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Forecasting monthly copper price: A comparative study of various machine learning-based methods

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ABSTRACT

Copper is one of the valuable natural resources, and it was widely used in many different industries. The complicated fluctuations of copper prices can significantly affect other industries. Therefore, this study aims to develop and propose several forecast models for forecasting monthly copper prices in the future based on various algorithms in machine learning, including multi-layer perceptron (MLP) neural network, k-nearest neighbors (KNN), support vector machine (SVM), gradient boosting tree (GBT), and random forest (RF). The monthly copper price dataset from January 1990 to December 2019 was collected for this aim based on other metals and natural gas prices. In addition, the influence of currency exchange rates of the countries that have the largest copper production around the world was also taken into account and used as input variables for forecasting copper price. The different set of predictors (t, t-1, t-2, t-3, t-4. t-5) were considered to forecast monthly copper prices based on the mentioned machine learning techniques. The results revealed that the currency exchange rates of the countries that have the most abundant copper production around the world have a significant effect on the volatility of monthly copper prices in the world, and they should be used to forecast monthly copper prices in the future. A comprehensive comparison of various machine learning techniques shows that MLP neural network (with deep learning techniques) is the best method for forecasting monthly copper price with an MAE of 228.617 and RMSE of 287.539. Whereas, the other models, such as SVM, RF, KNN, and GBT, provided higher errors with an MAE in the range of 308.691–453.147, RMSE in the range of 393.599–552.208. In this sense, MLP neural network can be used as a reliable tool to forecast copper prices in the future.

1. Introduction

Copper (copper ore) is one of the natural resources that was exploited early to serve various purposes of humans. Most of them are exploited from surface copper mines in the world and extracted in the form of copper sulfide (Sadowski et al., 2003). Some of the largest countries in exploiting and processing copper include Chile, United States, China, Australia, Peru and Indonesia (Kwakkel et al., 2013; Navarro Berdeal, 2019; Quiñones et al., 2020; Zhang et al., 2017). Copper is widely used in industries such as machine manufacturing, automobile manufacturing, agriculture, electronic components, household appliances, and even musical instruments and spiritual monuments (bronze statues) (Berillis et al., 2017; Elshkaki et al., 2016; Ma et al., 2019; Malandrakis et al., 2019). With the meager supply of copper compared to the high demand in reality, the prices of copper and its variants have undergone complicated fluctuations. Global copper

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scenarios indicate that global demand for copper will increase by about 2–3.5 times by 2050 (Zabala, 2018). This implies the complicated development of copper prices in the future, which significantly influences many industries and economies of nations (Nguyen and Hoang, 2020; Nguyen and Nguyen, 2020b). Therefore, an accurate forecast of copper price in the long term is of great concern to investors, policymakers, mining enterprises as well as other related industries.

To forecast the price of copper and some other metals, many scholars proposed different approaches, such as empirical methods, econometric models, and soft computing models (Gan et al., 2020; García and Kristjanpoller, 2019; Kriechbaumer et al., 2014; Ozozen et al., 2016), among which soft computing models that use machine learning algorithms and artificial intelligence (AI) are considered to be the most preeminent methods (Wang et al., 2019). They are not only employed to forecast the price of different metals but also widely used in policy, social, and financial forecasting (Ballestar et al., 2019; Lee et al., 2018; Wang et al., 2020; Nguyen et al., 2020a), and technical issues related to natural resources research (Fang et al., 2019a, 2019b; Guo et al., 2021, 2019; Nguyen and Bui, 2019; Nguyen et al., 2019a, 2020a; Jian et al., 2020, 2021a,b; Yingui et al., 2021). In other words, machine learning and AI techniques are recommended as robust techniques to forecast time series problems with high accuracy in the future (Nguyen et al., 2018, 2019c, 2020d; Le, 2020).

Regarding forecasting copper price, ARIMA and ANN models have been proposed and compared by Lasheras et al. (2015). Accordingly, they claimed that the ANN model could predict copper price better than the ARIMA model with lower mean forecast error and variance. Liu et al. (2017) also applied a decision tree model to forecast copper price for different horizon times and set of predictors. They concluded that the forecast models for short-terms are often more accurate than long-term. In another study, Carrasco et al. (2018) used the support vector machine (SVM) model for forecasting the fluctuation of copper price. Different structures of the SVM model were discovered and built for this aim. The Bat algorithm in machine learning was also applied to forecast copper prices with a superior result (Dehghani and Bogdanovic, 2018). Another approach based on hybrid and non-hybrid models was also conducted for forecasting copper price (García and Kristjanpoller, 2019). Finally, they found that the hybrid model (i.e., adaptive-GARCH-fuzzy inference system) forecasted copper price better than the other models. Using a similar hybrid approach, Alameer et al. (2019) also develop a hybrid model, namely GA-ANFIS, based on the optimization of the genetic algorithm and the fuzzy inference mechanism of an ANN system for forecasting copper price. A variety of other AI models, such as SVM, ANFIS, ARIMA, and GARCH, were also taken into account to assess the performance of the GA-ANFIS model. As a result, the GA-ANFIS was confirmed as the best model in their study with the most superior results. In another study, Díaz et al. (2020) considered the random walk and several other machine learning models for forecasting copper prices, such as simple regression tree, gradient boosting regression tree, and random forest (RF). Different horizons and set of predictors were taken into account in their study. Finally, they concluded that the daily copper prices can be forecasted by random walk model with the highest accuracy.

According to the best review of the authors, although the AI methods have been proposed for forecasting copper price; nevertheless, they did not take into account the effects of the exchange rate of countries that have the largest copper producer in the world (e.g., Chile, U.S, China, Peru and Australia). Prior literature shows that only the Chilean exchange rate was used to forecast metal prices by Brown and Hardy (2019). Furthermore, many machine learning algorithms, especially multi-layer perceptron (MLP) neural network with deep learning techniques, have not been applied in forecasting copper prices. Therefore, this study aims at solving two following novel problems: (i) evaluating the effect of the exchange rate of countries that have the largest copper producer in the world on the copper price (e.g., USD vs. CLP (Chile currency), USD vs. CNY (China currency), USD vs. PEN (Peru currency) and USD vs. AUD (Australia currency)); (ii) Comprehensive assessment of different machine learning techniques for forecasting monthly copper price, including MLP neural network, SVM, RF, k-nearest neighbors (KNN), and gradient boosting tree (GBT). The detail of the study is presented in the next sections.

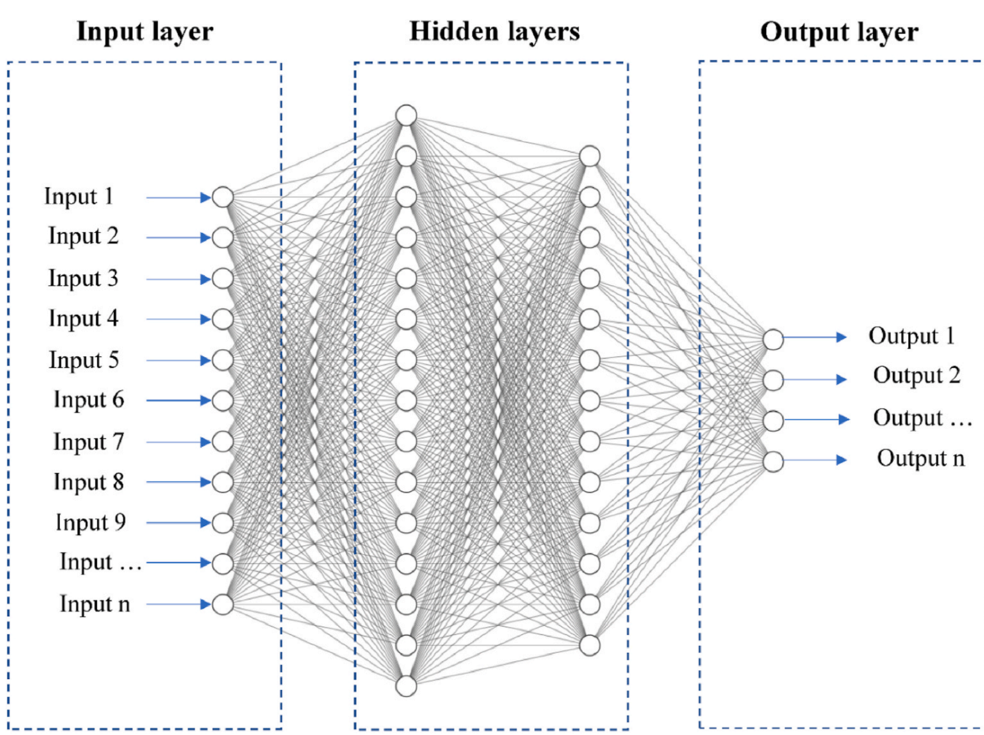


Fig. 1. Deep neural network with multiple inputs and outputs.

2. Machine learning-based methods

2.1. Deep learning and MLP neural network

The deep learning concept is introduced as a unique learning technique that allows computational models to process multiple layers at the same time to achieve a more accurate level (LeCun et al., 2015). The state-of-the-art of AI models in real-life problems has been dramatically improved by deep learning. It is capable of detecting complex data structures and adjusting algorithm parameters to understand and represent complex data structures (Zhang et al., 2020). Unlike the more straightforward problems of regression and classification, time series problems are complex due to the temporal dependence between observations or the complexity of the order (Längkvist et al., 2014). Therefore, deep learning for time series problems is considered a promising approach to solving this complex problem (Gamboa, 2017). They are known as the neural networks that are able to automatically learn complex mappings of datasets (i.e., from input variables to output variable), such as recurrent neural network, MLP, convolutional neural network, and long-short term memory neural network. Furthermore, they can support multivariate inputs and outputs (multiple inputs and outputs) (Brownlee, 2018). In this study, the deep learning for MLP neural network was taken into account for forecasting copper price in the world.

MLP neural network for time series is known as a valuable and robust method for a number of the following reasons:

(1) MLP neural network is robust to noise in input data, as well as in the mapping function. It even can process the data and predict the presence of missing values (Dorffner, 1996).
(2) MLP neural network can well-explain the non-linear relationship of the dataset (Dorffner, 1996).
(3) MLP neural network can support multivariate forecasting, whereas, the other simple techniques only support univariate forecasting (Sutskever et al., 2014).
(4) MLP neural network can support multi-step forecasting for the time series dataset (Sutskever et al., 2014).
(5) MLP neural network can fix the number of lag input and output variables. It is a challenge for deep neural networks because they require the inputs and output dimensional is known and fixed (Sutskever et al., 2014).

For structure, in general, MLP neural network for time series has a similar structure for the other problems (e.g., classification or regression). It includes three types of layers: an input layer, hidden layer(s), and output layer (Moayedi et al., 2019; Sharifi et al., 2019). A deep neural network includes multiple hidden layers. In each layer, neurons are the primary components that are connected through the weights. These weights can be computed and tuned via activation functions aiming to explain the relationship of the dataset (Nguyen et al., 2020c; Shang et al., 2020). Furthermore, for deep learning in MLP neural networks, many components, such as nodes and layers, gradient precision with batch size, loss functions, learning rate, can be adjusted to dramatically improve the accuracy of the model. This study focuses on some components, such as nodes, layers, loss functions, and learning rate in deep learning for MLP neural network. The general structure of deep MLP neural network is illustrated in Fig. 1.

2.2. Support vector machine

SVM is introduced as a robust machine learning method based on the statistical theory which was proposed by Cortes and Vapnik (1995). Similar to MLP neural network, SVM can solve both classification and regression problems (Nguyen et al., 2019b). In time series forecasting, SVM can also perform well both the time series classification and time series for regression (Mukherjee et al., 1997). One of the advantages of SVM for time series forecasting is it can map the input variables to output variables through non-linear functions. Furthermore, like MLP neural network, SVM can solve the time series problems with multivariate inputs and outputs (Cao and Tay, 2003), and time series forecasting with multi-steps. The main idea of SVM is to split data according to the linear form by a hyperplane. Herein, support vectors are the data points located near the hyperplane (Fig. 2). For non-linear datasets, SVM uses kernel functions to map data from two-dimensional to higher-dimensional space; subsequently, a hyperplane is applied to separate data similar to the linear form (Fig. 3). As a type of neural network, SVM also uses vectors between layers to transfer the information from input variables, and weights are presented for the value of vectors (Nguyen et al., 2020b). Loss function was also applied in SVM to minimize the error of the model. The detail of SVM can be found in the following papers (Cortes and Vapnik, 1995; Ghorbani et al., 2016; Hearst et al., 1998; Noble, 2006; Zhang, 2019).

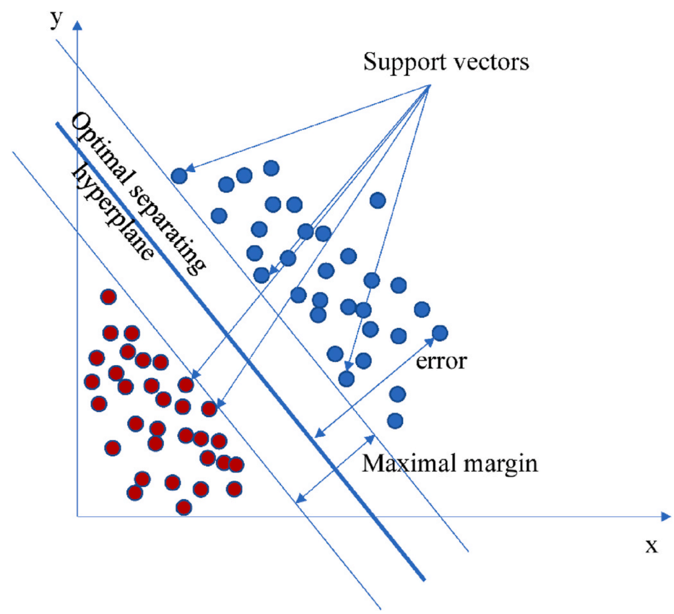


Fig. 2. SVM algorithm and its components.

2.3. Random forest (RF)

RF is well-known as an ensemble algorithm in machine learning proposed by Breiman (1999). Whereas the SVM can build only one model from the dataset, the RF model can build a set of models based on the bootstrap technique and then combine them (Nguyen and Bui, 2018), as illustrated in Fig. 4. In this way, RF can deal with complex problems with better performance (Lin et al., 2017). RF is also referred to as a type of decision tree algorithm, and for each bootstrap, an unpruned regression tree is created. Subsequently, they were pruned and split at each node and calculated the average of the regression tree as the model's output. Further details of the RF algorithm can be referred to in the literature (Breiman, 2001; Cutler et al., 2012; Genuer et al., 2017; Hastie et al., 2009; Pavlov, 2019).

2.4. K-nearest neighbors (KNN)

As a mature data mining technique, KNN is classified as a lazy algorithm in machine learning. Indeed, it does not learn anything from the training dataset. Instead, it considers the characteristics of the k-nearest neighbors on the training dataset and calculates the distance to them (Bui et al., 2019). In other words, if a point to be forecasted in the testing dataset, the KNN will consider it and all the near points in the training dataset. Then, it calculates the distance from the point to be forecasted

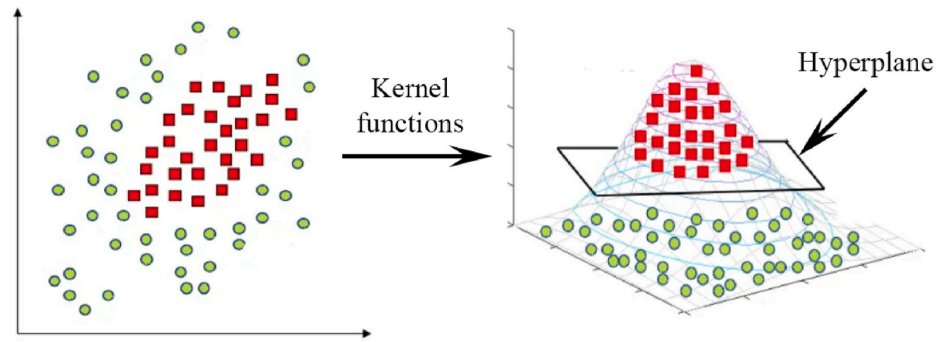


Fig. 3. Mapping data to higher dimensional feature space of SVM.

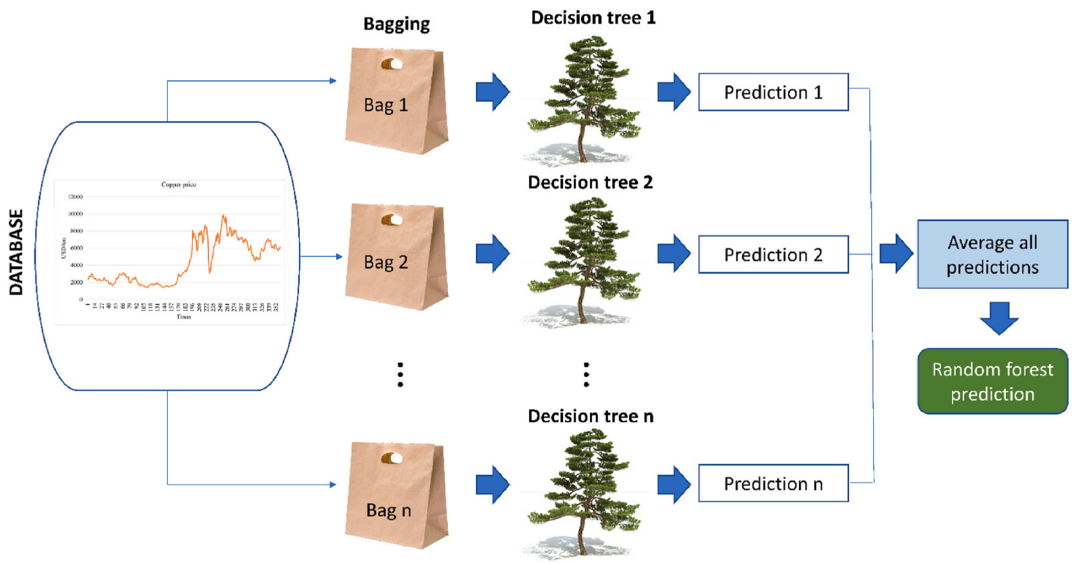


Fig. 4. RF algorithm for forecasting copper price.

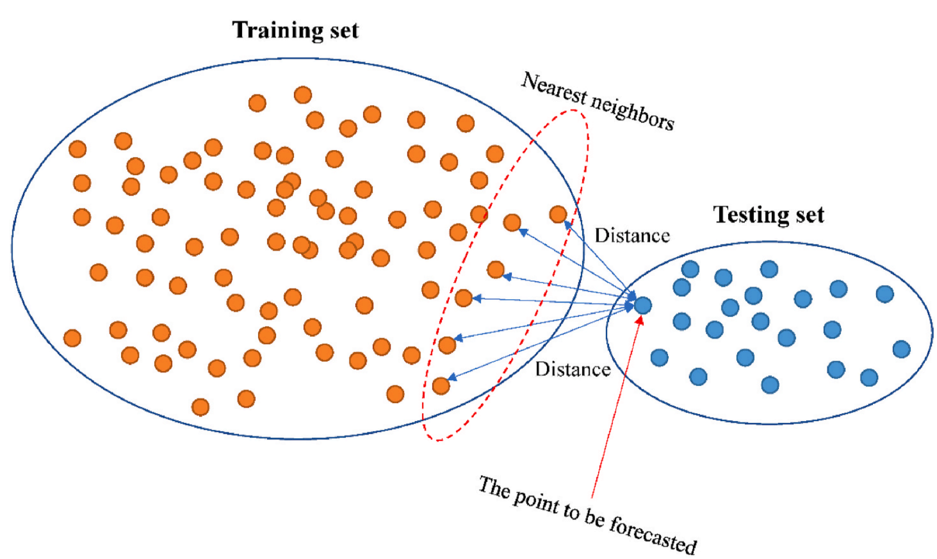


Fig. 5. Illustrating the mechanism of the KNN algorithm.

in the testing dataset to the near points to determine the nearest neighbor. Finally, it will assign the same attributes and features to the point to be forecasted, as shown in Fig. 5. Further details of KNN can be read in the literature (Batista and Silva, 2009; Bezdek et al., 1986; Ertuğrul and Tağluk, 2017; Peterson, 2009).

2.5. Gradient boosting tree (GBT)

The GBT model was introduced as a robust machine learning algorithm based on the combination of weak learners and the gradient algorithm (Ferreira and Figueiredo, 2012). Similar to the RF algorithm,

Algorithm 1: Gradient boosting

1. $F_0(x) = \arg\min_{\rho} \sum_{i=1}^{N} L(y_i, \rho)$

2. For $m = 1$ to M do;

3. $\tilde{y}_i = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}, \quad i = 1, \ldots, N$

4. $\boldsymbol{a}_m = \arg\min_{\boldsymbol{a},\beta} \sum_{i=1}^{N} [\tilde{y}_i - \beta h(x_i; \boldsymbol{a})]^2$

5. $\rho_m = \arg\min_{\rho} \sum_{i=1}^{N} L(y_i - F_{m-1}(x_i) + \rho h(x_i; \boldsymbol{a}_m))$

6. $F_m(x) = F_{m-1}(x) + \rho_m h(x; \boldsymbol{a}_m)$

7. End for

End algorithm

Fig. 6. Implementation of the GBT algorithm.

GBT is also classified to a decision tree algorithm, but the RF algorithm uses the bagging technique, and the GBT algorithm uses the boosting technique to improve the accuracy of the model (Dietterich, 2000; Sutton, 2005). Accordingly, the GBT focuses on the errors resulting at each step, combines weak learners, and repeats the learning until a stronger learner is obtained. The pseudo-code can describe the GBT algorithm in Fig. 6. Further details of the GBT algorithm can be referred to in the following papers (Bentéjac et al., 2021; Friedman, 2002; Guelman, 2012; Touzani et al., 2018).

3. Data analysis

As mentioned above, this study aims to forecast the chaotic behavior of copper price in the long-term using deep learning for MLP neural network. Accordingly, the relationship between oil, gold, silver, and copper were considered and claimed (Bildirici and Türkmen, 2015). A variety of previous studies also used the price of oil, gold, silver as the input variables for forecasting copper price (Alameer et al., 2019; Dehghani and Bogdanovic, 2018; García and Kristjanpoller, 2019). In addition, the iron price also has a significant impact on copper price and a close relationship with copper price (Ewees et al., 2020; Konishi, 2007). In addition to the above parameters, this study considers the relationship between copper price and the exchange rate of some countries with the largest cooper production globally, including Chile, China, Peru, and Australia. Correlation analysis and statistical significance of the exchange rate of Chile, China, Peru, and Australia countries and copper price were taken into account and conducted to interpret whether these variables should be used or not (Fig. 7).

Based on the analyzed results in Fig. 7, it can be seen that the correlation of exchange rates (i.e., USD/CLP, USD/CNY, USD/PEN, and USD/AUD) and copper price are very interesting. Whereas, the USD/PCL and USD/PEN variables have a low correlation with the copper price (i.e., R = 0.14 and 0.15), the variables of USD/CNY and USD/AUD have a higher correlation with the copper price variable (i.e., R = −0.37 and −0.75). It is worth mentioning that all these variables are statistically significant ($p < 0.05$). Therefore, they should be considered and used for forecasting copper prices in this study. The detail of the time series dataset used in this study is shown in Fig. 8.

Prior literature shows that the current price is the best predictor for forecast copper prices, and a random walk model is the best model for forecasting copper prices with such random walk data (Díaz et al., 2020;

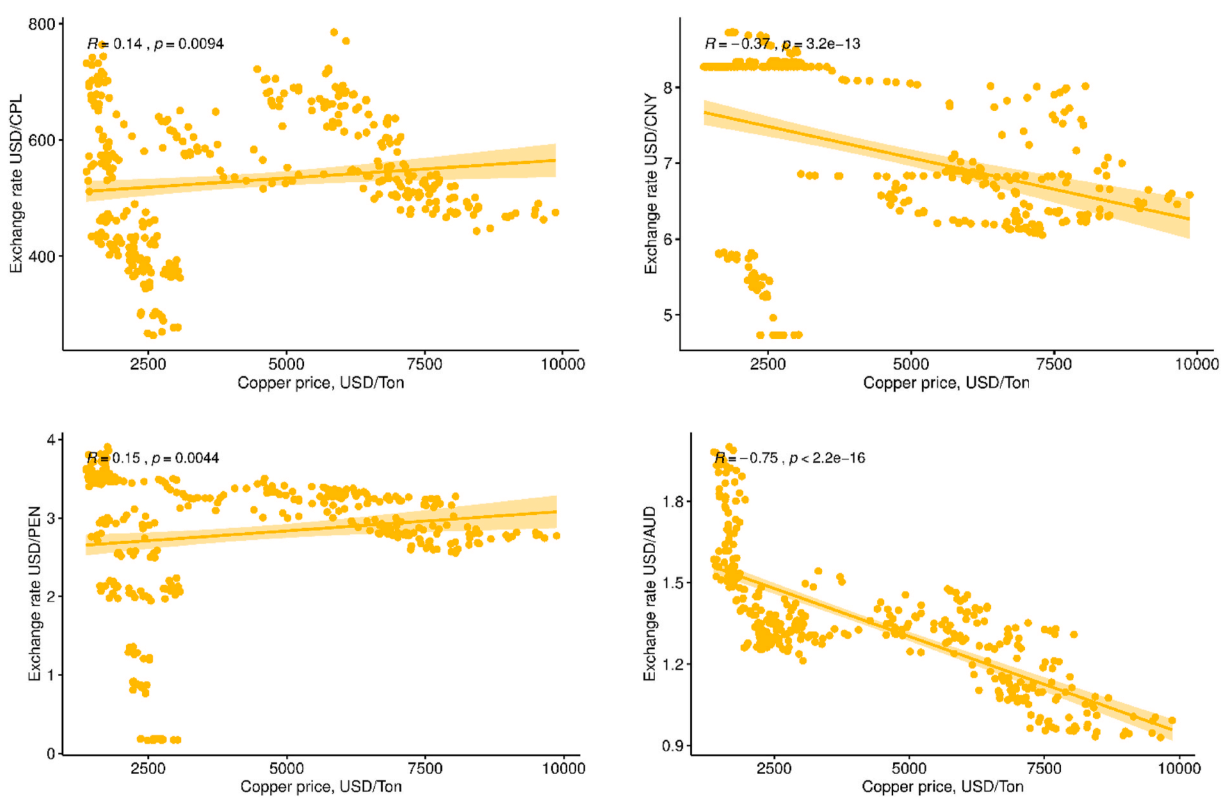


Fig. 7. Correlation analysis of exchange rate of Chile, China, Peru, and Australia countries and copper price.

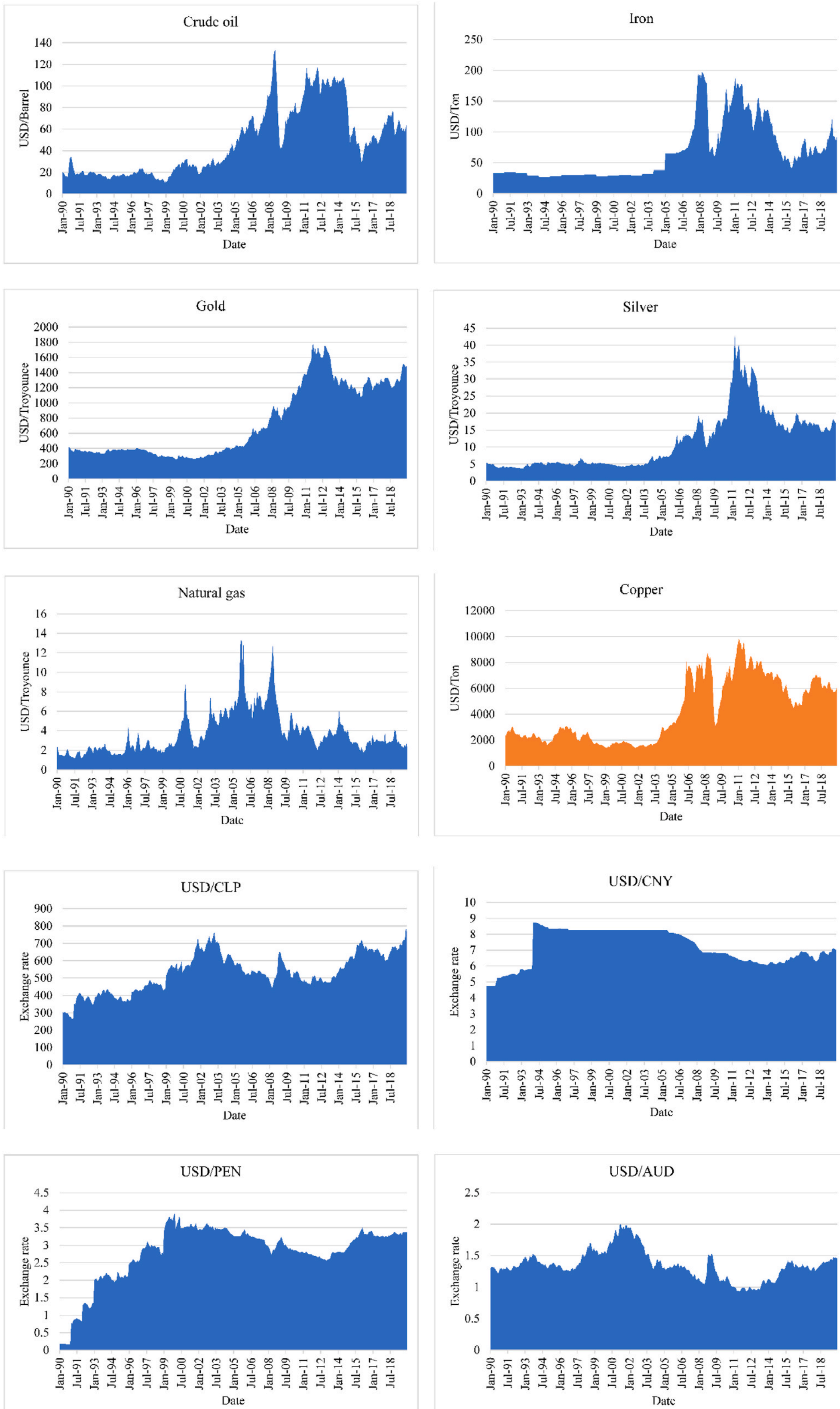


Fig. 8. Time series data of the copper price and other relevant indexes.

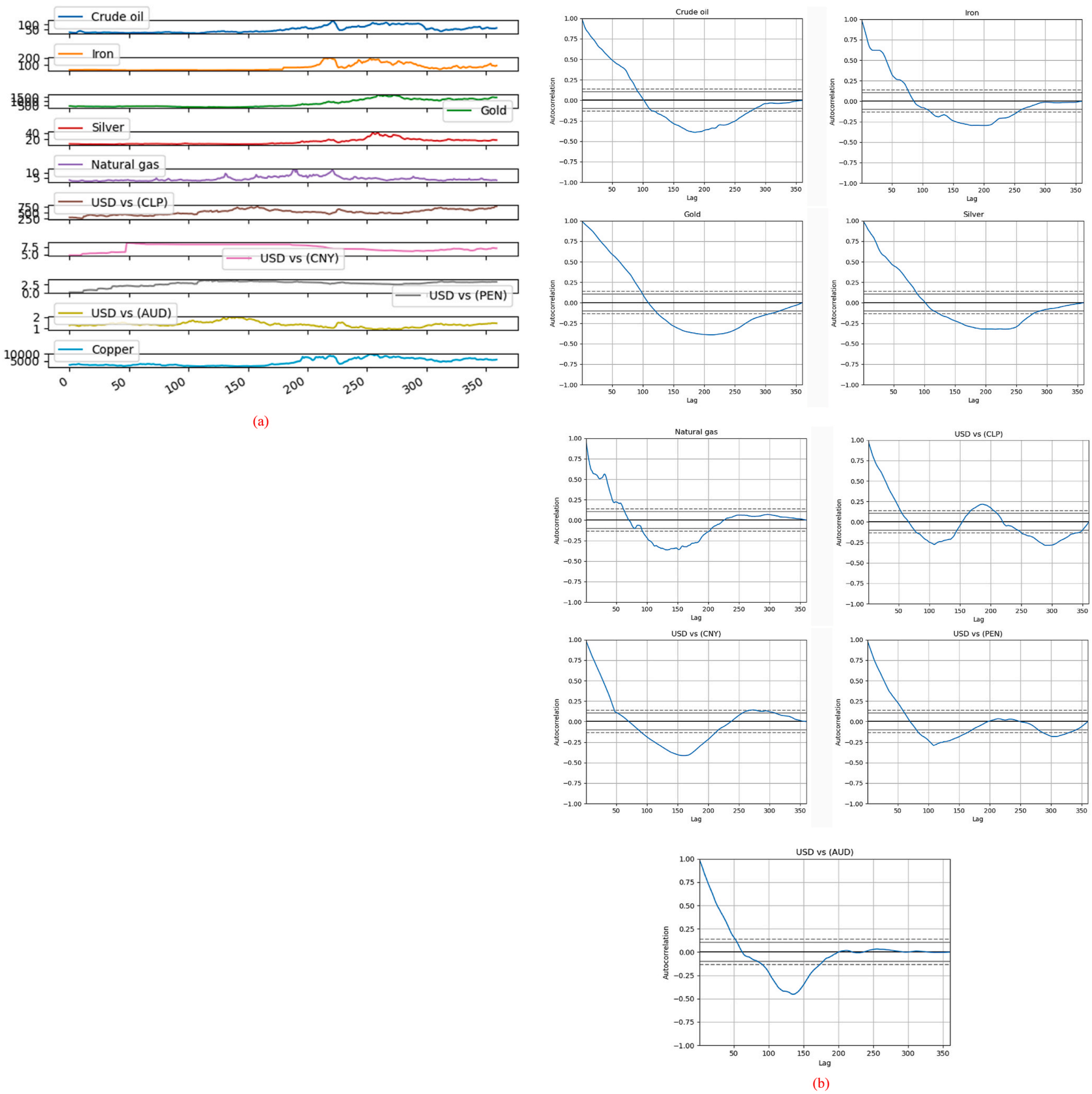


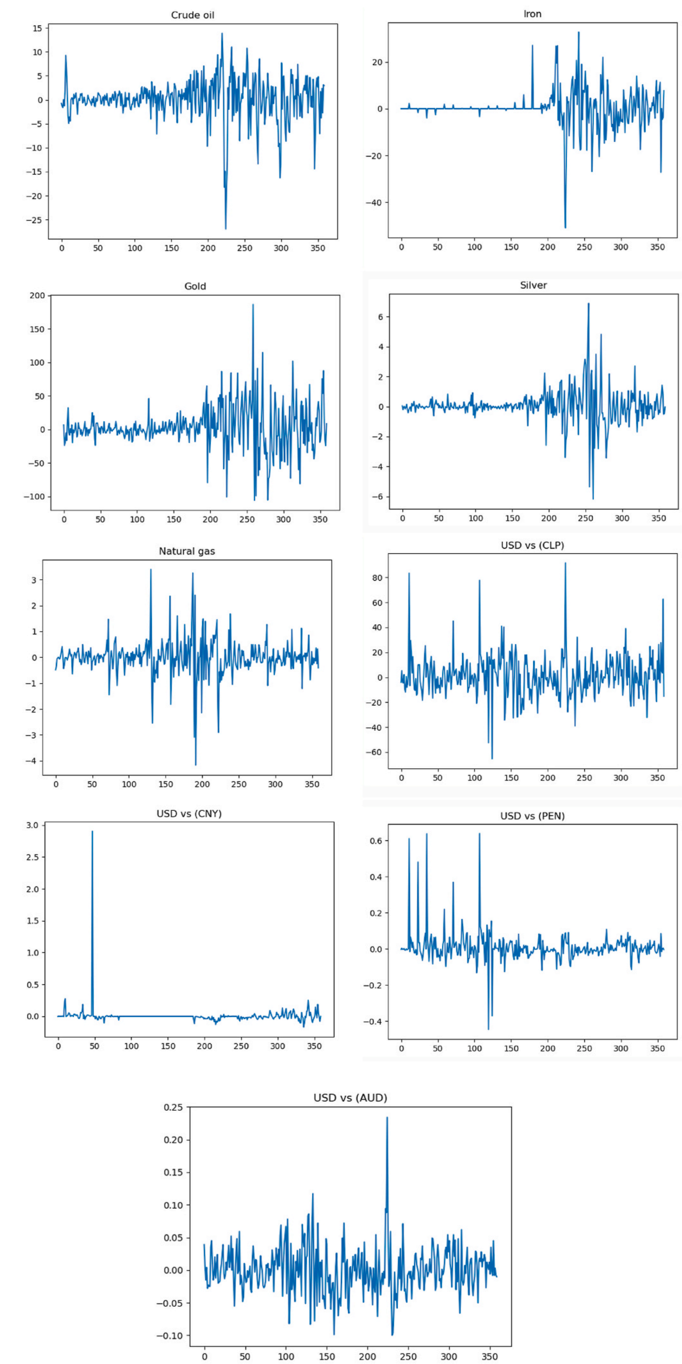
Fig. 9. Random walk analysis
(a) Random series; (b) Random walk and autocorrelation; (c) Differenced random walk; (d) Differenced random walk and autocorrelation.

Liu et al., 2017). However, the dataset used in those studies is daily copper price, and the dataset was in the form of random walk data. In the present study, the monthly dataset was collected to forecast monthly copper prices. It is necessary to check whether the monthly copper price is random walk data. This step aims at considering whether the random walk model should be used in this study or not. In other words, the use of random walk analysis can help understand the predictability of the monthly copper price dataset. Thus, we have conducted various analyses of random walks, such as random series, random walk, and autocorrelation, differenced random walk, and differenced random walk and autocorrelation, as shown in Fig. 9.

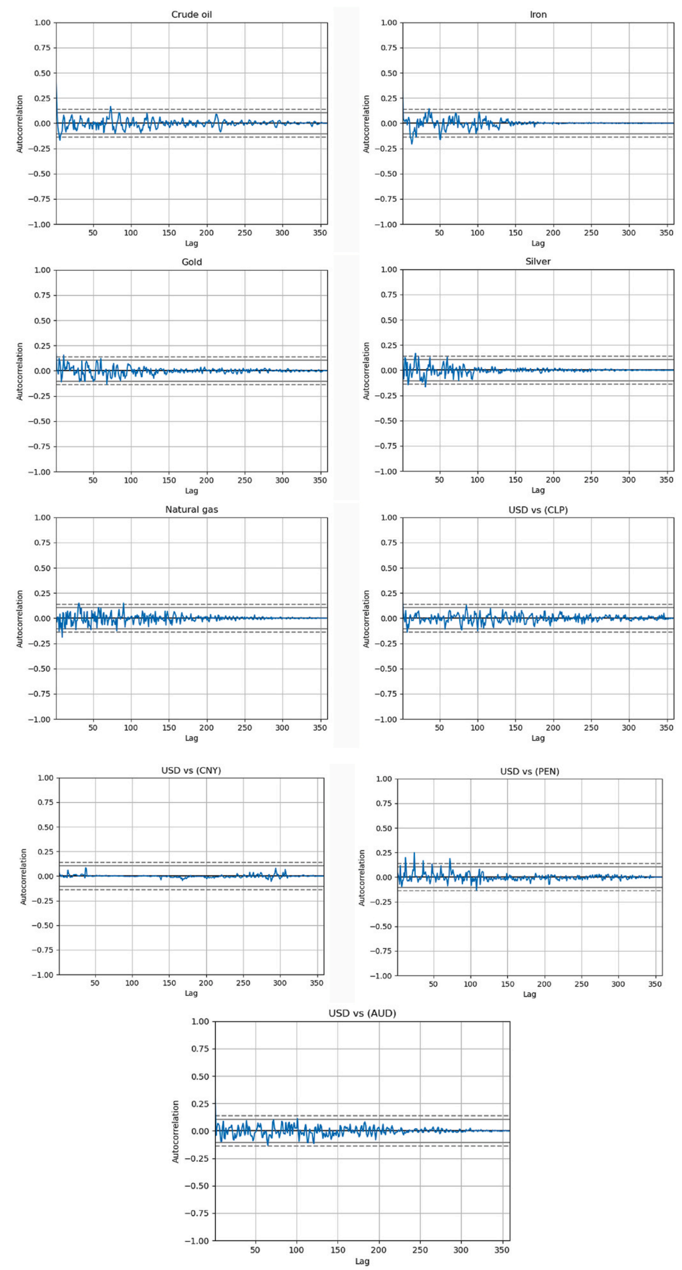
Looking at Fig. 9, we can see that the copper price dataset used in this study is not a random walk (Adhikari and Agrawal, 2014; Litterman, 1983). Therefore, a time series forecast model with random walk is not available for the monthly copper price dataset, as used in this study. In other words, it is much better to use non-random walk models through forecasting copper price in this study, such as MLP neural network, SVM, RF, KNN, and GBT, as mentioned above. The details of the development of these forecast models are presented in the next section.

4. Results and discussion

Before forecasting copper price, the time series data was divided into two parts: in-sample (80%) for training the models, and out-of-sample (20%) for testing the developed models (Fig. 10). The MinMax [-1,1] scale technique was applied to reduce the overfitting of the model. Mean absolute error (MAE), and root-mean-squared-error (RMSE) were used as the performance metrics to evaluate the accuracy and performance of



(c)



(d)

Fig. 9. (*continued*).

the forecast models. The equations for calculating MAE and RMSE are as follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{copper\_true} - y_{copper\_pred}\right| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{copper\_true} - y_{copper\_pred}\right)^2} \tag{2}$$

where n stands for the total number of observations in the copper price database; y_{copper_true} and y_{copper_pred} are the actual and forecasted copper prices.

As claimed by previous researchers (Díaz et al., 2020; Liu et al., 2017), cooper prices forecasted in a short-term are typically more accurate than cooper prices forecasted in a long-term. Indeed, they demonstrated that the daily forecasted copper prices are more accurate than weekly, monthly, 6 months, 1 year and 2 years forecasted copper prices. Therefore, in this study, the main objective is the monthly copper price forecast since the monthly copper price dataset was collected, and long-term forecasts are often inaccurate, as recommended by previous researchers. In addition, in order to develop the monthly copper price forecast models in this study, different steps of the datasets were considered with the following configurations of the predictors (D), specifically: (1) D = 1 (using the current price to forecast the next price);

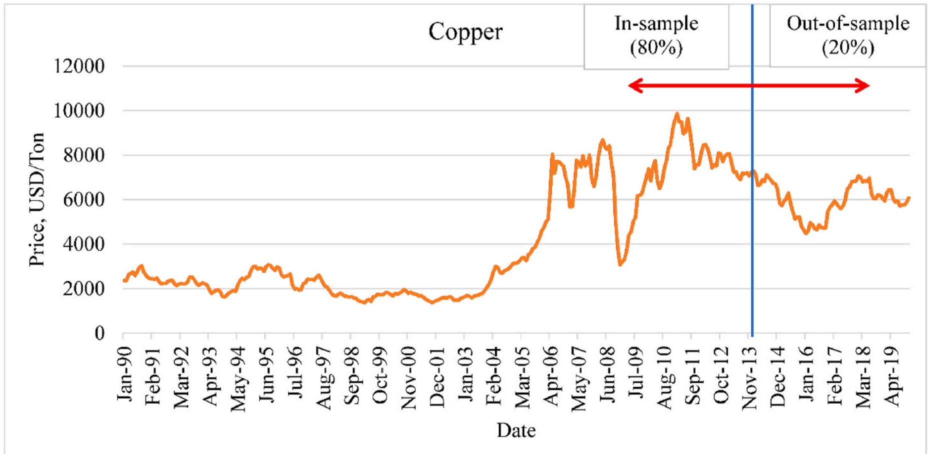


Fig. 10. Splitting monthly copper prices to in-samples and out-of-samples.

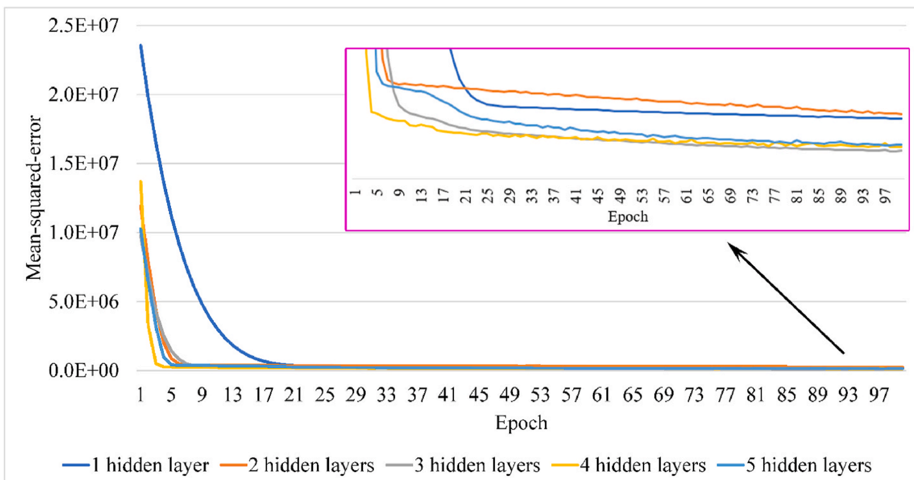


Fig. 11. MSE of the MLP neural network with different n_{hidden}.

(2) D = 2 (using from the current price until the 2nd lags of the predictors); (3) D = 3 (using from the current price until the 3rd lags of the predictors); (4) D = 4 (using from the current price until the 4th lags of the predictors); (5) D = 5 (using from the current price until the 5th lags of the predictors).

4.1. Development of MLP neural network model

Once the materials were well-prepared, the mentioned monthly copper price forecast models were developed and implemented based on the in-samples (training dataset). For MLP neural network modeling, as

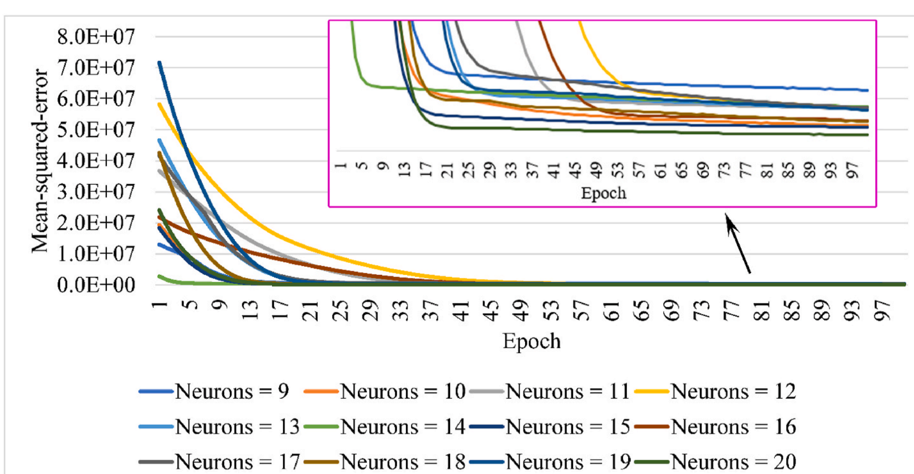


Fig. 12. MSE of the MLP neural network with different n_{neuron}.

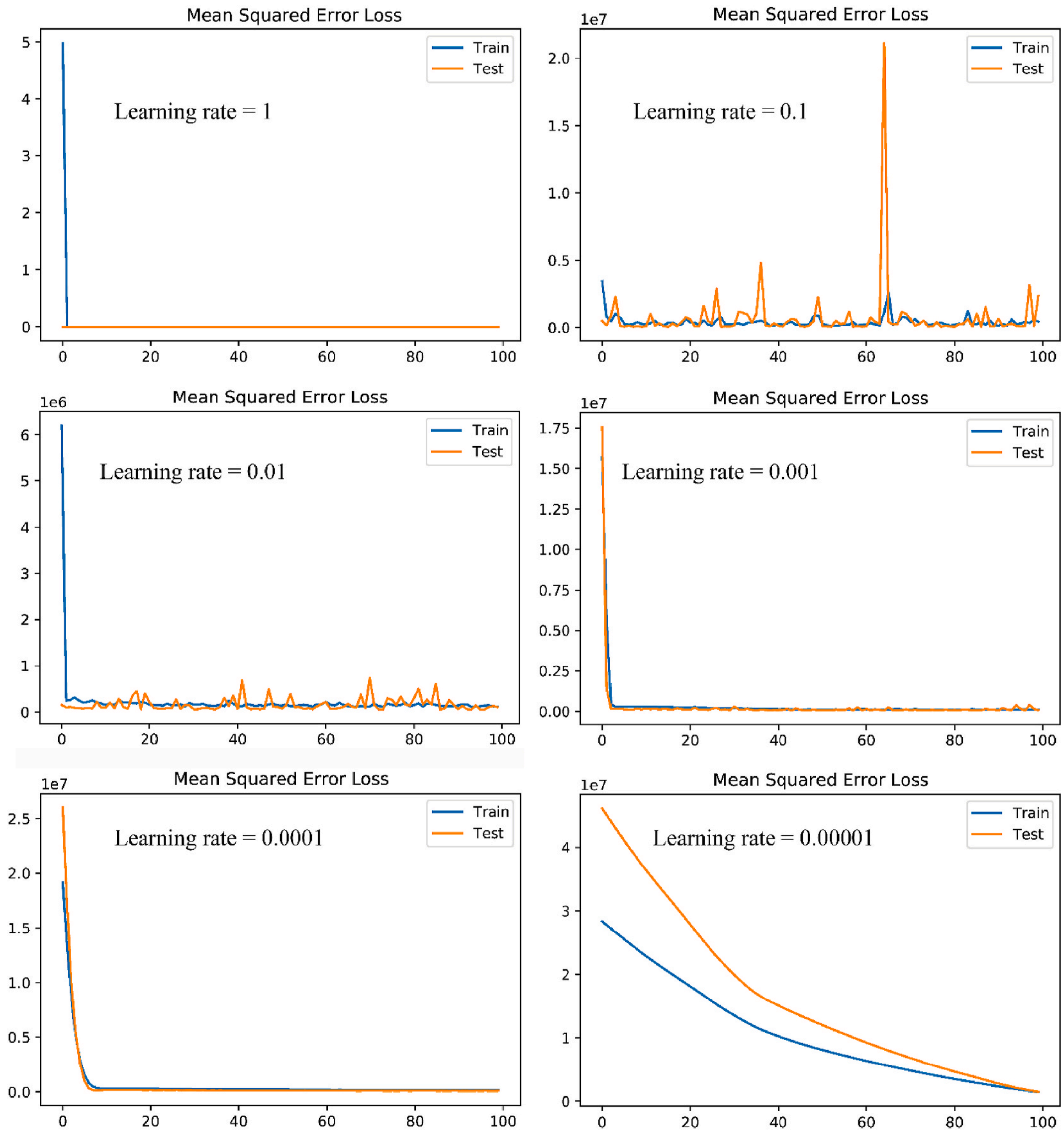


Fig. 13. MSE of the MLP neural network with different learning rate.

stated above, this study focuses on the optimization of an MLP neural network using deep learning techniques. The following parameters of the MLP neural network are important that decide the accuracy of the model: topology network, loss function, and learning rate. Herein, MSE was selected as the loss function because it has no outlier predictions (Shcherbakov et al., 2013).

To define the optimal topology network of the MLP model, a trial and error procedure for the number of hidden layers (n_{hidden}) and neurons (n_{neuron}) was performed with $n_{\text{hidden}} = [1, 5]$, $n_{\text{neuron}} = [9, 20]$. Finally, the optimal topology network of the MLP model was selected with 3 hidden layers and 20, 15, and 10, for the number of neurons in the first, the second, and the third hidden layers, respectively (Figs. 11 and 12).

Once the MLP neural network structure was well-built, the deep learning technique was continuously applied to tune the learning rate of the MLP neural network, as shown in Fig. 13. It was claimed as a potential parameter that can be used to control the accuracy of an MLP model (Fang et al., 2005). Finally, the optimal learning rate for the MLP neural network is 0.0001, as observed in Fig. 13. Herein, the training and testing errors are approximate. Eventually, the optimal MLP neural network 9-20-15-10-1 was defined as the best MLP neural network for forecasting copper price.

After the optimal configuration of the MLP neural network was selected, the MLP neural network model with different multi-steps was developed, as shown in Fig. 14. During the development of the MLP neural network models, the computational process was implemented with 1000 epochs to ensure the convergence of the forecast models. Throughout the performance curves in Fig. 14, it can be seen that the MLP neural network models were well-developed without overfitting or/and underfitting.

4.2. Development of SVM model

For the development of the SVM for forecasting monthly copper price, the radial basis function (RBF) was applied along with the following parameters: C = 1.0; kernel cache size = 200; degree = 3; epsilon = 0.1; gamma = "scale"; max inter = −1; shrinking = "True",

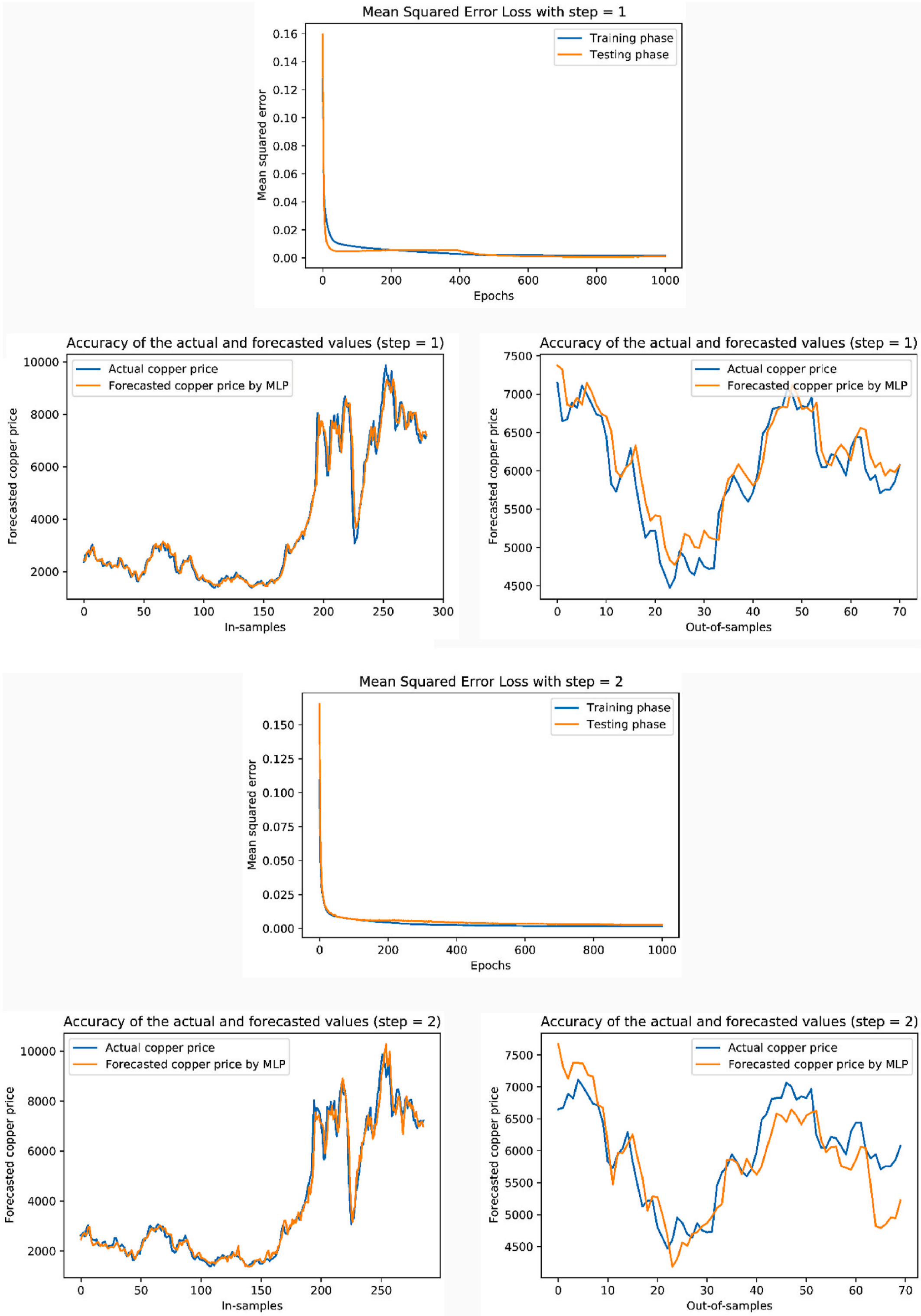


Fig. 14. MLP neural network models with different steps and accuracies.

and tolerance = 0.001. It is worth noting that the in-samples and out-of-samples used for the SVM development are the same as developing the MLP neural networks. The accuracy of the SVM model with different steps for forecasting monthly copper price is shown in Fig. 15.

4.3. Development of RF model

For RF modeling, the bootstrap technique was applied as one of the outstanding advantages of the RF model, and it used the MSE as the criterion. As mentioned above, the RF model was developed based on the decision tree algorithm, and it composed of many parameters of a tree that were set up as follow in this study: complexity parameter = 0.0; MSE was used to measure the quality of the trees split; the threshold to decrease of impurity was set equal to 0; minimum number of samples was set equal to 1 at each leaf node; an internal node was split with the minimum number of samples of 2, and the number of estimators was set

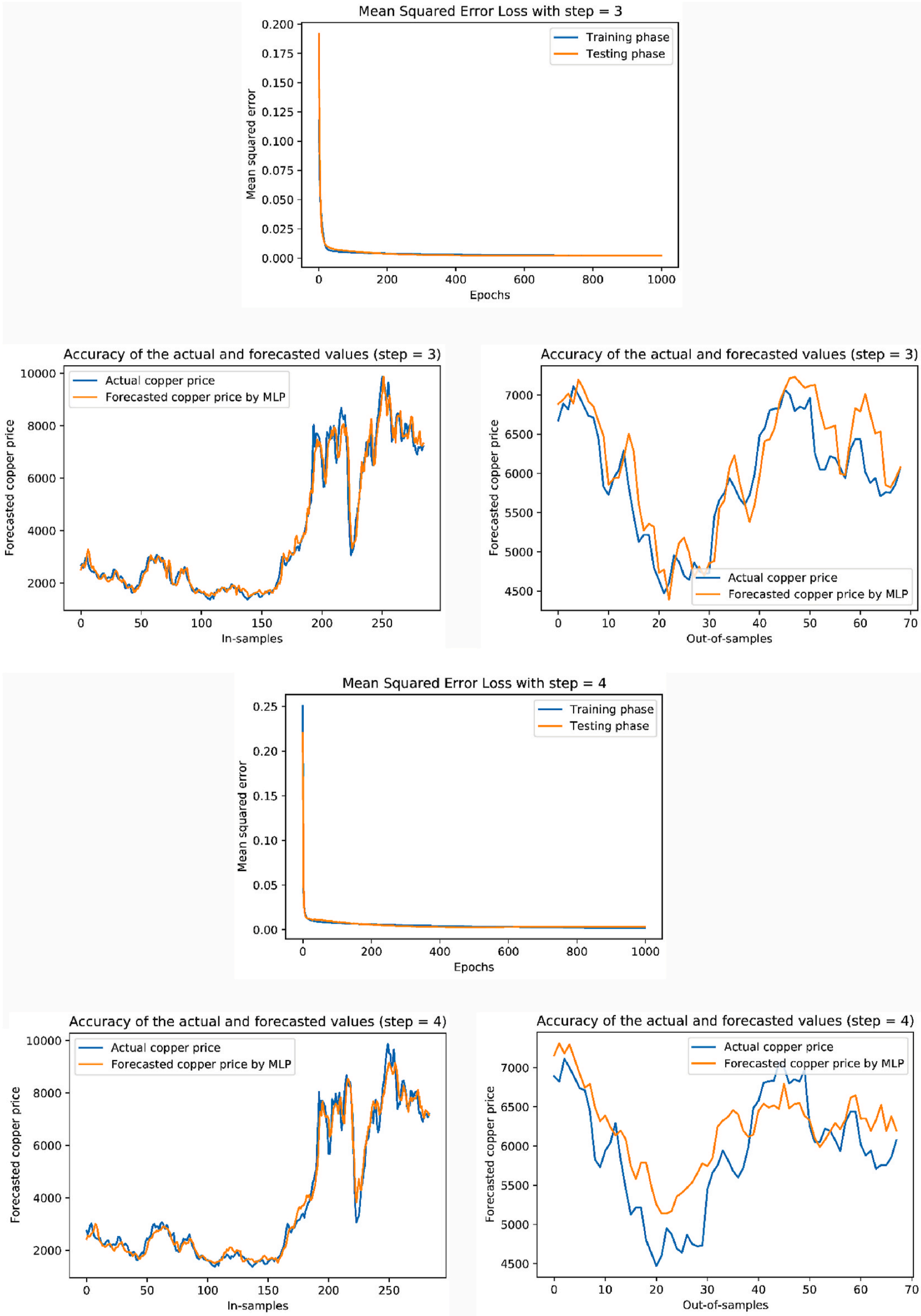


Fig. 14. (*continued*).

equal to 100. It is worth noting that the in-samples and out-of-samples used for the RF development are the same as developing the MLP neural networks and SVMs. The accuracy of the RF model with different steps for forecasting monthly copper price is shown in Fig. 16.

4.4. Development of KNN model

To develop the KNN model, similar techniques were applied as those used for the SVM and EF models. Also, it is worth noting that the in-samples and out-of-samples used for the KNN development are the

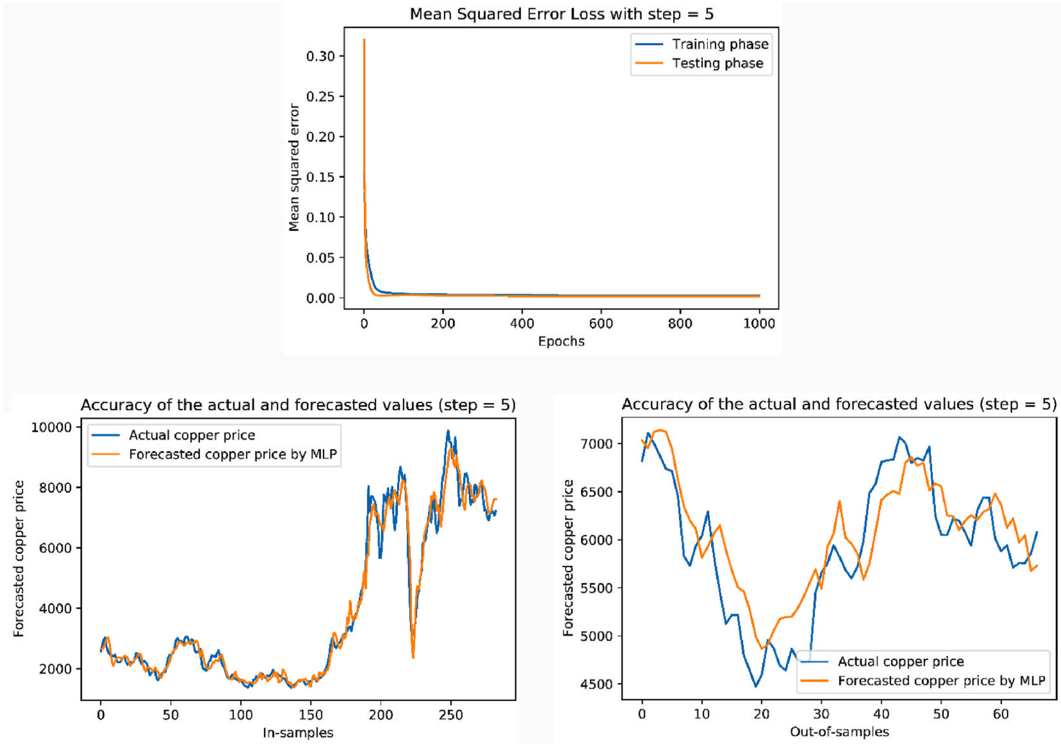


Fig. 14. (*continued*).

same as the development of the previous forecast models. Herein, the leaf size of KNN was set equal to 30, the number of neighbors equal to 5, 'minkowski' was used as the distance metric to use for the tree with the power parameter of 2. In addition, the weight function used in prediction is 'uniform'. The accuracy of the RF model with different steps for forecasting monthly copper price is shown in Fig. 17.

4.5. Development of GBT model

For the GBT development, an additive model was developed in a forward stage-wise fashion. GBT was developed based on a regression tree with the least-squares regression loss function. During development of the GBT model, the parameters were set up as follow: alpha = 0.9; complexity parameter for cost-complexity pruning = 0.0; the MSE that was improved by Friedman was used as the criterion to measure the quality of a split in the regression tree; learning rate of the model was set equal to 0.1; maximum depth of the estimators was set equal to 3; the threshold to decrease of impurity was set equal to 0; minimum number of samples was set equal to 1 at each leaf node; an internal node was split with the minimum number of samples of 2; the number of estimators (boosting stages) was set equal to 100; subsample = 1.0; tolerance = 0.0001, and validation fraction = 0.1. Besides, it is worth noting that the in-samples and out-of-samples used for the GBT development are the same as the development of the previous forecast models. The accuracy of the GBT model with different steps for forecasting monthly copper price is shown in Fig. 18.

4.6. Comparison and evaluation

Once the forecast models were developed, two measures of forecast errors were computed to evaluate the accuracy of the models on both in-samples and out-of-samples, i.e., MAE and RMSE, as described in equations (1) and (2). The accuracy of the forecast models was evaluated on both periods (i.e., in-samples and out-of-samples) to provide a comprehensive assessment of the models' performance. Also, the accuracies of the individual forecast models were considered with a different set of predictors (e.g., D = 1, 2, 3, 4, 5), as computed in Table 1.

Considering the accuracy of the forecast models on the in-samples with D = 1, we can see that the RF, KNN, and GBT models are better than the MLP neural network model. However, it can observe that the MLP neural network is the best model with an RMSE of 287.539 for the out-of-samples. Whereas, the other models provided higher errors on the out-of-samples (i.e., SVM = 474.486, RF = 393.599, KNN = 552.208, and GBT = 518.959). This finding shows the unstable (even to be underfitting) of the RF, KNN, and GBT models for forecasting monthly copper price in this study with D = 1. Observing other sets of predictors (D = 2, 3, 4, 5), similar results were reported for the forecast models with unstable RF, KNN, and GBT models. In contrast, the MLP neural network model provided a high level of stability for forecasting monthly copper prices.

Comparison between various sets of predictors shows that the accuracy of the forecast models is different. It does not appear to be a rule for the change (increase or decrease) of the number of predictors in forecasting monthly copper prices. For example, with the MLP neural network model, RMSE = 287.539 for D = 1, RMSE = 441.763 for D = 2, but RMSE = 377.427 for D = 3, and RMSE = 478.208, but RMSE increased with D = 5 (i.e., 388.004). Therefore, the number of set of predictors does not seem to be a reflection of the quality trend of the forecasting models. Overall review of scenarios with forecast models shows that the MLP neural network model with D = 1 provided the highest accuracy for forecasting monthly copper price with an MAE of 228.617 and RMSE of 287.539 for the out-of-samples. Therefore, it should be used as the best forecast model for forecasting monthly copper prices under the set of predictors equal to 1 (D = 1).

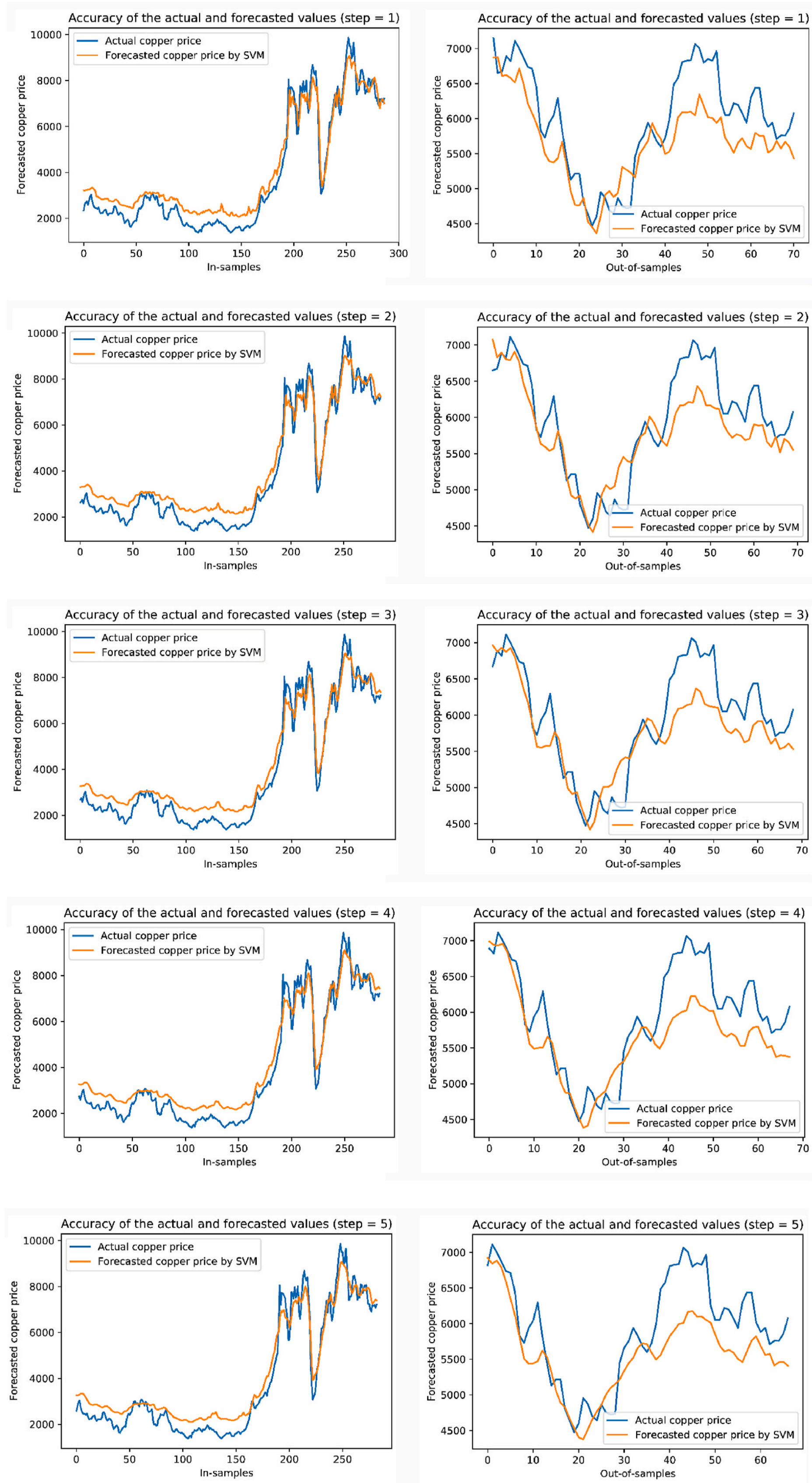


Fig. 15. Accuracy of the SVM model for forecasting monthly copper price with different steps.

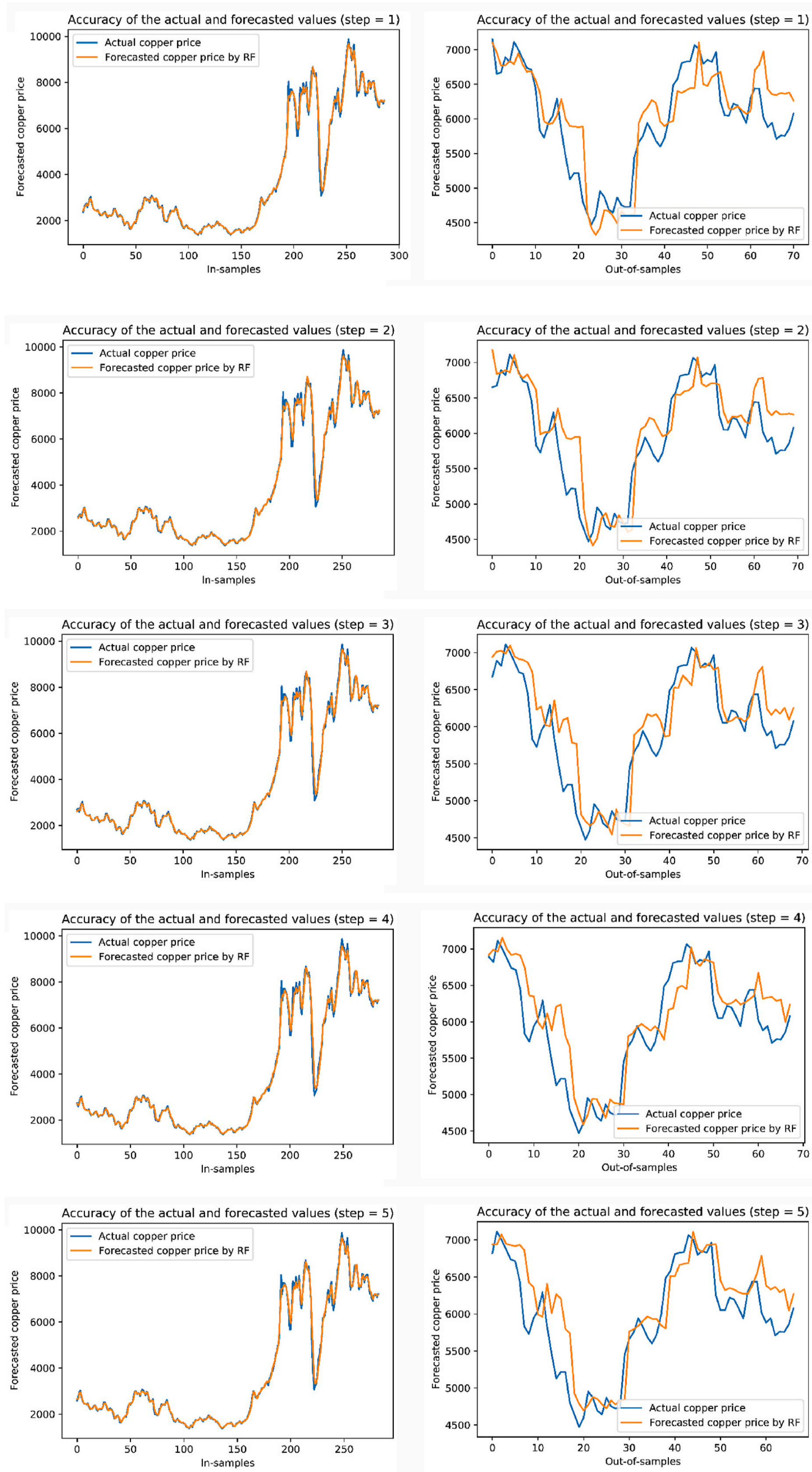


Fig. 16. Accuracy of the RF model for forecasting monthly copper price with different steps.

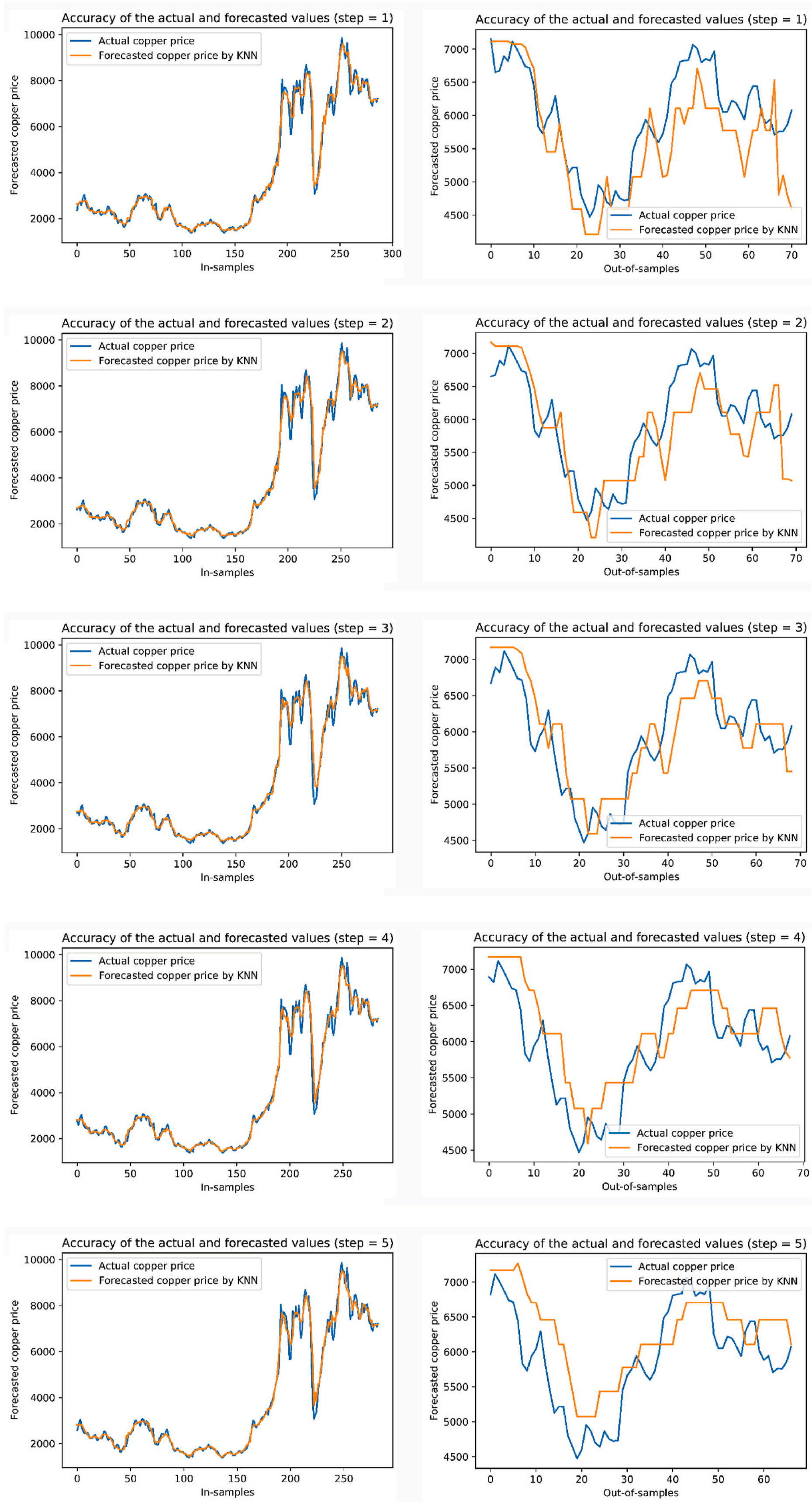


Fig. 17. Accuracy of the KNN model for forecasting monthly copper price with different steps.

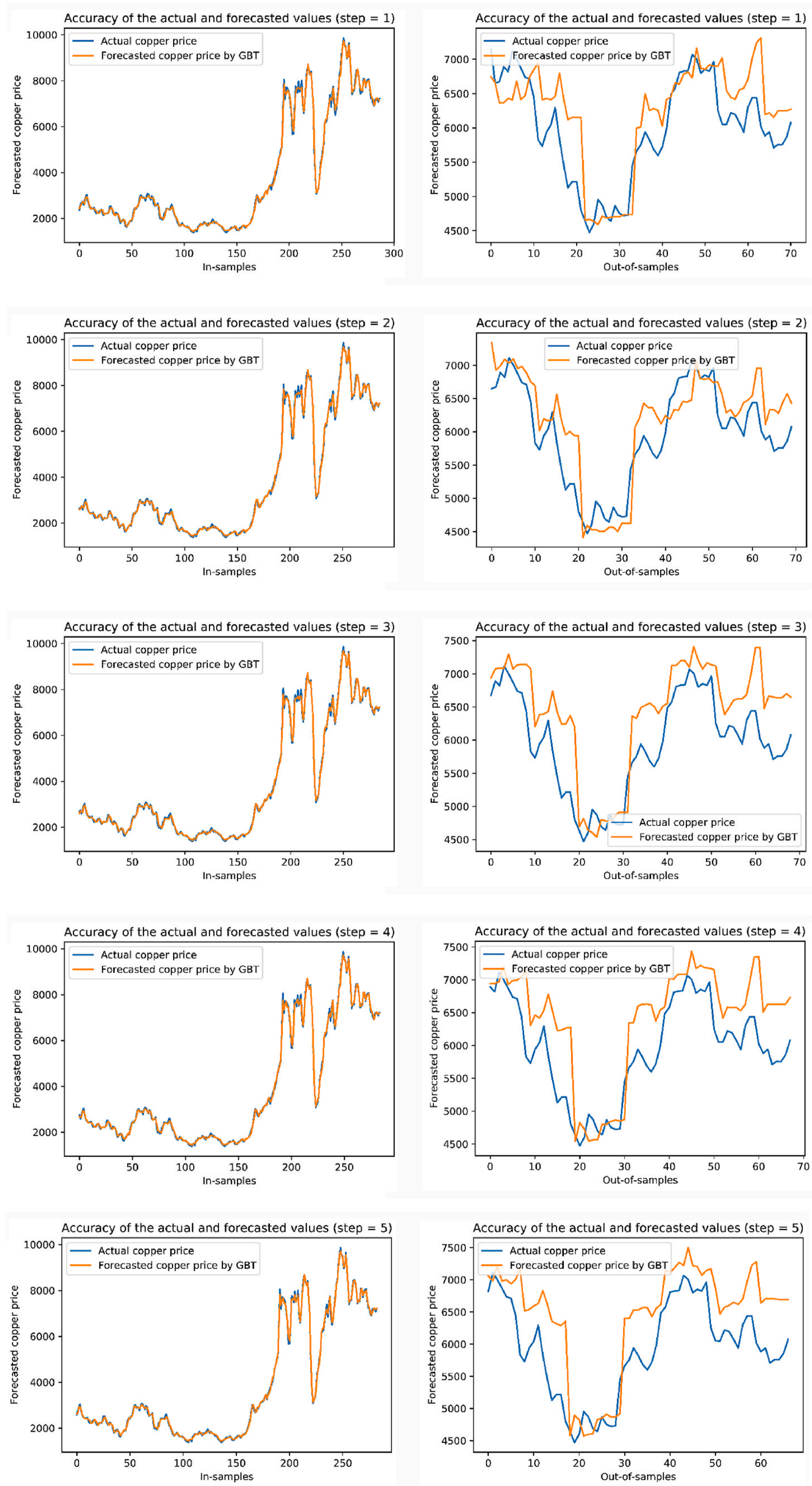


Fig. 18. Accuracy of the KNN model for forecasting monthly copper price with different steps.

Table 1
Measures of forecast errors of the developed models on the out-of-samples.

D	MAE					RMSE				
	MLP	SVM	RF	KNN	GBRT	MLP	SVM	RF	KNN	GBRT
In-samples										
1	195.639	503.355	78.758	158.252	71.110	335.053	554.640	136.139	271.325	103.124
2	219.650	514.484	79.665	156.613	62.024	339.969	570.130	151.484	283.742	86.375
3	240.153	518.913	79.593	158.126	59.708	370.788	577.519	139.530	274.392	79.500
4	253.154	513.016	83.609	158.847	56.620	364.838	571.487	158.911	270.719	76.195
5	266.016	496.896	76.021	160.764	53.757	406.538	556.027	135.103	283.698	72.137
Out-of-samples										
1	228.617	399.512	308.691	453.147	402.024	287.539	474.486	393.599	552.208	518.959
2	355.382	320.430	288.260	408.466	370.387	441.763	396.499	375.994	479.062	453.078
3	289.759	330.558	283.576	358.129	516.541	377.427	407.215	377.974	424.009	618.314
4	404.869	377.346	305.795	414.662	517.173	478.208	466.797	396.932	481.182	625.212
5	333.528	396.116	303.645	485.760	561.217	388.004	490.236	407.362	567.105	663.313

5. Conclusion

As copper is an essential metal that is widely used in various aspects in countries all over the world, the change in copper price may have a great impact on mining enterprises, investors, policymakers, copper-related industries, and copper-dependent countries. Thus, precisely forecasting copper price is important to stakeholders in making the right decisions. In this study, MLP neural network, SVM, RF, KNN, and GBT models were employed to forecast monthly copper prices based on the prices of oil, gold, silver, and iron ore, and four exchange rates, including USD/CLP, USD/CNY, USD/PEN, and USD/AUD. The analysis results confirmed the correlation between the four exchange rates and monthly copper prices and demonstrated that the forecasted monthly copper prices were close to the actual prices. Amongst, the MLP neural network was recommended as the best model for forecasting monthly copper price with the lowest error and the highest stable of the model.

CRediT authorship contribution statement

Hong Zhang: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Hoang Nguyen:** Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Diep-Anh Vu:** Conceptualization, Formal analysis, Data curation, Software, Visualization, Writing – original draft, Writing – review & editing. **Xuan-Nam Bui:** Conceptualization, Formal analysis, Data curation, Software, Visualization, Writing – original draft, Writing – review & editing. **Biswajeet Pradhan:** Conceptualization, Formal analysis, Data curation, Software, Visualization, Writing – original draft, Writing – review & editing.

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