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Copper Price Prediction Model for Various Economic Situations

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***Abstract*—**Copper is an essential raw material used in the construction industry. During 2021 and the first half of 2022, the global market suffered from a significant fluctuation in copper raw material prices due to the aftermath of both the COVID-19 pandemic and the Russia-Ukraine war which exposed its consumers to an unexpected financial risk. Thereto, this paper aims to develop two hybrid price prediction models using artificial neural network and long short-term memory (ANN-LSTM), by Python, that can forecast the average monthly copper prices, traded in the London Metal Exchange; the first model is a multivariate model that forecasts the copper price of the next 1-month and the second is a univariate model that predicts the copper prices of the upcoming three months. Historical data of average monthly London Metal Exchange copper prices are collected from January 2009 till July 2022 and potential external factors are identified and employed in the multivariate model. These factors lie under three main categories: energy prices, and economic indicators of the three major exporting countries of copper depending on the data availability. Before developing the LSTM models, the collected external parameters are analyzed with respect to the copper prices using correlation, and multicollinearity tests in R software; then, the parameters are further screened to select the parameters that influence the copper prices. Then, the two LSTM models are developed, and the dataset is divided into training, validation, and testing sets. The results show that the performance of the 3-month prediction model is better than the 1-month prediction model; but still, both models can act as predicting tools for diverse economic situations.

***Keywords*—**Copper prices, prediction model, neural network, time series forecasting.

I. Introduction

COPPER is a widely used metal in various industries. It is used in building infrastructure facilities such as railways and electrical transmission lines, refrigeration systems for preserving agricultural products, medical devices such as surgical robots and implants, and in manufacturing airplanes, automobiles, and other technological devices such as computers and smartphones that are nowadays essentialities [8]. This diversity in application owes to the unique properties of this metal as it is highly conductive, highly resistant to corrosion and temperature, durable, lightweight, and malleable [26]. Moreover, the demand for copper is bound to drastically increase, in the upcoming years, because of the shift towards electrical vehicles (EVs) in the transportation industry. Given the advancement in technology and the enhancement in the EV's performance, the sales of EVs exponentially increased in 2022 where 10.3 million EVs are sold compared to 6.5 million in 2021 and 3 million in 2020 [23]. This demand is expected to grow and reach 27 million in 2027 [22] which may make copper a highly demanded metal because EV requires around four times the amount of copper used in a traditional vehicle [22], [37].

The flourishment in the EV industry is not the only reason behind the increase in the global copper demand as other sectors such as energy and construction sectors cause such spike in demand [39]. This owes to the global movement towards building an eco-friendly environment with net-zero greenhouse gases which entails building renewable energy power stations such as wind and solar farms [39]. Additionally, various cities promote the development of smart cities and smart infrastructures such as China which is a global leader in this field [4], [39] and, in 2022, it consumed around 57% of the global copper [45]. Based on a study carried out by the International Energy Agency, the global consumption of copper in 2020 is 23.9 million tons and is expected to reach 28.6 million tons in 2030 [24].

Such growth in demand may cause fluctuation in copper prices depending on the availability of the metal; however, in times of global economic crises, such as the outbreak of the COVID-19 pandemic in 2020 and the Russia-Ukraine war in 2022, the fluctuation in the copper prices may be unexpected due to the impact of each event on the economy. After the outspread of the COVID-19 pandemic around the world and with each country taking the necessary lock-down measures to slow down the pandemic's outspread, the economy, at that time, was expected to experience a "microeconomic flu," as named by di Mauro [10]. Such is described as a temporary drop in the demand and supply for a short period followed by a rapid and full economic recovery. This was evidenced when looking at the global Gross Domestic Product (GDP), in the second quarter of 2020, that has sharply dropped by around 6% compared to the pre-pandemic level and then re-bounded, in the third quarter of 2020, by around 7.5% compared to its pre-pandemic level [15]. However, this sharp rebound in the global GDP, reflecting the increase in consumer demand, was faced with the shutting down of factories due to the necessary lockdown measures taken at that time. The dual effect of these two actions has caused a disequilibrium between the demand and supply side of the markets and has put upward pressure on

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the commodity prices as by the end of 2021, the producer price index (PPI) and consumer price index (CPI) in the European area increased by +23.4% and +5.9% respectively compared to the previous year [40]. The impact of such on the copper prices is seen in 2020 and 2021 where the monthly copper price dropped in the first half of 2020 and then rebounded to a level above the pre-pandemic level and continued to rise in 2020 and 2021 [45].

On February 24, 2020, the Russia-Ukraine war arose, whereas the world was still recovering from the long-term impact of the COVID-19 pandemic and the level of inflation was still higher than the pre-pandemic level. This war has further driven up commodity prices, especially energy products and metals as 14% of the global exports of oil and 5% of the global exports of copper are from Russia [12]. Such has prompted further financial stress, and, in March 2022, the copper price reached $10,500/mt, the highest nominal value of all decades, and remained higher than the copper price in 2019, till the end of 2022 [48].

By the end of the first quarter of 2023 and based on the commodity outlook report of April 2023 conducted by the World Group Bank, the copper price dropped in comparison to the first quarter of 2022 [49] but remained high in comparison to the copper prices in the fourth quarter of 2022 [45]. Such a drop in prices spreads out relief among copper consumers, however, the fear of facing a similar unexpected financial stress, especially knowing that the demand for copper is exponentially growing, creates a need for a tool that forecasts copper prices both for the normally stable economic times and economically unstable times caused by international crises. This research work aims to devise two price prediction models for the copper traded internationally in the London Metal Exchange. The first model is a multi-variate model that employs external parameters, and the second is a univariate model that uses past copper prices. The dataset used is from January-2009 to July-2022 to train the models on a diverse dataset and validate and test them during the crisis times.

This paper is organized in the following sequences: Section II presents the works by fellow researchers on copper price prediction models, Section III discusses the research methodology adopted in this work, Section VI illustrates the results of each model, and Section V concludes the work.

II. Literature Review

Various researchers developed diverse prediction models using different tools and parameters. Some researchers focused on time series forecasting models where the time series data are used as input variables [36]. For instance, [33] modeled the international daily copper future price for the period from January 1, 2005, to December 31, 2019, using LSTM and gated recurrent network (GRU) models. The models were combined with the wavelet transform to remove the noise in the dataset and the Bayesian optimization to optimize the model's hyperparameters. The results showed that LSTM is more accurate than the GRU model. Similarly, [46] developed a copper prediction model for the daily COMEX copper prices using the copper prices of the 10 previous days. The time frame studied is from July 2, 1959, to April 28, 2021, and the authors developed a model using neural network layers with LSTM layers. Reference [47] also predicted the daily, weekly, and monthly copper spot prices traded in COMEX using a price volatility network (PVN) transformation mechanism for structuring the dataset and three ANN tools for the prediction models. Reference [5] studied the possibility of predicting the variance in spot prices of daily copper traded in the London Metal Exchange (LME) using a genetic algorithm and using a dataset from February 24 to August 29, 2016. Also, [3] studied the possibility of predicting the LME copper closing prices for the upcoming 5, 10, 15, 20, and 30 days in the future using support vector regression (SVR). The prediction model is built using copper prices from January 2, 2006 till January 2, 2018 and the model's performance is measured by the root mean squared error (RMSE). The results showed that the 5-day and 10-day prediction models have a lower RMSE of 2.2% in comparison to the other models. In another work carried out by [2], the authors compared the performance of ARIMA (2,1,3), TGARCH (1,1), and stochastic differential models when used to forecast the monthly copper prices using a dataset from 1987 to 2014. The stochastic differential model provided the lowest mean absolute percentage error (MAPE) of 15.6% compared to a MAPE of 20.9%, and 54.36% from the ARIMA and TGARCH models respectively. Reference [6] used the ANN model to predict the LME copper prices using a dataset from January 22, 2015, till June 16, 2015, and the lagged metal prices of the previous six days. Another work conducted by [34] focused on predicting the daily LME prices of copper, zinc, and aluminum by integrating the feedforward neural network (FNN), LSTM, variational mode decomposition (VMD), and empirical mode decomposition (EMD) models and comparing these hybrid models with the ARIMA model. The models are univariate models based on the past daily metal prices for the past 30 days. The authors concluded that the best model is the hybrid VMD-LSTM as it has the least mean absolute error (MAE) and MAPE for copper, zinc, and aluminum. Reference [30] compared the performance of the ARIMA (1,1,0) model, Elman neural network model, and multilayer perceptron (MLP) neural network model by forecasting the COMEX copper daily spot prices using the time frame from January 2, 2002, till January 16, 2014. The results showed that the Elman neural network has the lowest forecast error of average -0.00123 and the proximity of both the machine learning models are higher than the ARIMA model as they are more accurate in predicting the fluctuation in copper price.

Other researchers used factor forecasting models where the forecasted metal price is predicted using external parameters [36]. Reference [28] purposed to predict the monthly copper prices using crude oil, coal, natural gas, aluminum, gold, iron ore, nickel, and lead as input variables to the models. The authors evaluated the performance of four different tools: gene expression programming (GEP), ANN, adaptive neuro-fuzzy inference system (ANFIS), and ant colony optimization (ACO) algorithm. The empirical results showed that ANFIS and ANN models are promising due to their lowest MAPE of 5.56% and 5.7% respectively. Reference [21] predicted the daily copper spot prices of Yangtze River metal traded in China using 21 input variables that are related to the stock market indices, other main metals traded in LME and Shanghai Futures Exchange (SHFE), and the interest rate of the Shanghai Interbank. The authors developed six different models by integrating generalized autoregressive conditional heteroskedasticity (GARCH), ANN, and LSTM models and the results showed that the two models of similar performance and having the highest accuracy are the GARCH-LSTM-ANN and LSTM-ANN. Reference [11] studied the prediction accuracy of random forest and gradient-boosted regression tree when used to predict the daily copper prices and compared its work with [32] who used the regression tree model. Both works used lag copper prices and other external parameters such as the stock market index, gold, silver, crude oil, natural gas, coffee, and lean hog. Reference [11] concluded that the random forest and gradient-boosted regression tree outperform the regression tree model. Reference [31] combined CNN with LSTM to predict the daily spot copper prices traded in LME using a dataset from July 7, 2008, till October 29, 2021. Eleven influencing external parameters are utilized as input variables. These selected parameters fall under five categories: supply and demand, energy costs, alternative metals, global macroeconomic conditions, and national policies. The results showed that the combined CNN-LSTM model outperform the normal LSTM and CNN models as it provided the lowest MAPE of 8.82%. Similarly, [9] also employed 23 external indicators to predict the variance in copper prices. These external factors fall under five major categories which are alternative metal prices, energy prices, USD exchange rates, global stock market index, and other commodity prices. The results of the GEP model outperformed that of the multivariate regression and time series functions as it had the lowest RMSE and MSE. In a similar vein, [1] analyzed the integration of a genetic algorithm and ANFIS and compared it with SVM, GARCH, and ARIMA models when predicting the fluctuation in copper prices. Nine variables are utilized to evaluate the model's forecast ability: the USD exchange rate of the Chilean Peso, Peruvian Sol, and Chinese Yuan, the inflation rate of China and the US, and the price of alternative metals such as iron, gold, silver, and oil. The hybrid model showed better performance than the other models. Reference [50] also utilized various neural network models such as MLP, K-nearest neighbor (KNN), SVM, gradient-boosted tree (GBT), and random forest (RF) and compared their performance in forecasting monthly copper prices. Reference [50] considered as well external parameters which are the USD exchange rates of the largest economies producing copper. The best-performing model that has the lowest error is the MLP neural network.

Other researchers purposed to compare the performance of these two different modeling methods: time series forecasting models (univariate) and factor forecasting models (multivariate). Reference [36] developed univariate and multivariate prediction models for the monthly copper price using the time frame from 1991 to 2021. The external parameters considered are crude oil, gold, iron ore, coal, nickel, silver, aluminum, and natural gas. The authors employed a GA optimization tool, LSTM, and an error correction model to predict copper prices. However, this research work did not consider international crisis events because they are stochastic events and have no evolution rule. Moreover, [43] developed a time-series model and factor forecasting model to predict the monthly price of zinc, nickel, aluminum, and copper using AR and VAR models. Four models are developed, where two are univariate models (AR and TAR) and the other two are multivariate models (VAR and TVAR). For the univariate models, the lag p is two months whereas, for the multivariate model, the additional input variables used are the exchange rate of USD. The results showed that the univariate models are better in performance than the multivariate models.

Based on the above review of the fellow researcher's works and having in mind the impact of international crises on metal prices, there is limited research found in developing prediction models that are generic and applicable in both normally stable economic times and unstable economic times. Thereto, this research focuses on developing two generic models using ANN-LSTM; the first is a multivariate copper forecasting model that predicts the copper prices for the next 1-month and utilizes external parameters some of which are previously introduced by fellow researchers and other are not, and the second model is the univariate copper forecasting model that predicts the copper prices for the upcoming three months. These two models are built to cover the above-mentioned gap in the literature review and compare the performance of univariate and multivariate copper prediction models to validate the conclusions of [36] and [43]. The novelty of this research is that the models are trained on a diverse dataset and validated and tested on crisis times, years 2020, 2021, and 2022, which are more challenging to predict than normal economic times.

III. Model Development

Below are the various steps to develop the proposed model as adopted from the work carried out by [19], [20].

A. Data Collection and Identification of the External Parameters

This study aims to predict the LME copper prices traded in the LME which is of grade A and complies with any of these standards; BS EN 1978:1998 – Cu-CATH-1, GB/T 468-2010-Cu-CATH-1 or ASTM B115-10-cathode Grade 1. It is traded in cathode shapes of lot sizes 25 tons [35]. The data of the daily closing copper prices are collected from [14] for the period from January 2, 2009, to July 31, 2022, and the average monthly copper prices are computed for modeling.

For the 3-month univariate prediction model, the input variable is set to be the 3-month lagged LME copper prices. For the 1-month univariate prediction model, the input variables are the 1-month lagged LME copper prices and additional seven external parameters which lie under two main categories: energy price, and macroeconomic indicators of six major exporting countries of copper.

For energy prices, the copper extracting process consists of three phases which are the mining process, the smelting process, and the refining process, and all of them are energy-based processes. Thereto, the basic raw material used for copper extraction is diesel fuel, a by-product of crude oil, which is the reason for including this parameter by other fellow researchers in their work [9], [11], [28], [31], [32]. Accordingly, crude oil prices are considered input variables since an increase in crude oil prices is presumed to affect the production cost of copper. The average monthly crude oil price is computed from the daily crude oil prices that are collected from [38].

TABLE I
STATISTICAL PROPERTIES OF EXTERNAL PARAMETERS

Property	LME Copper Prices (USD/ton)	Crude Oil (USD/Barrel)	Inflation Rate of Chile	Inflation Rate of Canada	Inflation Rate of US	International Reserve of Chile	International Reserve of Canada	International Reserve of US	Value of Exports of Chile
Count	162	162	162	162	162	162	162	162	162
Mean	6,922.25	76.22	0.03	0.02	0.02	1080.94	9184.19	127649.65	6131.52
Standard Deviation	1,504.54	25.55	0.02	0.01	0.02	663.72	4265.69	33396.43	1075.44
Minimum	3,328.41	26.53	-0.03	-0.01	-0.02	53.96	945.68	62157.74	3436.00
Maximum	10,229.74	124.56	0.12	0.08	0.09	3516.27	24267.02	242176.26	9288.69

For the macroeconomic indicators of six major exporting countries, the literature review includes limited research regarding the use of inflation rate and international reserves of assets and USD when predicting copper prices. Some researchers selected global economic indicators such as stock market indices, USD exchange index [11], [21], [31], [32], [49], whereas [1] focused on selecting the macroeconomic factors of the major consumer of copper instead of global economic factors. Given this initiative proposed by [1], and for the purpose of investigating different parameters that are not selected before by fellow researchers, the macroeconomic factors selected, in this work, are obtained for the six major exporting countries of copper based on the rationale that these exporting countries act as the main global suppliers of this metal so any change in their economic stand may consequently affect the copper prices. The major six exporting countries of copper are Chile, Peru, Australia, Canada, Mexico, and the United States which exported around 34.8%, 14.9%, 6.22%, 5.04%, 4.73%, and 3.94% of copper in 2020 respectively [41]. The first macroeconomic factor nominated is the inflation rate as it depicts the change in the prices over a specific period for each region. Thus, an increase in the inflation rate of one of the major exporting countries indicates that there is a rise in its commodity prices, and since copper is one of the commodities traded and exported so it may indicate an increase in the copper prices as well and vice versa in case of a decrease in the inflation rate. The inflation rate of each region is collected from [42] and due to the unavailability of data for the monthly inflation rate of Peru, Australia, and Mexico, the monthly inflation rate of Chile, Canada, and the United States are considered in this work. The second and third macroeconomic factors selected are the international reserves of assets and USD and the value of exports of the major exporting countries. To the best of the author's knowledge, these factors are not employed by fellow researchers when predicting copper prices. The rationale behind considering these two factors is based on the fact that a global increase in copper demand will reflect a higher level of exports from these major exporting countries. From 2010 till 2021, the increase in copper demand is greater than the increase in copper production as the consumption has increased by 37.5% compared to an increase of 31.8% in copper production [17], [18]. So, based on the law of supply and demand, such high demand may cause an increase in the copper price because the increase in the demand is greater than the increase in the supply. Thereto, the copper price is presumed to be directly related to the level of exports, and such a relationship is further investigated in this work. While for the international reserves of assets and USD, any exports of copper will cause an inflow of US dollars to the country which is reflected in the international reserve of USD and assets of the country. Thereto, an increase in copper prices may cause more inflow of USD dollars which will increase the international reserve of assets and USD of the exporting country. Accordingly, this external parameter is considered to further investigate this relationship. These factors are collected from [25] and due to the limited data found for the value of exports of Canada and the United States, the monthly value of exports of Chile, the monthly international reserve of assets, and USD of Chile, Canada, and the United States are considered. Table I shows the statistical properties of the LME copper price and the external parameters considered in the 1-month univariate model.

Two tests will be carried out to investigate the capability of the selected external factors in predicting the copper prices which are the correlation test and the ganger-causality test which are explained below.

B. Correlation Analysis

The widely used correlation test is the Pearson correlation [1], [21], [31], [32], [50] which is efficient for normally distributed data [44]. When carrying out the Shapiro-Wilk test to check for normality, the p-value of the external parameters and copper price is less than 0.05, as shown in Table II, which infers that both the external parameters and copper price are not normally distributed. Thereto, the Spearman correlation test is employed instead. The interpretation of the Spearman correlation coefficient is based on Table III.

C. Screening of External Parameters

In this step, the external parameters that have at least a strong Spearman correlation will be selected and the other parameters will be ruled out from the model.

D. Multicollinearity Analysis

After carrying out the first screening process, the selected external parameters are tested for multicollinearity to eliminate any collinearity between the external parameters and each other as such may affect the prediction model accuracy [16]. To investigate the multicollinearity between the external parameters, initially, a correlation matrix is plotted to identify the highly correlated parameters, and the Variance Inflation Factor (VIF) of each parameter is computed using (1) where R_i^2 is the regression coefficient between the parameter investigated and the ith parameter. The parameter that is highly correlated with the other parameters and has a VIF value that is larger than the threshold value, which is 10, is eliminated. Afterward, the VIF is re-computed for the remaining parameters to ensure that they are below 10.

$$VIF_i = \frac{1}{1-R_i^2} \tag{1}$$

TABLE II
RESULTS OF SHAPIRO-WILK TEST

Variables	W-Value	p-value
Copper Price	0.97664	0.007355
Brent Crude Oil	0.93448	8.441e-07
Inflation rate in Chile	0.86354	5.304e-11
Inflation rate of Canada	0.83568	2.97e-12
Inflation rate of the United States	0.84134	5.19e-12
International Reserve of Chile	0.66454	< 2.2e-16
International Reserve of Canada	0.5209	< 2.2e-16
International Reserve of United States	0.69567	< 2.2e-16
Value of Exports of Chile	0.98258	0.03822

TABLE III
INTERPRETATION OF SPEARMAN CORRELATION COEFFICIENT

Spearman Correlation Coefficient (r_s)	Strength of Correlation
0.0 – 0.19	Very Weak Correlation
0.2 - 0.39	Weak Correlation
0.4 – 0.59	Moderate Correlation
0.6 – 0.79	Strong Correlation
0.8 – 1.0	Very Strong Correlation

E. Development of ANN-LSTM Model

Based on the above literature review, various tools can be used to predict time-series data such as the ARIMA model, the VAR model, ANN, RNN, CNN, LSTM, and hybrid models. Although, the ARIMA model shows promising results in predicting copper prices, however, the machine learning model outperformed the ARIMA models as they are more accurate in predicting the volatility in copper prices [6], [30]. The utilization of the LSTM model in the prediction models is evidenced to be effective especially when combined with other machine learning tools such as VMD, ANN, CNN [21], [31], [33], [34], [46]. This owes to the advantageous property that the LSTM has over the other machine learning models as it includes a memory cell which consists of a cell state that stores the data of the previous time step, a forget gate, and input gates that determine whether the previous cell state, given the current input values, will be stored or not, a memory cell (C_t) that combines the results of forget and input gates and stores the newly updated cell state, and an output gate that provides the output result to the next layer [34]. This mechanism eliminates the occurrence of the vanishing gradient and the short-term memory problems that exist in the ANN, RNN, and CNN models. Thereto, the integration of the machine learning tools with the LSTM model elevates the performance of the model and increases its performance as shown in the work of fellow researchers who concluded that a hybrid model with LSTM outperforms other models [21], [31], [33], [34], [46]. Accordingly, a hybrid model of the ANN and LSTM is employed when developing the 1-month multivariate model and the 3-month univariate model using Python.

F. Data Processing and Splitting of Dataset

For the ANN-LSTM models, initially, the copper prices and external parameters are normalized by (2) to unify the order of magnitude of all the parameters since some of them are in percentages and others are in an order of 10^3 as shown in Table I. Then, the dataset is divided into a training set which is 80% of the dataset, a validation set which is 10% of the dataset, and the remaining 10% is the testing dataset.

$$v' = \frac{v_i - min_i}{max_i - min_i} \tag{2}$$

where v' is the normalized value, v_i is the i^{th} variable before normalization, and min_i and max_i are the minimum and maximum values of the i^{th} variable [27].

G. Hyperparameters Tuning

Afterward, the architecture of the models is utilized by varying the number of layers, the number of neurons of each layer, activation function, learning rate, mini-batch size, and the number of epochs. This is carried out in two stages. Stage 1 includes varying the number of layers, the number of neurons of each layer, and the activation function through a trial-and-error method, while keeping the learning rate, the mini-batch size, and the number of epochs set at 0.0001, 4, and 1,000 respectively. After arriving at the best architecture having the lowest MAE and RMSE for the validation and testing datasets, the next step includes varying the other hypermeters, that were previously kept constant, the learning rate is changed to be 0.0001 and 0.00001, the mini-batch size is changed to 4 and 8, the number of epochs is changed to 1,000, 5,000 and 10,000. To cover all the possible options when varying these three hyperparameters, 12 attempts are considered as shown in Table IV to investigate the MAE and RMSE errors of the validation and testing datasets.

H. Performance Measure and Model Applicability

The MAE as in (3) [7] and RMSE as in (4) [7] are used when tunning the model's hyperparameters and the absolute percentage error (APE) as in (5) [29] and MAPE as in (6) [29] are used when evaluating the model's prediction accuracy of the testing dataset.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - \acute{y}_t| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_t - \acute{y}_t)^2} \tag{4}$$

$$APE = \left|\frac{y_t - \acute{y}_t}{y_t}\right| \times 100 \quad (5)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \acute{y}_t}{y_t}\right| \times 100 \quad (6)$$

where y_t is the copper price at the time (t), $\acute{y}_t$ is the predicted copper price at the time (t), and n is the size of the dataset.

TABLE IV
HYPERPARAMETER COMBINATION

No. of Trails	Learning Rate	Min-batch Size	No of Epochs
1	0.0001	4	1,000
2	0.0001	8	1,000
3	0.0001	4	5,000
4	0.0001	8	5,000
5	0.0001	4	10,000
6	0.0001	8	10,000
7	0.00001	4	1,000
8	0.00001	8	1,000
9	0.00001	4	5,000
10	0.00001	8	5,000
11	0.00001	4	10,000
12	0.00001	8	10,000

Lastly, to test the applicability of this model, a prediction code is developed for each model to predict the copper prices of the next one month and three months for the 1-month multivariate model and 3-month univariate model respectively, and compare it with the actual copper prices.

IV. RESULTS AND DISCUSSION

A. Correlation Analysis

This step is conducted for the selected external parameters of the 1-month multivariate model. The Spearman correlation coefficient (r_s) between each external parameter and the copper price is illustrated in Table V.

TABLE V
RESULTS OF THE SPEARMAN CORRELATION TEST

External Parameters	r_s	p-value	Strength of Correlation
Brent Crude Oil	0.715	< 2.2e-16	Strong Positive Correlation
Inflation rate of Chile	-0.011	0.8904	Very Weak Negative Correlation
Inflation rate of Canada	0.424	1.835e-08	Moderate Positive Correlation
Inflation rate of the US	0.572	1.984e-15	Moderate Positive Correlation
International Reserve of Chile	0.632	< 2.2e-16	Strong Positive Correlation
International Reserve of Canada	0.837	< 2.2e-16	Very Strong Positive Correlation
International Reserve of US	0.821	< 2.2e-16	Very Strong Positive Correlation
Value of Chile's Exports	0.789	< 2.2e-16	Strong Positive Correlation

From the correlation results, there is a strong Spearman positive correlation between the crude oil prices and the copper prices, since crude oil is the energy source in the copper's extraction process; so, an increase in the crude oil prices will reflect in higher production cost; thus, higher copper prices. For the inflation rate, the copper prices are moderately correlated with the inflation rate of Canada and the US and strongly correlated with the inflation rate of Chile since it is the top copper exporter, and Canada and the US are the fourth and sixth top exporters in 2020. This result confirms that the inflation rate of the major exporting countries of copper can indicate whether copper prices will increase or decrease. Whereas for the international reserve of assets and USD, the copper prices are very strongly correlated with the international reserve of Canada and the US, and strongly correlated with the international reserve of Chile. Such correlation between the copper prices and the international reserves of USD and assets affirms that an increase in the copper prices reflects in more inflow of USD dollars to the exporting countries, and thus is a potential economic indicator of the copper price's trend. Also, the copper prices are strongly correlated to the value of exports in Chile which also asserts the presumption that an increase in the global demand for copper will consequently increase the level of copper exports which will increase the copper prices, given that the increase in demand is greater than the increase in the supply.

B. Screening of External Parameters

The external parameters that have at least a strong correlation with the copper prices are crude oil, the international reserve of Chile, Canada, and the US and Chile's export. So, these five input variables and the past copper price are selected to be employed in the 1-month multivariate model. These variables will be lagged by 1-month where the input variable at time (t-1) is used to predict the copper prices at time (t).

C. Multicollinearity Analysis

The correlation matrix for all the variables is plotted in Fig. 1 and the computed VIF for each external parameter is illustrated in Table VI. It is observed that there exists a strong correlation between the international reserve of Canada and all the other remaining three input variables; it is strongly correlated with crude oil (correlation coefficient = 0.64), and with the inflation rate of Chile (correlation coefficient = 0.70), and with exports of Chile (correlation coefficient = 0.65). This is also evidenced in its high VIF value (60.62) shown in Table VI. The same case applies to the international reserve of Chile and the US. However, since the international reserve of Canada has a higher Spearman correlation coefficient with the copper prices compared to the Spearman coefficient of Chile and the US; thereto, eliminating this variable from the model may decrease the accuracy of prediction. So, the second and third variables that are strongly correlated with the other variables will be removed which are the international reserve of Chile and the US.

The VIF is re-computed for the remaining external parameters and the results are shown in Table VI where all the values are less than five inferring that there is no significant multicollinearity between the external parameters.

D. Development of 1-Month Multivariate ANN-LSTM Model

The copper prices and the external parameters are normalized to unify the order of magnitude among all the variables and Table VII shows the statistical properties of the normalized variables. The training dataset is from February 2009 to October 2019, the validation dataset is from November 2019 to February 2021, and the testing dataset is from March 2021 to July 2022.

Fig. 1 Correlation Matrix of Variables

TABLE VI
VIF OF EXTERNAL PARAMETERS

External Parameters	VIF	Recomputed VIF
Crude Oil	3.68	1.32
International Reserve of Chile	**24.73**	-
International Reserve of Canada	**60.62**	1.92
International Reserve of US	**37.55**	-
Value of Chile's Exports	3.32	2.31

TABLE VII
STATISTICAL PROPERTIES OF NORMALIZED VARIABLES

Property	LME Copper Prices (USD/ton)	Crude Oil (USD/Barrel)	International Reserve of Canada	Value of Exports of Chile
Count	162	162	162	162
Mean	0.52	0.51	0.36	0.46
Standard Deviation	0.22	0.26	0.19	0.18

The optimum architecture arrived at, after various iterations, is using five ANN layers and 1 LSTM layer of 150 neurons, 50 neurons, 50 neurons, 25 neurons, 25 neurons, and 25 neurons respectively, and using the tanh activation function in all the layers. For the second stage of hyperparameter tuning, the lowest summation of MAE and RMSE errors for the validation and testing datasets is 1520 which is reached when using a learning rate of 0.0001, 10,000 epochs, and a mini-batch size of 8.

The model is trained on 129 data points from Jan-2009 till October 2019 and can predict the copper prices with a MAPE of 3.7% and an APE ranging between 0% and 12.25% for the training dataset. For the validation dataset, the model can predict the copper prices with a MAPE of 4.2%, and an APE ranging between 0.5% and 8.5%. For the testing dataset, the model can predict copper prices with a MAPE of 5.7% having an APE between 1.05% and 12.5%. When comparing the ranges of the APE of all the datasets together, it is observed that the APE of both the validation and testing datasets falls within the upper and lower error boundary of the training dataset; meaning that the model's performance is consistent within the three datasets.

When determining the APE of this model, it is more accurate to refer to the testing dataset only because it reflects the true performance of the model after all the model's parameters are set and determined using the training and validation dataset and the model is tested using a different dataset that was not processed before. Thereto, this model can predict copper prices with a MAE of 5.7%, and Fig. 2 shows the predicted copper prices versus the actual copper prices for the whole dataset.

For the applicability of the model for both economically stable and crises times, the model is trained and validated in the time frame from January-2009 till Februaury-2021 wherein the average monthly copper prices sharply increased in 2010 due to the global financial crises of 2008 and continued till 2010, and then dropped sharply in May-2020 due to the outspread of COVID-19 pandemic as shown in Fig. 2. Thereto, the diversity in the training and validation datasets are sufficient to develop a general model that can predict the average monthly copper prices in both economically stable and unstable times. This is further evidenced in the ability of the model to accurately predict the testing dataset (March-2021 till July-2022) with a MAPE of 5.7% wherein the time frame of this dataset is from March-2021 till July-2022 which resembles a crisis time due to COVID-19 and Russia-Ukraine war that is more challenging for predicting its copper prices due to the stochastic nature of these events and its unanticipated impact on the trend of prices [36].

To further investigate the applicability of this model, a prediction code, on Python, is developed to predict the average copper prices for the next month (August 2022). The input variables are the external parameters and copper price of July 2022 and the average predicted copper price of August 2022 is 6,987.8145 USD per ton. The actual daily copper prices are shown in Fig. 3 and have an average price of 7,962.607 USD. Thereto, the model can predict an average price of copper in August 2022 with an APE of 12.2% which lies within the APE range of the testing dataset.

E. Development of 3-Month Univariate ANN-LSTM Model

The architecture of the 1-month multivariate model is also the best architecture for the 3-month univariate model; the only difference is in the input layer which consists of 3 neurons instead of 4 neurons. After running the 12 attempts shown in Table IV, the selected hyperparameters are a learning rate of 0.0001, 10,000 epochs, and a mini-batch size of 8, similar to the 1-month multivariate model.

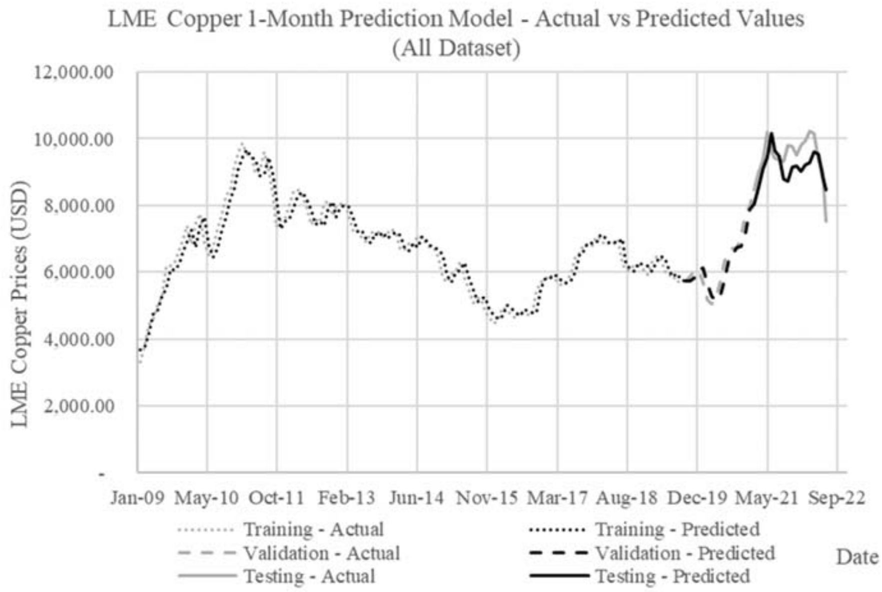

Fig. 2 Results of 1-Month Multivariate Model

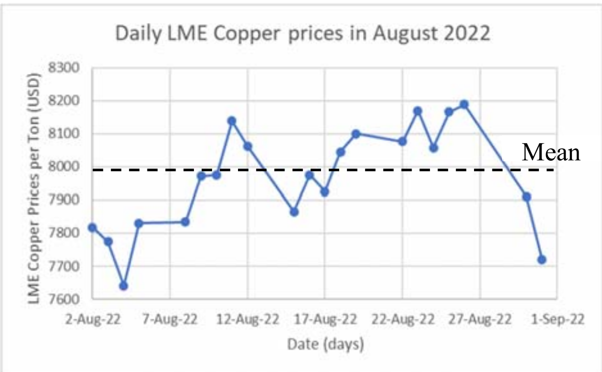

Fig. 3 Daily LME Copper Prices of August 2022

For the training dataset, the model can predict copper prices with a MAPE of 3.59% ranging between 0.06% and 13.51%. While for the validation dataset, the model can predict the copper prices with a MAPE of 4.1% ranging between 0.06% and 8.9%, and for the testing dataset, the model can predict the copper prices with a MAPE of 4.2% ranging between 0.12% and 17.91%. It is observed that the MAPE of all the datasets of this model is slightly less than the MAE of the 1-month multivariate model although the range of the APE is slightly larger by 1.2% for the training dataset and 6.34% for the testing dataset. This owes to the evidence given in Fig. 4 which shows the relationship between the volatility of copper prices, computed using (7), and the forecast error, computed using (8). The larger linear regression coefficient of the 3-month univariate model indicates that, when the volatility of copper prices increases, the forecast error is higher in the 3-month univariate model compared to the 1-month multivariate model which leads to a higher APE for these points in the 3-month univariate model and thus a wider range of APE.

$$\text{Volatility (\%)} = \frac{\mathrm{P_{(t+1)}} - \mathrm{P_t}}{\mathrm{P_t}} \times 100 \tag{7}$$

$$\text{Forecast Error (\%)} = \frac{\mathrm{P'_t} - \mathrm{P_t}}{\mathrm{P_t}} \times 100 \tag{8}$$

where $P_{(t+1)}$ is the actual copper price at the time (t+1), P_t is the actual copper price at the time (t), and P_t' is the predicted copper price at the time (t).

Moreover, when further analyzing the frequency of the APE for each model, it is observed, based on Fig. 5, that around 94% and 95% of all the datasets of the 1-month multivariate model and the 3-month univariate model respectively have an APE of 10% or less which means that both models are highly accurate in predicting the copper prices as it is below the accepted APE of 10% for prediction models [13].

Similar to the 1-month multivariate model, the developed model is generic and can be used to predict prices during both economically stable times and crisis times. Fig. 6 shows the results of the 3-month univariate model which can predict copper prices with a MAPE of 4.2% compared to 5.7% for the 1-month multivariate model.

Based on the MAPE of each model, the 3-month univariate model is slightly higher in accuracy when compared to the 1-month multivariate mode, also the applicability of the 3-month univariate model is larger as it can predict for the upcoming 3 months or more due to the rolling forecast method used in developing the model. For instance, to predict the average copper price of September 2022, the prediction code uses the copper price of June 2022, July 2022, and the predicted value of August 2022, and so on can follow for the next month. Table VIII shows the results of the predicted average copper prices versus the actual average copper prices of August 2022, September 2022, and October 2022. The APE lies within the overall APE range of the testing dataset; noting that the model is also able to predict that the average monthly copper price will drop in September 2022 and October 2022 which is similar to the actual trend in these three months.

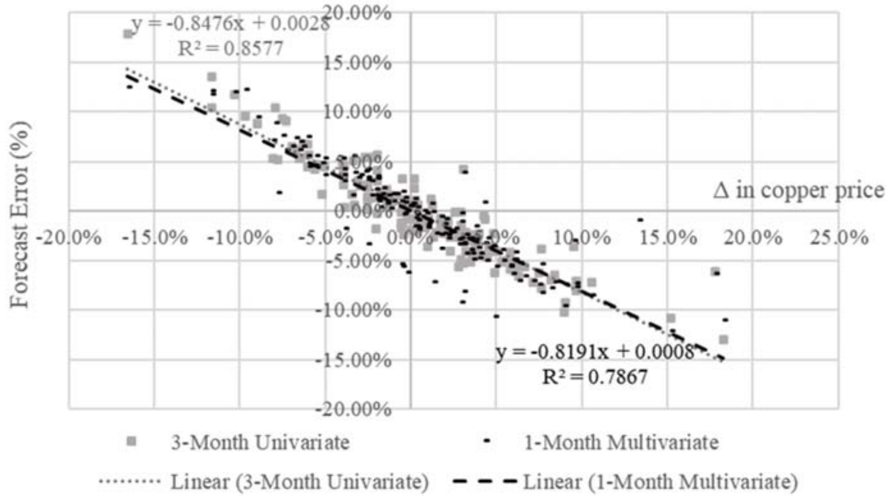

Fig. 4 Relationship between Volatility in Copper Price and Forecast Error

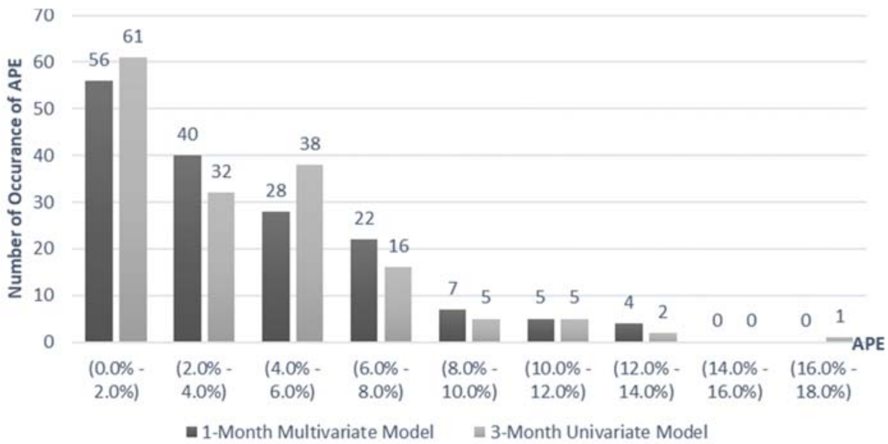

Fig. 5 Frequency of APE

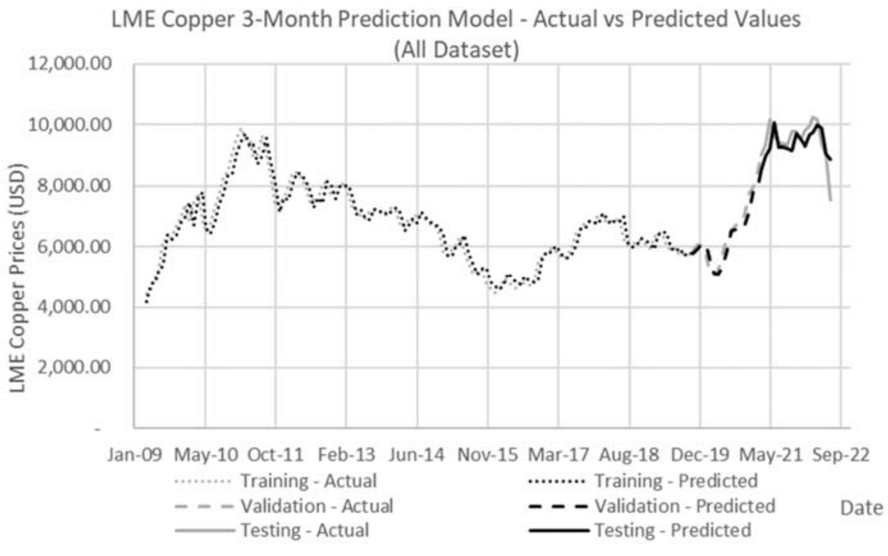

Fig. 6 Results of the 3-Month Univariate Model

V. CONCLUSION

This work shows that the use of macroeconomic factors of major exporting countries of the studied metal is efficient in predicting metal prices instead of general macroeconomic factors. This view can be applied when predicting other ferrous or non-ferrous metals. Also, the developed models are generic and can predict copper prices during both normally economically stable times and crisis times. To ensure such a generic applicability, the model was trained on a diverse dataset and was validated and tested during the crisis times of COVID-19 and the Russia-Ukraine war which is more challenging to predict than at any other time because of the unexpected rises and drops in this time frame. Additionally, this work shows that the 3-month univariate model is higher in performance compared to the 1-month multivariate model which supports the results of [43], [36] and provides more evidence to the limited research in this area.

TABLE VIII
ACTUAL AND PREDICTED COPPER PRICES FOR THE 3 UPCOMING MONTHS

Date	Actual Copper Price	Prediction Copper Price	APE
Aug-22	7,962.607	7,155.703	10.13%
Sep-22	7,737.407	7,113.072	8.07%
Oct-22	7,612.658	7,089.601	6.87%

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