COPPER MARKET SENTIMENT, VALUATION AND NEAR-TERM DEVELOPMENT USING SENTIMENT ANALYSIS

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Abstract: This paper examines the development of the global copper market using sentiment analysis to analyse the opinions, feelings, and subjectivities of the research subject. Particular attention is paid to one of the most important international mining companies in the world, Freeport-McMoRan. Texts related to Freeport-McMoRan and the relevant copper market were processed using MS Excel software and artificial intelligence, specifically recurrent neural networks. Sentiment analysis was followed by regression analysis to track the copper price trend over the same period. Confirmed the existence of inverse relationship between the copper price and the results of the sentiment analysis performed. Positive results of the sentiment analysis affect the sentiment of the copper market, thereby affecting the copper price with a time lag.

Keywords: Copper price, copper consumption, copper market sentiment, sentiment analysis, Freeport-McMoRan.

1 Introduction

Sentiment analysis is an important tool for gaining deeper insight into public opinion and sentiment around various topics, copper, valuations and short-term developments. This analysis can be used to monitor whether public opinion on topics is predominantly positive, negative or neutral. For example, in copper mining, sentiment analysis can help identify reactions to changes in copper prices and developments in the mining industry.

Copper is considered one of the most important minerals in the world (Mendiola et al., 2022). Copper as a strategic raw material attracts wide attention due to its price changes (Shen, Huang, 2022). Global copper production has increased more than 80 times in the last 135 years (Stuermer, 2022). Singer (2017) argues that copper demand is not driven by time but by population size and income. Given the increase in population, an increase in demand can be expected, bringing the resource closer to depletion. Understanding the metals market and forecasting price changes can help players plan for future changes in supply and demand (Shojaeinia, 2023).

According to (Harmsen et al., 2013), there has been an increase in demand for minerals in recent years due to the development of the global economy and increased product sophistication. The global transition to cleaner energy sources is intensifying pressure on the mining industry to secure the supply of minerals for the energy transition (Jiskani et al., 2023). The clean energy transitions require a large volume of minerals to handle its diverse technologies (Islam et al., 2022).

The global market has announced copper as a modern energy metal and finds its extensive use in construction, wiring, power transmission lines, alloying, anti-corrosion coatings, heat exchangers, refrigeration piping, etc. (Jena et al., 2022). Copper is expected to play a big role globally as solar; wind and electric vehicles increase (Shojaeinia, 2023). Copper ore is primarily mined from deposits of sulphide minerals (Jena et al., 2022). Copper is essential to achieving a sustainable development path due to its important role in the electromobility and renewable energy sectors. In 2019, 23.5 million tonnes of refined copper were used, with primary copper supplying 86.3% and secondary metal providing the remaining 13.7%. In the future, recycling of copper would increase significantly in terms of primary copper supply to meet the GHG reduction target. Secondary copper production reduces energy consumption by 85% and GHG emissions by 65% compared to average primary sources (Rivera et al., 2021). Humanity is using mineral resources at unprecedented levels and demand will continue to grow over the next few decades before stabilising by the end of the century due to the economic development of populated countries and the energy and digital transformation (Vidal et al., 2022). An adverse consequence of the increasing demand for copper is the depletion of resources, where resource saving and better utilization can delay their depletion. However, there is no doubt that in the future, a desirable and scarce raw material will no longer be available to humanity (Castillo & Eggert, 2020). According to estimates and speculations concerning the feared resource depletion, it can be expected in the order of decades (Villena & Greve, 2018). According to (Ponomarenko et al., 2021), the depletion of mineral resources will mainly affect economies based on these resources. With the depletion of high-grade copper sulphide deposits, attention has now shifted to recovery from various poor oxide and mixed ore deposits (Jena et al., 2022).

Metal mining is limited by the quantity of metallic raw materials in the crust. Currently, the known mineral deposits in the Earth's crust exceed current ore reserves (Patiño Douce, 2016). Gradual depletion of ores is expected for all minerals (Kuipers et al., 2018). Undiscovered mineral deposits are not likely to occur in sufficient quantities to meet the projected global demand for the remainder of this century (Patiño Douce, 2016).

The primary source of information on reserves and resources is the United States Geological Survey (USGS), which collects extensive information from mines and deposits and all mineral commodities around the world. During the epidemic, some mines, particularly in the United States (US), were closed, reducing US by an estimated minimum of 13 %. Currently, there is a global increase in material extraction. The United States Geological Survey (USGS) reports that global copper production has increased significantly over the past decade. Given the current population growth, there are growing concerns about the availability of raw materials (USGS, 2021).

Reijnders (2021) points out that in the case of copper, unfortunately, there is still no systematic and comprehensive study on substitutability and fungibility for any precious metal. Schipper et al., (2018) use regression and stock dynamics to developed copper demand models with the estimation of until 2100. With the assumption that copper reserves are constant and consumption will occur gradually, due to exponential mining and with the aim of satisfying the growing demand, (Calvo et al., 2017) propose the use of the Hubert peak model which can identify the types of minerals that will become scarce in the next decades. Reaching the so-called peaks does not indicate the depletion of raw materials but rather a warning indicator.

Renner & Wellmer (2020) point to the fact that fluctuations in mineral prices can threaten the economies of developing countries as they are heavily dependent on mineral production. With regard to newly developed technologies, (Korhonen, 2018) states that overcoming mineral scarcity will be achieved through innovation and technology. This is confirmed by (Aydin, 2020), who claims that since the 1980s and the recession in the mining industry, companies have survived mainly due to the introduction of innovation and technological changes, which has led to higher productivity. (Mitra, 2019) points that the development of technology is moving forward, which helps to cope with the detrimental effects of depletion on the productivity of the copper sector. With the growing problems and impending ban on the use of copper in some sectors, it is necessary to look for an effective substitution for copper. This is confirmed even by (Reijnders, 2021), who also mentions the necessity of the substitution of copper in certain sectors, while according to (Henckens & Worrell, 2020), it is impossible to replace copper in electricity transport.

The basic type of substitution is element-for-element, where the existence of absolute scarcity depends on the perceived possibility of substitution. We can speak of absolute scarcity only if there is no substitute for the given scarce resource, i.e., copper metal in this case. Every scarcity that economics has studied so far has been solved through substitution. To substitute metal X for an alternative or substitute X´, it must be first available and have specific, at least partial, substitution properties (Månberger & Stenqvist, 2018).

According to information from the US stock exchange, Freeport-McMoRan's shares rallied sharply in 2021 and 2022 due to the increasing price of metal commodities and market sentiment (PATRIA).

This paper aims to provide insight in the global copper market sentiment over the past few years. Therefore, the following research questions were formulated:

RQ1: How has the copper market evolved over the past few years?
RQ2: What is the sentiment of the relevant copper market that is served by a major mining company?
RQ3: What is the predicted development of the copper market in the future?

2 Literature Review

Kaliyadan & Kulkarni, (2019) address three important aspects related to statistics, namely the element of variables, the aspects of descriptive statistics, and the issue of sampling. Variable is a basic component of statistical data whose value varies. In defining a variable, qualitative or quantitative data can be used. In general, descriptive statistics can be divided into two categories: sorting/grouping and illustration/visual display; summary statistics. Detailed sample size calculation is an essential aspect of a good study design. A statistical creative model was created to address the descriptive statistics problem in mixed methods research using an exploratory sequential mixed methods design. The descriptive qualitative method is used to create statistical creative models, while the existence of significant differences in the statistical creative models is tested using quantitative methods. The results of this research confirmed the existence of three levels of statistical creative model of descriptive statistical activity: imitation, modification, and construction (Malang 2021).

Alvarez Pardo & Barreda Jorge (2020) studied the theoretical, methodological, and practical conditions in which the training process of the art instructor was developed to achieve adequate training in research training and knowledge of descriptive statistics. The students increased their level of commitment, interest, and creativity by acquiring knowledge of descriptive statistics.

Methods of data analysis in the management sciences are becoming increasingly sophisticated, leading to problems that include the increasing likelihood of incorrect performance and/or interpretation of analyses presented in published research, the increasing reliance on statistical significance as the main criterion for evaluating results, and the increasing difficulty in describing the research and explaining the findings to lay public (Murphy, 2021).

Attitudes towards statistics are of interest to many researchers. In this paper, the reliability and construct validity of the Attitudes Towards Descriptive Statistics Education Scale (EAEDE) are examined. The reliability and construct validity of the EAEDE are analysed using a descriptive correlational quantitative methodology. The results show adequate psychometric characteristics of the scale and better fit the theoretical distribution of the items (Ruz et al., 2022).

As such, sentiment analysis aims to automatically reveal the underlying attitude that is taken towards an entity. The aggregation of observed sentiments in a population is represented by opinion polling and is used in many fields, especially in marketing. The current textual sentiment analysis relies on the construction of dictionaries and machine learning models. With the development of social media usage, a new setting of sentiment analysis is also emerging (Soleymani et al., 2017).

Extracting the latent aspect structure and sentiment polarity helps to discover customer preferences, including the reasons for these preferences. (Almars et al., 2017) proposed Structured Sentiment Analysis (SSA) as an approach to understand the feelings and opinions expressed by people in short texts. The advantages of SSA include a hierarchical tree of hot product aspects, which is automatically extracted from short texts, hierarchical analysis of people's opinions on these aspects, and the generation of a summary and evidence of the results. Experimental results suggest that the proposed SSA approach can effectively extract the sentiment tree from the used texts (Almars et al., 2017).

The proposed modification to the Turney's algorithm should eliminate the need for a search engine using sentiment weights when the general version of Turney's algorithm requires the use of the NEAR Alta Vista operator. The used sentiment weights should be derived from a lexicon of words annotated with its corresponding polarities, allowing the application to run offline and eliminate the need for an external search engine (Das, 2017). The development of e-commerce goes hand in hand with extracting valuable information from consumer comments. The comments are classified either as positive class or negative based on sentiment polarity. Sentiment classification method based on machine learning shows excellent performance and is widely used. Most of the existing research does not consider the semantic relationships between words. Zhang et al., (2015) use a sentiment classification method based on word2vec and SVMperf to extract the semantic features. The experimental results of this research showed the excellent performance of the method in sentiment classification Zhang et al., 2015).

Medhat et al. (2014) define sentiment analysis (SA) as the computational processing of opinions, feelings, and subjectivity of texts. They explore and briefly present many algorithm improvements and various SA applications. Their research is categorized according to the contributions to various SA techniques. The main contributions include categorization of articles and specification of the research trend in sentiment analysis and related areas.

Saif et al. (2016) state that both commercial and public sectors use sentiment analysis on Twitter. Their paper introduced SentiCircles, a lexicon-based approach to sentiment analysis that differs from typical lexicon-based approaches by offering a fixed and static prior sentiment polarities of words regardless of their context. SentiCircles considers the patterns of co-occurrence of words in different contexts in tweets and enables sentiment detection at the level of entity, at the tweet level, and is evaluated on three Twitter datasets. The results confirm that the approach significantly outperforms the baselines in accuracy and F-measure for entity-level (neutral/polar) and polarity (positive/negative) sentiment detection.

According to (Schouten & Frasincar, 2016), sentiment analysis has received a lot of attention in recent years. The research conducted is focused on the aspect-level sentiment analysis aimed at finding and aggregating sentiment on entities mentioned in documents or aspects of them. Sentiment analysis provides very detailed sentiment information that can be useful for applications in various domains. A standardized evaluation methodology was used for quantitative evaluation of the proposed methods. The semantically rich concept level of sentiment analysis was identified as one of the most promising directions for future research.

As illustrated in this paper, sentiment analysis has been the topic of many research papers in the last few years. Over time, several sentiment measurement methods have been developed, including lexical and machine learning methods. Despite the tremendous interest in this area and the widespread popularity of some methods, it is not entirely clear which method provides the most reliable results. The evaluation of the reliability of the methods was based on a benchmark of eighteen labelled datasets including messages posted on social media, movie, and product reviews, as well as opinions and comments in news articles. The results of the paper show the extent to which the predictive performance of the used methods varies (Ribeiro et al., 2016).

Zhang et al. (2018) review deep learning and provide a comprehensive overview of its current applications in sentiment analysis. Deep learning is used as a powerful machine learning technique that draws on multiple layers of data representation or features to further produce state-of-the-art prediction results. Deep learning has also been used in sentiment analysis in recent years.

Chen et al. (2017) state that different types of sentences express sentiment in very different ways. Focusing on traditional sentence-level sentiment classification research, the authors use a single-technique solution or focus on one special type of sentences. In this paper, the classification of sentences into different types is discussed and then sentiment analysis is performed separately on each type of sentences which tend to be more complex when they contain multiple sentiment targets. Based on these findings, a neural network based on a sequential model was proposed to classify sentiment sentences into three types according to the number of targets appearing in the text. The chosen approach was evaluated on four sentiment classification datasets and compared with a wide range of baselines. As a result of the experiment, it was confirmed that sentence type classification can improve the performance of sentence-level sentiment analysis, while the proposed approach achieves state-of-the-art results on several benchmark datasets.
Rezaeinia et al. (2019) considers sentiment analysis as a rapidly growing area of research in natural language processing (NLP) and text classification. Sentiment analysis technique is an essential part of many applications including politics, business, advertising, and marketing. There are various techniques of sentiment analysis, but recently, word embedding methods have been used for sentiment classification tasks. Word2Vec and GloVe methods are considered as one of the most accurate and applicable word embedding methods, but they do not consider the sentiment information of texts and need a large corpus of texts for training and generating accurate vectors. In this paper, a new method, Improved Word Vectors (IWV), was proposed to improve the accuracy of pre-trained word embedding in sentiment analysis. This method is based on part-of speech (POS) tagging techniques, lexicon-based approaches, word position algorithm and Word2Vec/GloVe methods. The results of the conducted experiments declare that the Improved Word Vectors (IWV) are very effective for sentiment analysis.
Yang et al. (2019) argue that sentiment analysis is to predict the sentiment polarity of specific targets in a specific text based on aspect. Previous research demonstrates considerable interest in modelling the target and context using the attention network. Using the average target vector to compute attention scores is considered unfair and very simple. Therefore, it is reasonable to further improve the mechanism. The authors proposed a coattention mechanism that alternatively models the target-level and context-level attention to subsequently focus on keywords of targets to produce a more effective representation of context. On this basis, a Coattention-LSTM network was implemented, which learns non-linear representations of context and target simultaneously, and can extract sentiment feature from the coating mechanism more efficiently. Another proposed network, Coattention-MemNet, uses a multiple-hops coattention mechanism. Extensive experiments on two public datasets demonstrate the effectiveness of all the proposed methods, and the findings provide new insights into the future development of using the attention mechanism and deep neural network for aspect-based sentiment analysis.

Ahmed et al. (2020) argue that sentiment dictionary has a great value to sentiment analysis, which is widely used in sentiment analysis compositionality. The polarity of sentiment and intensity of the word can vary from one domain to another. The authors present a novel approach to build domain-dependent sentiment dictionary. First, a weak supervised neural model was proposed and trained on unlabelled data with weak supervision by reconstructing the input sentence representation from the resulting representation. Next, an attention-based LSTM was also proposed to solve the aspect-level sentiment analysis task based on the sentiment score obtained from the proposed dictionary. The experiments conducted on both English and Chinese benchmark datasets showed that compared to the state-of-the-art alternatives, the proposals of the authors can effectively improve polarity detection.

Wen et al. (2019) present a complete memristor-based long short-term memory (MLSTM) network hardware design solution. During the design process, the external and internal structures of long term memory (LSTM) were considered, both effectively implemented by memristor partitions. To minimize the hardware design scale, a parameter-sharing mechanism between LSTM cells was utilized by designing a circuit that requires only one memristor rung for each unit in an LSTM cell. The activation function of each unit is approximated in parts, which is designed with the given hardware. To validate the efficiency of the system, it was tested on IMDB and SemEval datasets, and word2vector encoding was used to encode the input data. The experimental results of the paper verify the effectiveness of the proposed MLSTM system. Based on the research conducted on the appropriate methods applicable in sentiment analysis, content analysis methods will be used to analyse the sentiment of the copper market, and then neural networks will be used to process the data for predicting the future development of the copper market sentiment, when LSTM is considered the best method to predict the required time series.

3 Material and Methods

The data for the analysis was collected through the social network Twitter-official site (2022). The research data pertained to one of the world's most prominent international mining companies, Freeport-McMoRan published for the period from January 1, 2020 to November 10, 2022. The research data for determining the copper market trends was taken from Investing.com (2022) for the period from January 1, 2020 to November 10, 2022. All the research questions formulated assume basic statistical and scientific description, comparison, and correlation analysis followed by regression analysis. The tools of formal logic, namely deduction, induction and generalization will be used to obtain answers to the research questions. Before the data processing, it is necessary to consider whether a relevant result will be achieved by using the data of the whole time series or only a part of it. Neural networks with the LSTM layer also include a forget gate; given the use of relatively recent data, it is assumed that the neural network result will not be biased by information from the beginning of the time series evolution (Vochozka et al., 2020). The answer to RQ1 will be based on the research data related to the copper market, specifically the copper price evolution over the entire 2020-2022 study period from Investing.com (2022), when the daily evolution of the copper price provides information on whether the price evolution is negative, positive, or neutral. The analysed data was further examined using the statistical methods mentioned above.

To find the answer to the research question RQ2, the entire time series for the period 2020-2022 will be used to analyse the sentiment of the relevant copper market, which is served by a major mining company. Freeport-McMoRan has been selected as the major mining company. The data collected from the social networking site Twitter-official site was analysed using a trained neural network on a classification task, with the output being information on whether the message was negative, positive, or neutral. The network primarily determines thresholds or probabilities and then selects the message with the highest probability as the output of the sentiment analysis. All the data collected will enter the sentiment analysis and will be examined by the neural network and then the sentiment will be classified. Artificial neural network ("NN") will be used, containing Long Short Therm Memory ("LSTM") and consisting of a total of 9 layers, whereupon the result is the training set. Long-Short Term Memory Layer. The LSTM may be an individual NN. It is a sophisticated recurrent NN whose structure consists of four basic blocks: input gate, output gate, forget gate, and memory gate. Mathematica version 13 wolfram software, classify function was used for sentiment analysis.

The answer to research question RQ3 will be obtained by considering the answers to the previous two research questions. The development of the copper market development will be predicted on the basis of the developed sentiment analysis and then verified or refuted using Pearson correlation coefficient. Correlation coefficient measures the dependence between two variables. Pearson correlation coefficient is denoted r and its calculation is based on a bivariate random vector of magnitude n.

$$\binom{x_1}{y_1}, \binom{x_2}{y_2}, \dots, \binom{x_n}{y_n}, \tag{1}$$

The following formula is used to calculate Pearson correlation coefficient:

$$r = \frac{\sum_{i=1}^{n}(x_i-\overline{x})\,(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{n}\overline{(x_i-\overline{x})^2}\;\sum_{i=1}^{n}\overline{(y_i-\overline{y})^2}}} = \frac{\sum_{i=1}^{n}x_i y_i - n\overline{x}\overline{y}}{(n-1)s_x s_y} \tag{2}$$

where

$\overline{x}$ and $\overline{y}$ sample averages,

s_x and s_y standard deviations,

x and y random variables.

The resulting value will be graphically illustrated.

Next, the regression function will be used to describe the dependence of two or more quantitative variables in the form of a functional dependence. Due to the very large amount of the data, it was proceeded to average the monthly data in each year and subject them to examination using statistical indicators.

4 Results

The copper price trend in the 2020-2022 period provides answer to RQ1: The price of copper depends not only on supply and demand, but also on the overall global economy, the current dollar exchange rate and other factors that tend to cause volatility and fluctuations. Different economic, geopolitical, and technological factors affect the price of commodities positively or negatively, and since these price and market trends are inconsistent, they are very difficult to predict (Tapia Cortez et al., 2018).

Classical forecasting approaches have not proven very successful in recent years characterized by significant fluctuations in the prices of mineral resources such as copper; new approaches such as ARIMA allow accurate estimates of price changes (García & Kristjanpoller, 2019). Similarly, according to (HU & Won, 2018), the GARCH model, led to a low forecast horizon. due to price variations and subsequent forecasting performance capability.

The potential of using neural networks in the context of forecasting in chaotic copper price series, was examined by (Carrasco et al., 2018).

Neural network-based methods are considered the most reliable ones for predicting future copper price trends. When dealing with the development of the copper price achieved in the past period, proven statistical methods using Microsoft Excel software are applied.

Using statistical methods, the copper price trend was compared with sentiment analysis at the level of individual days. The resulting data is presented in Table 1, with the confidence level in both cases being above 0.05, indicating that the normal distribution of the data analysed.

Table 1: Comparison of copper price development and sentiment analysis in the period under review

Real		*Sentiment*	
Mean value	0.0673901	Mean value	0.32726359
Error Wed values	0.0403808	Error Wed values	0.02652698
Median	0.0476190	Median	0.30769231
Modus	0.0000000	Modus	0.30000000
Standard deviation	0.2388962	Standard deviation	0.15693571
Variance of selection	0.0570714	Variance of selection	0.02462882
Pointiness	0.0072631	Pointiness	0.02387870
Skewness	0.5301559	Skewness	0.62428642
Max-min difference	0.9363636	Max-min difference	0.65178571
Minimum	-0,3000000	Minimum	0.06250000
Maximum	0.6363636	Maximum	0.71428571
Sum	2.3586545	Sum	11.45422557
Count	35.0000000	Count	35.00000000
Confidence level (95.0 %)	0.0820637	Confidence level (95.0 %)	0.05390930

The table shows the copper price development in comparison with development of sentiment. Figure 1 graphically illustrates the development of the entire time series (2020-20221) on a monthly basis, as the graph is not transparent when using a daily basis. The copper price and sentiment analysis are related, but as can be seen from the graph, the impact of market sentiment on the copper price shows some time lag.

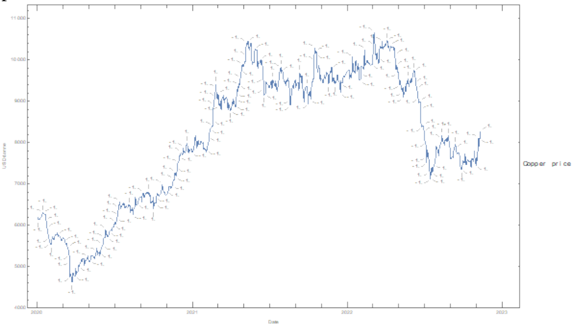
Fig. 1. Evolution of copper lunar for the period 2020-2022

Performing sentiment analysis using neural networks provides the answer to research question RQ2: Yin et al. (2017) discussed the drawbacks of using a convolutional neural network utilized for sentiment analysis. The newly proposed lexically augmented convolutional neural network (SCNN) for sentiment analysis outperforms the baseline methods where it can better utilize the information found in sentiment analysis. S. Chen et al., (2018) state that with the development of social networks, sentiment analysis has become one of the most important research topics. LSTM deep neural network model is very often used. The authors propose a deep neural network model combining convolutional neural network and regional long short-term memory (CNN-RLSTM), which provides better performance compared to other neural network models.

Sentiment expresses a person's attitude, thoughts or expression triggered by a feeling. Sentiment analysis refers to the conversion of a text into a structured format when the problem in analysis is the insufficient number of labelled information. This problem can be eliminated by using a deep neural network (Moholkar et al., 2020).

Recently, people have been seeking opinions about products and services on their own, thus making opinions and sentiment analysis an everyday part of human activities. Wazery et al. (2018) use two main approaches for sentiment analysis, namely support vector machine, naive Bayes, decision tree and K-nearest neighbour machine learning approaches, and deep neural network, recurrent neural network using long short-term memory (LSTM). The results show that the recurrent neural network using LSTM achieves the highest accuracy (Wazery et al., 2018) Figure 2 shows the output of sentiment analysis using neural networks. The price trend is presented in the form of a text. According to the prediction, a slight decrease in the price of copper can be expected in the world markets in the near future.

Fig. 2. Sentiment analysis for the period 2020-2022 including prediction



The interdependence of copper price and sentiment analysis provides answer to RQ3: Measuring the dependence between random observations plays a crucial role in statistics. We are often interested in condensing the strength of the dependence into a single number, which is usually defined in the interval [-1,1] or [0,1]; such a number is called the correlation coefficient. The most commonly used correlation coefficient is Pearson correlation coefficient, which, for random variables X and Y with finite and positive variances, denotes the variance of Z through the covariance of X and Y and for any random variable Z. It has been confirmed that the converse implication of Pearson correlation coefficient is not true (Edelmann et al., 2021).

In a smart household of the twenty-first century, the ability to recognize everyday activities depends primarily on the strategy used to select appropriate features related to these activities. The selection strategy of daily activity features was based on Pearson's correlation coefficient. The experimental results demonstrate that the proposed approach provides higher recognition rates and achieves an average improvement in F-measure of 1.56 % and 2.7 %, respectively (Liu et al., 2020). Armstrong, (2019) investigated the use of Pearson correlation coefficient, arguing that it is important to focus on the non-linear relationship between two variables, on bivariate normal data, r (correlation coefficient) representing a significant portion of the variance (Y), outliers in the data, appropriate sample size, and the causality indicated by significant correlation. The problems and limitations of r imply a more cautious approach regarding its use, including the application of alternative methods.

From the regression analysis performed measuring the daily copper price in USD/tonne and the output of the sentiment analysis on a daily basis for the period 2020-2022, the coefficient of determination was 0.00188, suggesting that the sentiment in the copper market does not affect the copper price, but this may only be due to the time lag, as seen in Figure 1.

Tab. 2. Regression analysis

Multiple R	0.04339048
Reliability value R	0.00188273
Reliability set point R	-0.02836324
Erros Wed values	0.24226045
Observation	35.00000000

Tab. 3. ANOVA

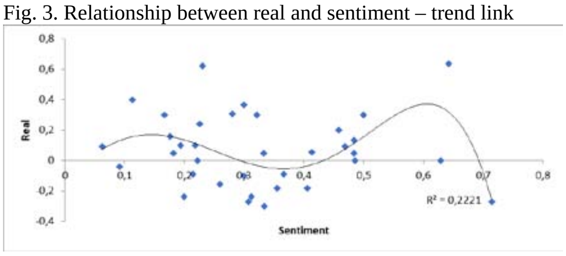
	Difference	*SS*	*MS*	*F*	*Significance F*
Return	1.00000000	0.00365331	0.00365331	0.06224739	0.80452497
Residues	33.00000000	1.93677410	0.05869012		
On the whole	34.00000000	1.94042740			

Tab. 4. statistical indicators of regression analysis

	Coefficients	*Error Wed values*	*t Stat*	*P-value*	*Bottom 95%*	*Top 95%*	*Bottom 95%*	*Top 95%*
Boundary	0.08900634	0.095829894	0.928795146	0.359739655	-0.10596104	0.28397372	-0.10596104	0.283973726
Sentiment	0.066051377	0.264741049	0.249494278	0.804524967	0.60467109	0.47256833	0.60467109	0.472568337

The resulting regression equation from the regression analysis has the following form: y = - 0.06605x + 0.08901. The correlation between the sentiment analysis and the copper price is shown in Figure 3, where the best fit appears to be a sixth degree polynomial trend line with a reliability R2 value of 0.2221. The low value of this indicator points to an inverse relationship between the selected variables.

Fig. 3. Relationship between real and sentiment – trend link



The correlation coefficient between copper prices and sentiment analysis is calculated at -0.04339, which means that the two variables examined are not dependent on each other.

Tab. 5. Correlation between copper price and sentiment analysis

	Real	*Sentiment*
Real	1.00000	
Sentiment	**-0.04339**	1.00000

Due to the use of data on a daily basis, the set of analyzed data is very wide. Therefore, the development in individual months of the specific years under study is presented below. The years monitored are 2020, 2021 and almost the complete year of 2022 (excluding December). It shall be pointed out that in the case of the copper price, the data are for working days, but the sentiment analysis processes data for all days of the year.

Table 6 shows the average copper price and average sentiment analysis values for each month in 2020.

Tab. 6. Relationship between real and sentiment 2020

Moon	Real	Sentiment
12	0.10000000	0.21875000
11	0.61904762	0.23076923
10	0.00000000	0.48571429
9	0.36363636	0.30000000
8	0.30000000	0.50000000
7	0.30434783	0.28000000
6	0.63636364	0.64285714
5	0.05263158	0.41379310
4	0.20000000	0.45833333
3	-0.27272727	0.71428571
2	0.00000000	0.62962963
1	-0.27272727	0.30769231

The data contained in Table 6 are graphically represented in Figure 4 below.

Fig. 4. Relationship between real and sentiment 2020 – trend link

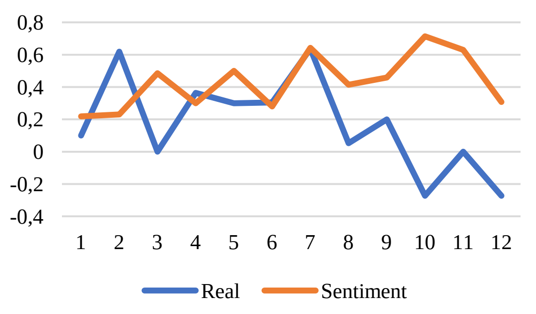


Table 7 shows the average copper price values and the average sentiment analysis values in each month of 2021.

Tab. 7. Comparison of the development of copper prices and sentiment analysis in 2021

Moon	Real	Sentiment
12	0.23809524	0.22580645
11	-0.09090909	0.36666667
10	0.04761905	0.48387097
9	-0.18181818	0.40625000
8	-0.23809524	0.31250000
7	0.09090909	0.46875000
6	-0.18181818	0.35483871
5	0.15789474	0.17647059
4	0.30000000	0.16666667
3	-0.04347826	0.09139785
2	0.40000000	0.11369048
1	0.10000000	0.19354839

The data from Table 7 are graphically represented in Figure 5.

Fig. 5. Relationship between real and sentiment 2021 – trend link

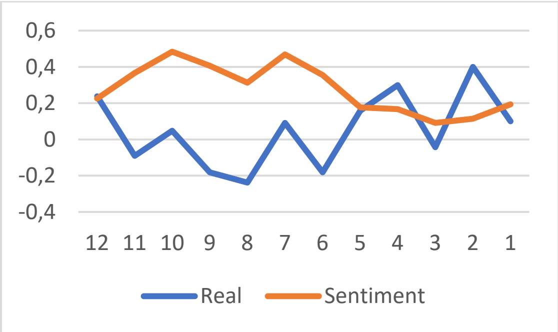


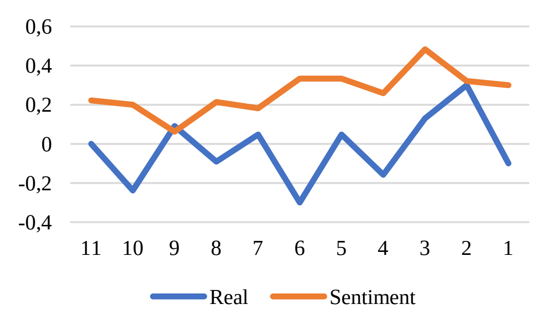
Table 8 shows the average copper price and average sentiment analysis values for each month of 2022.

Table 8. Comparison of copper price development and sentiment analysis in 2022

Moon	Real	Sentiment
11	0.00000000	0.22222222
10	-0.23809524	0.20000000
9	0.09090909	0.06250000
8	-0.09090909	0.21428571
7	0.04761905	0.18181818
6	-0.30000000	0.33333333
5	0.04761905	0.33322581
4	-0.15789474	0.25925926
3	0.13043478	0.48387097
2	0.30000000	0.32142857
1	-0.10000000	0.30000000

The data from Table 8 are graphically represented in Figure 6 below.

Fig. 6. Relationship between real and sentiment 2022– trend link



5 Discussion

5.1 RQ1: How has the copper market evolved over the past few years?

The answer to this research question and partial answers to RQ2 and RQ3nd three can be found in the individual sections of the presented results, where the copper price time series and sentiment analysis development in 2020-2022 and subsequently in each of the monitored years are graphically illustrated for better clarity; the tables show statistical data related to the copper price and sentiment analysis development. Based on the regression analysis performed comparing the daily copper price in USD/tonne and the output of the sentiment analysis on a daily basis for the period 2020-2022, the coefficient of determination was determined at 0.00188, indicating that the sentiment in the copper market does not affect the copper price, but this may be due to time lag only.

According to (Mendiola et al., 2022), copper is considered one of the most important minerals in the world. The authors decided to analyse the effect of changes in spot copper prices and futures on the stock returns of copper mining companies. Changes in copper prices turn out to have a greater impact on the stock returns of these mining companies traded in more developed markets than stocks traded in less developed markets.

Elshkaki et al., (2016) examined the demand, supply and energy implications associated with copper production over the period 2010-2050. Energy efficiency improvements in primary copper production would lead to a reduction in energy demand of 0.5% of the projected total global energy demand by 2050.

Taking into account the findings from the available literature and the results of the correlation coefficients of the indicators studied, it can be concluded that the sentiment of the copper market changes inversely proportional to copper price. This implies that copper price is influenced by the copper market sentiment, but with a considerable time lag. Based on this finding, the copper market sentiment can be predicted for the next decade on the basis of the current copper market price.

5.2 RQ2: What is the sentiment in the relevant copper market, which is served by a major mining company?

A sentiment analysis was focused on one of the world's most important international mining companies, Freeport-McMoRan. In the period 2020-2022, there was a significant fluctuating trend in copper market sentiment, but one that is relatively more stable compared to copper price. The development of the sentiment analysis over the period under review is presented in the calculation section, both numerically, in the form of tables, and graphically, using graphs. The correlation between the sentiment analysis and the copper price is shown in Chart 2, where the most appropriate trend line appears to be a sixth-degree polynomial trend line with a reliability R2 value of 0.2221.

According to (Siami-Namini et al., 2018), time series data forecasting techniques are not only important for economics. Deep learning-based algorithms such as LSTM outperform traditional algorithms such as ARIMA, showing a lower error rate compared to ARIMA. Based on these findings, it can be stated that LSTM is suitable for the commodity market and is considered the best method for predicting the required time series of copper prices.

Daily closing historical copper prices were investigated by (Vochozka et al., 2021) using artificial intelligence and recurrent neural networks (LSTM) with great potential for predicting the time series of copper price With a longer time series, the question of whether to use the whole time series or only a part of it to obtain a relevant result remains. Neural networks use LSTM and forget-gate layers, but the result might be biased by information from the beginning of the time series and data (Vochozka et al., 2020). The data required for analysis and prediction was collected using the content analysis method.

The copper market sentiment follows the copper price trend with some lag. It is thus clear that the copper price affects the market sentiment indirectly, with other factors affecting the market sentiment also playing a role.

5.3 RQ3: What is the predicted development of the copper market in the future?

Based on the findings, it can be argued that the copper market sentiment will evolve indirectly depending on the copper price, but it is the copper price that increases its value in the minds of investors, thus improving the copper market sentiment.

Rising demand for copper will cause resource depletion, while saving resources and their more efficient use may delay their depletion. However, it is evident that a situation may arise where this required and scarce raw material will not be available for humanity (Castillo & Eggert, 2020). Harmsen et al. (2013) confirm an increasing demand for minerals in recent years mainly due to the developing global economy and higher product intensity.

Schipper et al. (2018) use regression and stock dynamics to develop copper models with demand estimates to 2100. Copper reserves are more or less constant and will be consumed gradually. Due to exponential mining and with the aim to satisfy the increasing demand, (Calvo et al., 2017) propose the possibility of using Hubert's model, which can identify the kinds of minerals that will become scarce in the next decades. The reaching of the so-called peak, however, will be considered a warning sign instead of indicating the depletion of these minerals.

The analysis of the individual years suggests that the market sentiment and the copper price almost coincide towards the end of the calendar year, but then diverge again at the beginning of the new calendar year and then converge again, with the curves crossing in some parts of the year. Considering the observed evolution in 2020-2022, a similar pattern could be seen for the years 2021 and 2022. The performed sentiment analysis using neural networks to describe the development of the copper price on world markets shows that in the near future, a slight decline in the copper price to the level recorded at the beginning of 2021, i.e., before the crisis related to the situation in Ukraine, can be expected.

6 Conclusions

The aim of the article was to explain the market development in terms of price and sentiment in the relevant market in the example of a major mining company and the global copper market. The experiment involved data collection, the application of descriptive statistics tools, and models based on artificial neural networks - NNs with an LSTM layer in the case of sentiment analysis. Regression analysis was used for the copper sales price data for the 2020-2022 trading days. Using neural networks and descriptive statistics tools, the evolution of market sentiment was analyzed and predicted as a function of the copper price, successfully answering all the research questions. The answers to the research questions were confronted with data from published academic articles, indicating that the sentiment of the copper market is indirectly influenced by the copper price as well as by other factors affecting customer perception.

After a detailed examination of copper market sentiment, we predicted the trend for 2023, concluding that the copper price in the coming months will be influenced by copper market sentiment like previous years with the inclusion of the effects of extraordinary events affecting the global economy. Singer (2017) found that copper demand is not driven by time, but predominantly by population size and income. Given the increase in world population, we can expect an increase in demand, which will result in earlier depletion of resources.

A sentiment analysis conducted by Freeport-McMoRan, one of the world's most important international mining companies over the period 2020-2022 indicates a fluctuating development in the copper market sentiment. However, compared to the development of the copper price, this development is relatively more stable. Market sentiment will be more often influenced by social media sentiment, which is becoming an important indicator in the development of the price of more than just copper.

By conducting a sentiment analysis using neural networks in commitment to the development of the copper price on the world markets, it was concluded that the copper price in the near future will decline slightly to the level of early 2021, before the crisis related to the situation in Ukraine.

It can thus be concluded that the objective of the article has been met, which is confirmed by the results of the application section, showing similarities in the development of market sentiment and copper price in all the years under study.

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Primary Paper Section: A

Secondary Paper Section: AH, AJ