, but still only moderate, correlation is between the price of steel rebar and the price of crude oil.

**Table 1.** Correlation coefficients r

Commodity	Crude oil	Natural gas
Hot rolled coil steel	0.1723	0.3592
Steel rebar	0.5004	0.3431

Source: Authors

The results, therefore, show that it is not appropriate to base future steel price projections on available price forecasts of crude oil and natural gas, as the prices of these commodities are not strongly correlated. A similar conclusion regarding the correlation between the prices of major commodities and steel was also reached by Ma & Wang (2019) and Kim et al. (2022). The strongest correlation, but only at a medium level, between the price of steel rebar and crude oil is also visible in the graphical representation of the line graph in Figure 2.



**Figure 2.** Historical price development of crude oil and steel rebar  
Source: Authors, based on data from TradingEconomics.com (2023)



**RQ3a: What price of iron can be estimated taking into account available price forecasts for other commodities in future years (2023-2028)?**

As discussed in RQ2, a strong correlation has not been shown between the price of steel and the other major commodities. Thus, RQ3a was not addressed, but instead, it was proceeded directly to RQ3b.

**RQ3b: Given the historical price development of iron, what price can be estimated for future years (2023-2028)?**

Multilayer perceptron neural networks were used to project future prices. Neural networks have been successfully applied to project future commodity prices by e.g. Shiha et al. (2020), Mir et al. (2021), Vochozka et al., and Alcalde et al. (2023), with all of them particularly highlighting the high performance of neural networks in the applicability of individual future forecasts. The results were based on three experiments (Experiment 1, Experiment 2, Experiment 3), with the performance of individual neural networks varying across the experiments. The highest performance was achieved by the neural networks within Experiment 1, where the resulting correlations were greater than 0.95 for steel rebar and greater than 0.97 for coil steel. An overview of individual networks can be seen in Table 2 below.

**Table 2.** Correlation coefficients for Experiment 1

Steel rebar				Hot rolled coil steel			
Name of Network	Price (USD/T) Training	Price (USD/T) Testing	Price (USD/T) Validation	Name of Network	Price (USD/T) Training	Price (USD/T) Testing	Price (USD/T) Validation
1.MLP 12-7-1	0.962679	0.952103	0.956211	1.MLP 12-5-1	0.969318	0.967859	0.973020
2.MLP 12-8-1	0.965726	0.963630	0.953366	2.MLP 12-7-1	0.979258	0.978096	0.975766
3.MLP 12-7-1	0.959296	0.949821	0.955081	3.MLP 12-7-1	0.978651	0.973673	0.974446
4.MLP 12-8-1	0.967176	0.968927	0.953290	4.MLP 12-7-1	0.977503	0.975192	0.972309
5.MLP 12-5-1	0.963999	0.956093	0.955810	5.MLP 12-5-1	0.976032	0.979593	0.974582

Source: Authors

The second highest performance was achieved by the neural networks in Experiment 2, where the resulting correlations were higher than 0.92 for steel rebar and higher than 0.94 for coil steel. The lowest performance was achieved by the neural networks in Experiment 3, where the resulting correlations were higher than 0.83 for steel rebar and higher than 0.81 for coil steel, i.e. they least followed the historical price trend of each type of steel. However, in all experiments, the top 5 performing networks were always selected and used to project the future price of each type of steel.

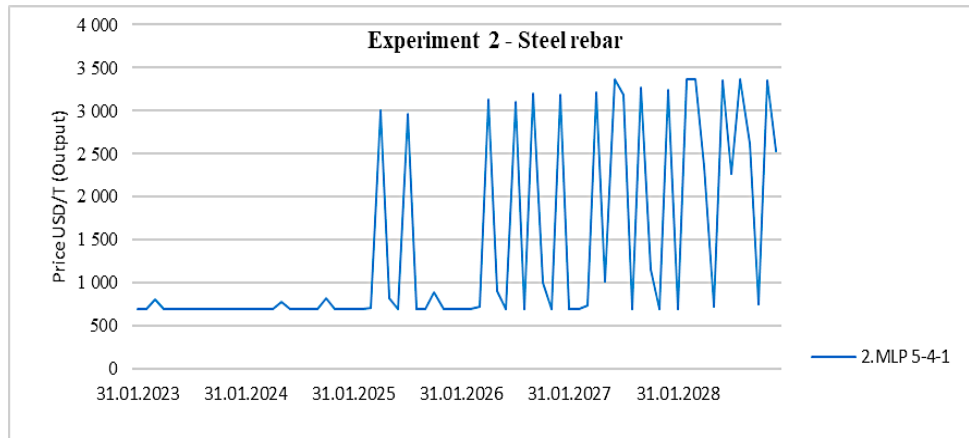
When considering the forecast results of future prices of steel rebar by the individual neural networks in the experiments conducted, it is evident that the networks achieved very different results. It is also very interesting to note that the networks with the highest and second highest performance for the forecast steel rebar price predicted minima within the negative price levels, which can be considered a poor and unusable result for this future price forecast. A summary of the negative price minima is presented in Table 3 below.

**Table 3.** Statistics of networks with negative price forecast (forecast minima)

Future Forecast Statistics	Experiment 1				Experiment 2			
	1.MLP 12-7-1	2.MLP 12-8-1	3.MLP 12-7-1	5.MLP 12-5-1	1.MLP 5-8-1	3.MLP 5-11-1	4.MLP 5-9-1	5.MLP 5-4-1
Minimum forecast	-376.99	-376.63	-377.00	-372.90	-342.58	-368.70	-373.00	-377.00

Source: Authors

In Experiment 2 (see Figure 3 below), the 2.MLP 5-4-1 network forecasts future prices of steel rebar at very extreme volatility, with the price fluctuating widely between USD 500/t and USD 3 500/t over the 2025-2028 period, which seems highly unlikely given the historical price trend, and thus is not applicable for further conclusions.



**Figure 3.** 2.MLP 5-4-1 network forecast

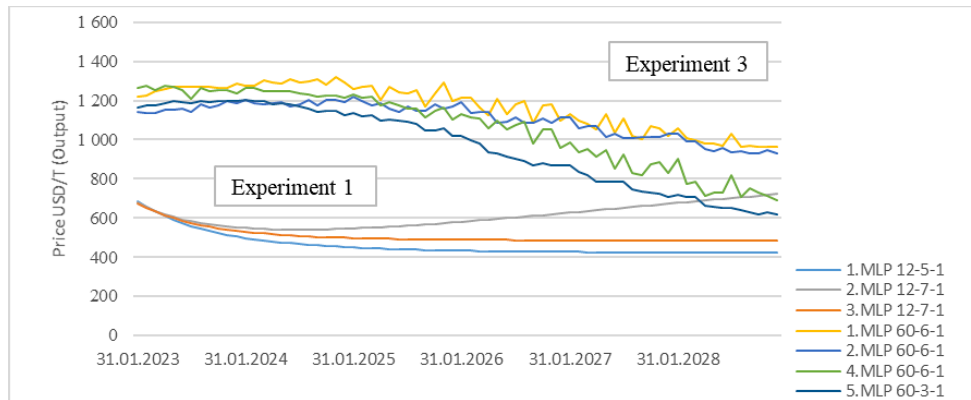
*Source:* Authors

Based on the historical price development and taking into account the performance of the individual networks (according to correlations), the best forecasts of the future price of steel rebar from the three conducted experiments are related to the results of the 4.MLP 12-8-1 network in Experiment 1, as well as the results of the forecasts of four neural networks, namely 1.MLP 60-6-1, 2.MLP 60-6-1, 4.MLP 60-6-1 and 5.MLP 60-3-1 in Experiment 3.

As regards the resulting forecasts of the future prices of hot rolled coil steel, the forecasts of each neural network also varied across the experiments conducted. The results of the forecasts within the second experiment can be seen as the least applicable, with the 2.MLP 5-3-1, 3.MLP 5-5-1, 4.MLP 5-6-1 and 5.MLP 5-3-1 networks forecasting a price of around USD 1 400/t at the beginning of 2023, which seems very unlikely given the price decreased to USD 700/t at the end of 2022.

The resulting forecasts according to Experiment 1, namely the forecasts of the 1.MLP 12-5-1, 2.MLP 12-7-1 and 3.MLP 12-7-1 networks, as well as the results according to Experiment 3, namely the forecasts of the 1.MLP 60-6-1, 2.MLP 60-6-1, 4.MLP 60-6-1 and 5.MLP 60-3-1 networks can be considered applicable given the historical price development of hot rolled coil steel and taking into account the performance of the individual networks (according to correlations).

However, even in these cases, there are some differences in the forecasts presented in a line graph in Figure 4. In Experiment 1, the neural networks forecast a price of hot rolled coil steel reading just under USD 700/t in early 2023, whilst in Experiment 3, the neural networks forecast a price of around USD 1 200/t. However, under both Experiments 1 and 3, the neural networks forecast a similar future downward price trend until the end of 2028 (see Figure 4 below).



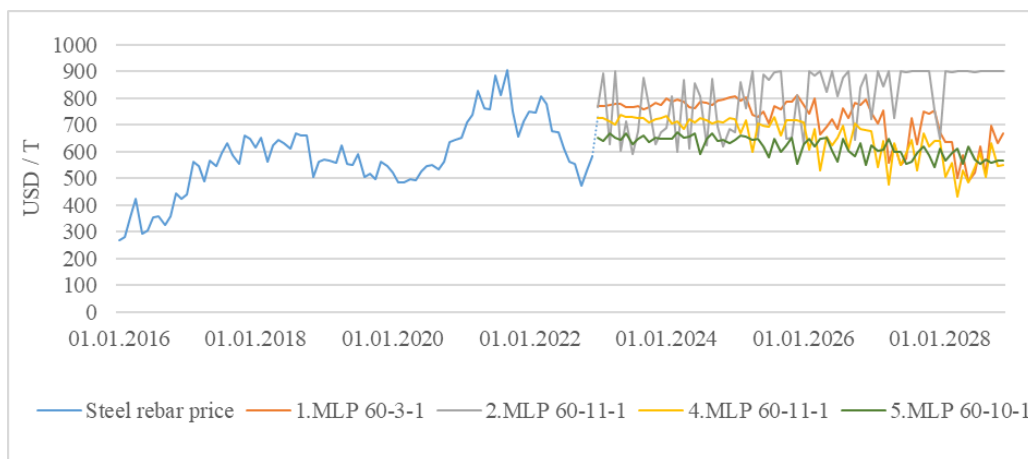
**Figure 4.** Forecast of future price of hot rolled coil steel according to Experiment 1 and Experiment 3

Source: Authors

Related discussion of the results shows that multilayer perceptron neural networks can be successfully used to forecast future prices of steel, and the conclusions of Shiha et al. (2020), Mir et al. (2021), Vochozka et al. (2021) and Alcalde et al. (2023) that neural networks achieve high performance can be confirmed.

**RQ4: What iron procurement strategy can be proposed for manufacturing companies in the South Bohemian Region until the end of 2028?**

To answer RQ4, it was necessary to select a suitable forecast variant of future prices of steel based on which it would be possible to recommend a specific iron procurement strategy for manufacturing companies in the South Bohemian Region for the 2023-2028 period. Within the processed results, forecasts of neural networks in the framework of Experiment 3 were selected for both analyzed types of steel, although within this experiment the networks achieved the lowest performance, expressed by the lowest level of correlation. As for the price projection of steel rebar, the projections of the 1. MLP 60-3-1, 4. MLP 60-11-1 and 5. MLP 60-10-1 networks in the third experiment seem to be the most appropriate, as shown in the following Figure 5. In all cases, these networks forecast a gradual stabilization of the steel rebar price level between USD 600-800 per tonne (in 2023-2026) and a subsequent decline in the future price to USD 500-600 per tonne in 2028.

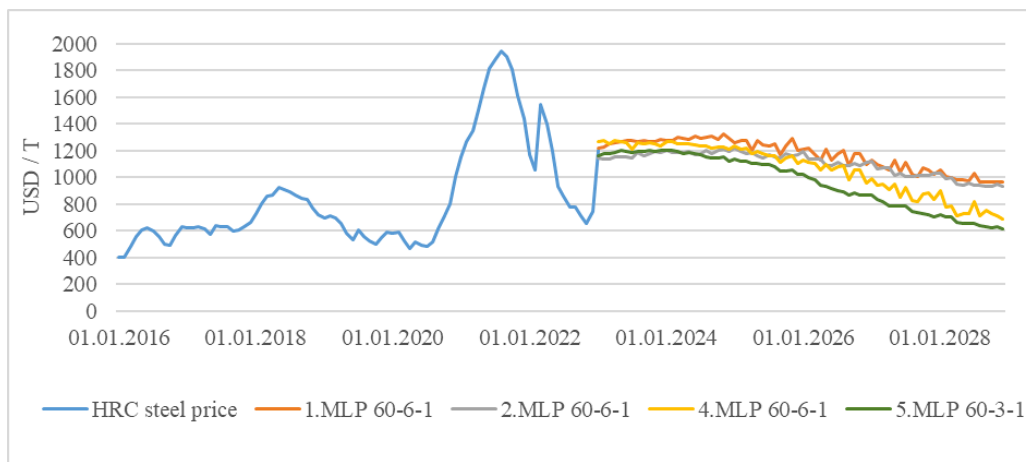


**Figure 5.** Real and forecast price development of steel rebar

Source: Authors

In Experiments 1 and 2, only the forecasts of two networks proved to be applicable, namely 4.MLP 12-8-1 in Experiment 1 and 2.MLP 5-4-1 in Experiment 2. The forecast related to 4. MLP 12-8-1 appears to be less applicable given the smooth and continuous decline in the price of steel in 2023 and 2024, whereas, in the following years, it is essentially constant at USD 280/t, which cannot be realistically predicted given the ongoing conflict in Ukraine. In this case, however, there is also a continuous decline and the overall trend is similar to the results of Experiment 3—the forecast of the only suitable network, i.e., 2.MLP 5-4-1 was found to be inapplicable in the discussion of the RQ3b results about the very extreme volatility, with the price fluctuating extremely between USD 500/t and USD 3 500/t over the 2025-2028 period.

In terms of price projection of hot rolled coil steel, using projections of neural networks in Experiment 3, namely 1. MLP 60-6-1, 2. MLP 60-6-1, 4. MLP 60-6-1 and 5. MLP 60-3-1, also seems to be the most appropriate, as shown in the following Figure 6.



**Figure 6.** Real and forecast price development of hot rolled coil steel

*Source:* Authors

The individual forecasts assume a future gradual decline in the price of steel, except for the years 2023-2026, when the price tends to increase slightly and the price level is between USD 1 200-1 300 per tonne. However, a decline to a level between USD 600-900 per tonne is forecast in 2027-2028. The forecasts of the 1.MLP 12-5-1, 2.MLP 12-7-1, 3.MLP 12-7-1 and 4.MLP 12-8-1 networks in the first experiment appear less applicable given the smoothed and continuous decline in the price of steel in 2023 and 2024, except for 2. MLP 12-7-1, forecasting a subsequent increase, with an essentially constant price of USD 400-500/t being forecast in the following years, which cannot be realistically predicted due to the ongoing conflict in Ukraine. However, there is also a continuous decrease and the overall trend is similar to the results under Experiment 3, i.e. except for the forecast of 2.MLP 12-7-1, where the price increases to a level of USD 710/t by the end of 2028.

According to the discussion of the results related to RQ3b, the forecasts of the 2.MLP 5-3-1, 3.MLP 5-5-1, 4.MLP 5-6-1 and 5.MLP 5-3-1 networks in the second experiment proved to be the least applicable about the price forecasting that in all cases reaches a level of around USD 1 400/t in early 2023, which seems very unlikely given the price fell to USD 700/t at the end of 2022. However, even in the case of the second experiment, there is a gradual price decline and a future stabilization of the price in the last part of the forecast period, thus supporting the results of the third experiment.

The above discussion of the results confirmed the appropriateness of the forecasts selected according to RQ3b, and it can therefore be concluded that the manufacturing companies can be advised to gradually purchase iron on

a regular basis, as stated in this section of the paper. That is to say, the volume of stocks to be purchased will be set to cover the total consumption in a given year, particularly for the years 2023-2026, taking into account the selected results of the forecasts for these periods. Even for the next forecast period, i.e. 2027 and 2028, it cannot be recommended to the manufacturing companies that they pre-stock up with a larger volume of iron for a longer production period, again taking into account the forecast future decline in the price of both types of steel.

## 5. Conclusions

By observing the development of the prices of steel rebar and hot rolled coil steel in monthly time intervals for the years 2010-2022, the historical price development of iron was evaluated using the content analysis method. It was found that in January 2010, both types of steel were trading at approximately similar price levels represented by USD 570/t. However, it was further shown that in subsequent years, the price of each type of steel developed in different ways. In both cases, the highest price was in 2021, with the price of steel rebar rising to USD 905/t in September 2021, whereas the price of hot rolled coil steel was the highest in August 2021 trading at USD 1 950/t. It could be seen that the prices increased either slightly or more continuously over time but started to decline significantly again within the period under review, specifically at the end of the period (i.e., at the end of 2022). Regarding the aforementioned, the first research question was answered.

To answer RQ2, the content analysis method was also applied to collect data on historical prices of crude oil and natural gas, with the data obtained being evaluated with the use of the correlation analysis method, specifically the Pearson correlation coefficient method, where the CORREL function available in Microsoft Excel was used to process and produce the results. The correlation between crude oil and hot rolled coil steel was the weakest, with a correlation coefficient  $r$  of 0.19. On the other hand, the correlation between crude oil and prices of steel rebar was the highest, but the correlation strength was still only at a medium level, with a correlation coefficient  $r$  of 0.50. Thus, in all cases, the correlation reached very weak to medium values. This also completely answered this research question. Since a very strong correlation between the prices of the different types of steel and the prices of crude oil or natural gas failed to be determined in RQ2, RQ3a was not answered further.

About answering RQ3b, a prognosis of the future price of steel was determined with the use of multilayer perceptron networks. There were 3 experiments (Experiment 1, Experiment 2, Experiment 3) conducted with different software settings. The performance varied across individual experiments and networks, with the best performance at levels greater than 0.97 being achieved by the networks in the first experiment (for the price of hot rolled coil steel). On the contrary, the networks within the third experiment achieved the lowest performance, where the resulting correlations were greater than 0.83 for steel rebar and greater than 0.81 for rolled steel, thus least closely following the trend of historical price development for each type of steel. In all experiments, the top 5 performing networks were always selected and used to project the future price of each type of steel. It was evident from the resulting future price forecasts of steel rebar in the experiments conducted that the individual networks performed very differently, which was also true for the price forecasts of hot rolled coil steel. It also proved to be very interesting that the networks with the highest and second highest performance for the price forecasts of steel rebar predicted minima within the negative price levels, which was a poor and unusable result of these forecasts. The best future price forecasts of steel rebar from the three experiments conducted, considering the historical price development and the performance of each network, were the results of the 4.MLP 12-8-1 network under Experiment 1, as well as the forecast results of four neural networks, namely 1.MLP 60-6-1, 2.MLP 60-6-1, 4.MLP 60-6-1 and 5.MLP 60-3-1 under Experiment 3. Again, the resulting forecasts of neural networks under Experiment 1, namely the forecasts of the 1.MLP 12-5-1, 2.MLP 12-7-1 and 3.MLP 12-7-1 networks, as well as the results under Experiment 3, namely the forecasts of the 1.MLP 60-6-1, 2.MLP 60-6-1, 4.MLP 60-6-1 and 5.MLP 60-3-1 networks were considered to be usable results given the historical price development of hot rolled coil steel and taking into account the performance of each network (according to the correlations). Therefore, RQ3b was completely answered in this respect.

To answer the fourth (and final) research question (RQ4), suitable variants for forecasts of future prices of steel were selected. Based on these selected variants, it was possible to recommend a specific iron procurement strategy for manufacturing companies in the South Bohemian Region for the 2023-2028 period, with the neural network forecasts in Experiment 3 being selected for both analyzed types of steel, even though in that experiment the neural networks achieved the lowest performance expressed by the lowest level of correlation. Regarding the price projection of steel rebar, the projections of the 1. MLP 60-3-1, 4. MLP 60-11-1 and 5. MLP 60-10-1 networks were selected as the most suitable. It was found that in all cases these networks forecast a gradual stabilization of the steel rebar price level between 600-800 USD/t (in 2023-2026) and a subsequent decline of the future price to the level of 500-600 USD/t. In terms of the price projection of hot rolled coil steel, the use of projections of the neural networks in the third experiment, namely the 1. MLP 60-6-1, 2. MLP 60-6-1, 4. MLP 60-6-1 and also 5. MLP 60-3-1 networks also seemed to be the most appropriate. The individual forecasts assumed a future gradual decline in the price of steel, except for the years 2023-2026, when the price tended to increase slightly, and the price level was between USD 1 200-1 300/t. In 2027-2028, however, a decline to a level between USD 600-900/t was forecast.

Based on these findings, it was possible to recommend to the manufacturing companies concerned that they purchase iron on a gradual, regular basis, with the volume of stocks purchased being set to cover the total consumption each year, particularly for the years 2023-2026, considering the selected forecast results for these periods. Even for the next forecast period, i.e., 2027 and 2028, it was not possible to recommend to the companies pre-stocking more iron for a longer production period, again considering the forecast future price decrease for both types of steel. Thus, RQ4 was fully answered in the manner described above. However, given the different results of the forecasts, it is advisable to define the validity or set limitations of the conclusions presented on the condition that the results are to be confronted in the future with the actual prices of each commodity in the markets to verify that the neural networks forecast realistic projections of future prices. Thus, the conclusions of this paper are further applicable and usable for the iron procurement strategy of manufacturing companies in a given future time horizon.

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