



Forecasting copper price by application of robust artificial intelligence techniques

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ABSTRACT

Metal price is one of the most important and effective parameters in assessing different projects such as industry and mining. In this regard, price variations can play a vital role in the correct decision-making of managers to develop or limit mining activities. Considering the increasing use of artificial intelligence (AI)-based networks in different fields such as price estimation, four methods were used in the present work for the first time to predict the price of important and extensively used copper-grade A cathode. These methods include Gene expression programming (GEP), Artificial neural network (ANN), Adaptive neuro-fuzzy inference system (ANFIS), and ANFIS-ACO (ant colony optimization algorithm). In this process, coal, aluminum, crude oil, gold, iron ore, natural gas, nickel, and lead were selected as the copper price parameters from 1990 to 2020. In this study, the ANN model with one hidden layer comprising 13 neurons, RMSE of 356.51, MAE of 239.105 (\$/ton), MAPE of 5.70% (\$/ton), and coefficient of determination (R^2) of 98.1% for network test data was selected as the best model in predicting copper prices. In terms of their performance, ANFIS, ANFIS - ACO and GEP models were ranked next in the order of their appearance. Overall, an acceptable performance was found through all four AI methods in this study for predicting copper prices.

1. Introduction

Prediction is defined as the art and science of forecasting future events (Jay and Barry, 2001). Typically, the prediction process includes obtaining historical information and generalizing it to the future using various mathematical models. For effective planning in all business areas, it is essential to accurately predict the future such that prediction is one of the most important instruments for managers to manage organizations, particularly within competitive environments. Product price is the most important and effective parameter in assessing the projects, such as mining projects. Awareness of changes in ore prices can play a key role in accurate decision making, developing, or limiting the mining activities through mining project managers and shareholders (Dehghani and Bogdanovic, 2018). However, predictions are never consistent with the truth completely, and no exclusive method exists as the best way of predicting.

The forecasting experts are mainly responsible for finding the best possible model for the studied subject and making predictions with the least error. Metals are important materials for trading; therefore,

predicting their price has important commercial and economic consequences (Wang et al., 2019; Hatayama and Tahara, 2018; Li and Li, 2015). Despite many studies on metals and their prices, there is no exact pricing mechanism in the metals market (Watkins and McAleer, 2004). It has been argued that the price of metals is the major factor of diversities in the income resultant from mining operations, and price prediction is important to evaluate the possibility of economic exploitation of reserves (Dooley and Lenihan, 2005). Regarding the extensive applications of copper in several industries such as electrical wiring, construction, and equipment manufacturing, the price of this metal significantly affects the performance of companies and related economies (Lasheras et al., 2015; Watkins and McAleer, 2004; Gargano and Timmermann, 2014). Furthermore, metals are an important source of export earnings for many countries, especially the developing ones, such as Chile and Zambia (Chen et al., 2016; Morales and Andreosso-O'Callaghan, 2011).

Copper is one of the oldest metals discovered by humans, and it is normally found in mineral form. Minerals such as azurite, malachite, and Bornite, sulfides such as chalcopyrite (CuFeS₂), choline (CuS),

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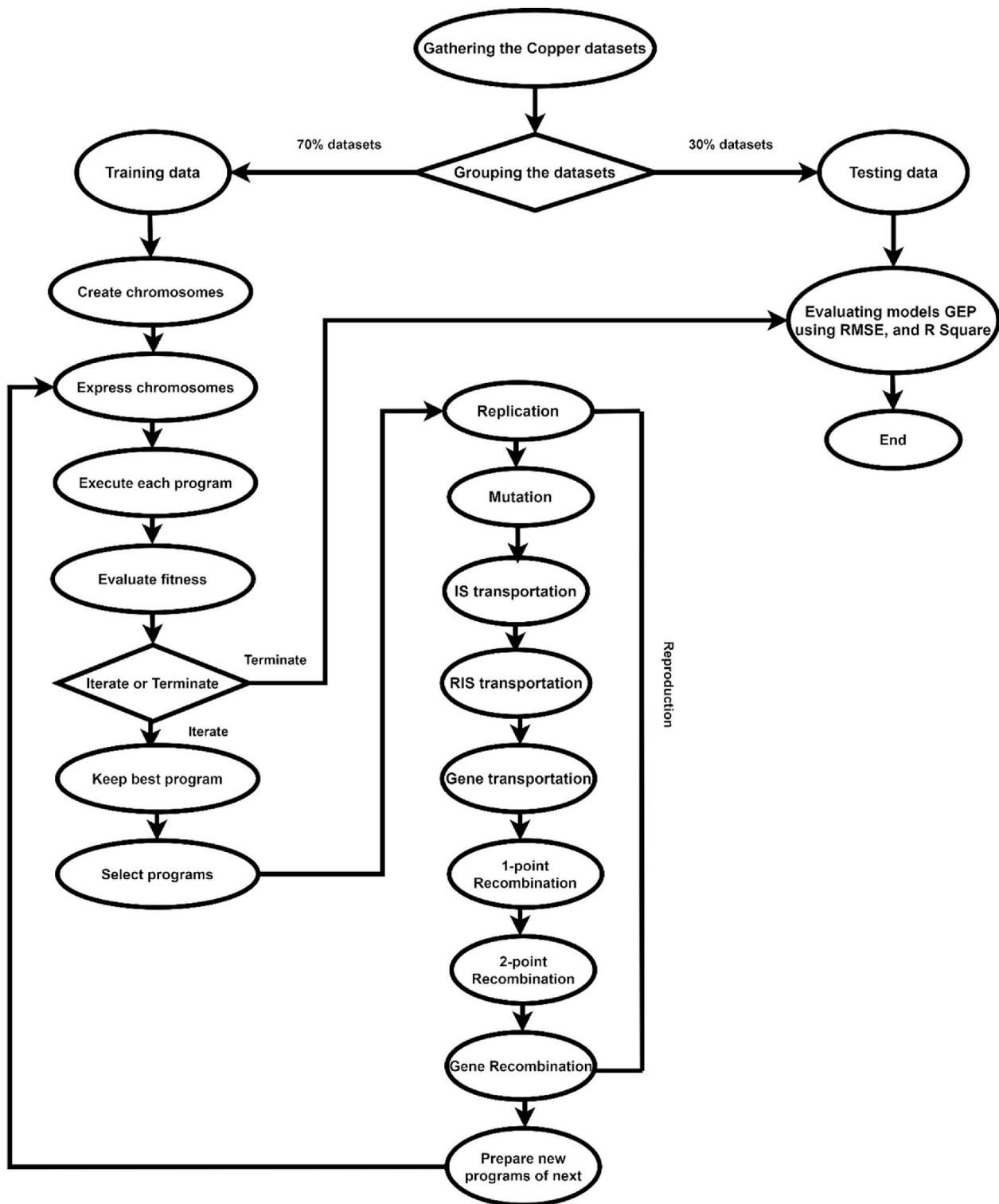


Fig. 1. The flowchart of the GEP Algorithm (Ferreira, 2001).

chalcopyrite (Cu_2S), and oxides like Cuprite (Cu_2O) are among the main copper sources. Several researchers have investigated and predicted the prices of metals (Malanichev and Vorob'yev, 2011; Kapl and Müller, 2010; Alameer et al., 2019) and energy sources such as oil (Dehghani and Zangeneh, 2018; Mostafa and El-Masry, 2016) and coal (Alameer et al., 2020; Matyjaszek et al., 2019). Among these resources, copper has attracted the attention of many researchers owing to its numerous applications. Copper prices play a major role in today's economy (Gargano

and Timmermann, 2014; Buncic and Moretto, 2015).

In recent years, the considerable fluctuations in the prices of minerals such as copper have resulted in lower performance of classical forecasting approaches (e.g., ARMA and GARCH) to accurately estimate price changes (Hu et al., 2020; García and Kristjanpoller, 2019; Kim and Won, 2018; Kristjanpoller and Hernández, 2017; Kristjanpoller and Minutolo, 2015). Therefore, several researchers have predicted the copper price using statistical and intelligent methods. Flores et al.

(2020) used artificial intelligence techniques, particularly random forests, to develop predictive models for copper recycling through leaching using a company's data in northern Chile for more than 20 years. Carrasco et al. (2019) forecast copper market fluctuations over a certain period, taking several participants such as producers, consumers, governments, and investors. Satari et al. (2020) employed technical analysis tools such as the Fibonacci series, Elliott waves, and Ichimoku cloud to accurately assess and predict copper price changes while considering all copper prices from 2008 to 2016. Taking into account the relationships introduced by Elliott Waves and clouds made by Ichimoku, they predicted the copper price as approximately \$ 16,000 per ton by 2022. Alipour et al. (2019) investigated the applications of various forecasting methods in econometrics and financial management fields (e.g., ARIMA, TGARCH, and stochastic differential equations) for the series of monthly copper prices from early 1987 to late 2014. They showed that the method of stochastic differential equations yields better results compared to the other methods. Dehghani and Bogdanovic (2018) applied the Bat algorithm to predict copper price fluctuations. Brownian motion with mean return (BMMR) was accordingly selected as the most appropriate time series function. Then, the parameters for estimating the equation were modified through the Bat algorithm. Their findings indicated that the proposed equation could estimate well the copper price compared to the classical methods. Dehghani (2018) utilized the gene expression programming (GEP) method for predicting copper price fluctuations and compared the results with other classical forecasting methods. The results revealed the superiority of the GEP method in terms of prediction accuracy compared to the time series and multivariate regression methods. Accordingly, in the present work, it was attempted to predict the world copper price from 1990 to 2020 using the mentioned intelligent methods, and the most appropriate model is proposed.

2. Methodology

2.1. Applied AI techniques

The current study deals with predicting the copper price through powerful artificial intelligence methods, including gene expression programming algorithm (GEP), artificial neural network (ANN), adaptive neuro-fuzzy system (ANFIS), and adaptive neuro-fuzzy system - ant colony optimization algorithm (ANFIS-ACO).

2.1.1. Gene expression programming

The gene expression programming (GEP) algorithm is used to develop computer programs and mathematical modeling based on evolutionary calculations inspired by natural evolution. This algorithm, introduced by Ferreira (2001), integrates the leading aspect of the two previous inherited algorithms to cover their weaknesses. In this method, the genotyping of chromosomes has a linear structure similar to the genetic algorithm (GA), and their phenotype has a tree structure with variable length and size similar to the genetic programming algorithm (GP). In the GEP algorithm, the Karva language and multiple genes are used for multiple chromosome structures and creating subtrees to provide better compatibility and responsiveness to the algorithm (Ferreira, 2001, 2006; Faradonbeh et al., 2016; Baykasoglu et al., 2008; Dindarloo, 2015; Armaghani et al., 2018). The GP-based techniques have been developed to solve numerous complicated engineering problems (Shakeri et al., 2020; Ramesh et al., 2020; Mahdiyar et al., 2020).

Fig. 1 shows the flowchart or trend of the GEP algorithm, based on which the initial stage of the algorithm begins with the random production of the initial population (chromosome). Then, the generated population is expressed, and each individual is assessed and selected based on the evaluation function and starts to reproduce the population with new traits by applying corrections to the selected individuals. Like their old generation, these new populations replicate the processes until the right solution is obtained (Ferreira, 2001, 2006; Faradonbeh et al.,

2016; Baykasoglu et al., 2008; Dindarloo, 2015; Armaghani et al., 2018).

The simplicity of the gene expression algorithm allows for coding at any part of the program and makes the evolution more effective. The Expression tree and the chromosome are the main parameters of this algorithm. Expression trees present the information encoded on chromosomes by converting the information from the chromosome to the expression tree. This code reveals the one-to-one relationship between chromosomes, functions, and terminals. The components of a linear chromosome include Terminals (A, B, C, ...) and Function (+, -, and ...). A chromosome in GEP can have at least one gene and a structure consisting of a head (h) and a tail (t) (Eq. (1)). The GEP designer determines the head length, but the tail length is calculated using the equation below (Ferreira, 2001; Khandelwal et al., 2016; Güllü, 2012):

$$t = h(n-1) + 1 \quad (1)$$

where t is the length of the tail, h is the head lengths, and n is the maximum argument of the functions. In the GEP algorithm, the lengths of chromosomes and genes are constant, and only the length of the frames (ORF) changes. This behavior makes the GEP endpoint incompatible with the gene endpoint due to non-coding regions at the end of the gene. These non-coding regions in GEP allow operators to operate without restriction and generate genetic diversity, which is one way to achieve evolution (Ferreira 2001, 2006; Shakeri et al., 2020; Alkroosh and Sarker, 2019; Wang, 2019; Mollahasani et al., 2011).

2.1.2. Artificial neural networks (ANNs)

Nowadays, ANNs are extensively used in various fields. Such networks are inspired by and modeled based on the human nervous system (He and Xu, 2007; Nguyen and Bui, 2019). So far, several studies have been done using ANNs to predict engineering problems (Lu et al., 2020; Rad et al., 2020; Shakeri et al., 2020; Shojaeian and Asadizadeh, 2020). The structure of an ANN model includes an input layer, hidden layer(s), and an output layer (Çelik, 2020; Yegnanarayana, 2009). The use of only one hidden layer reduces the complexity of the model, although there is no theoretical limitation in this regard (Sumathi and Panneerselvam, 2010).

Multi-layer perceptron or feedforward neural network with backpropagation training algorithm is one of the most useful types of these networks (Sumathi and Panneerselvam, 2010). Each layer comprises several neurons, among which the number of input and output layer neurons represents the number of input and output parameters of the model, respectively, and the number of neurons in the hidden layer/s is normally determined by trial and error. The raw data are placed in the input layer neurons, and a weight value related to the importance of that input is considered for each input, which is multiplied by the numerical value of the input. An input with a unit value and weight b is also inserted into the neuron as a bias value and the standard inputs. These values are then added together in the neuron to obtain the output value using the transfer function.

Moreover, this process takes place in all neurons to calculate the output value. Comparing this value with the actual output, we calculated the error value and adjusted the return path as a backpropagation algorithm. The process continues until the desired result is achieved with the least amount of error. These networks are further detailed in the literature (Grosan and Abraham, 2011; Guoqiang Zhang et al., 1998; Fan et al., 2016; Monjezi et al., 2011; Díaz-Rodríguez et al., 2015; Mendez et al., 2019; Zeinolabedini et al., 2013; Nguyen and Bui, 2019).

The criterion of mean squared error (MSE) or root mean square error is employed to investigate the efficiency of networks with various structures and compare and judge them in choosing the best network. RMSE denotes the root mean square of the error between the analysis results and the models' output measured in real terms (Haykin, 1999).

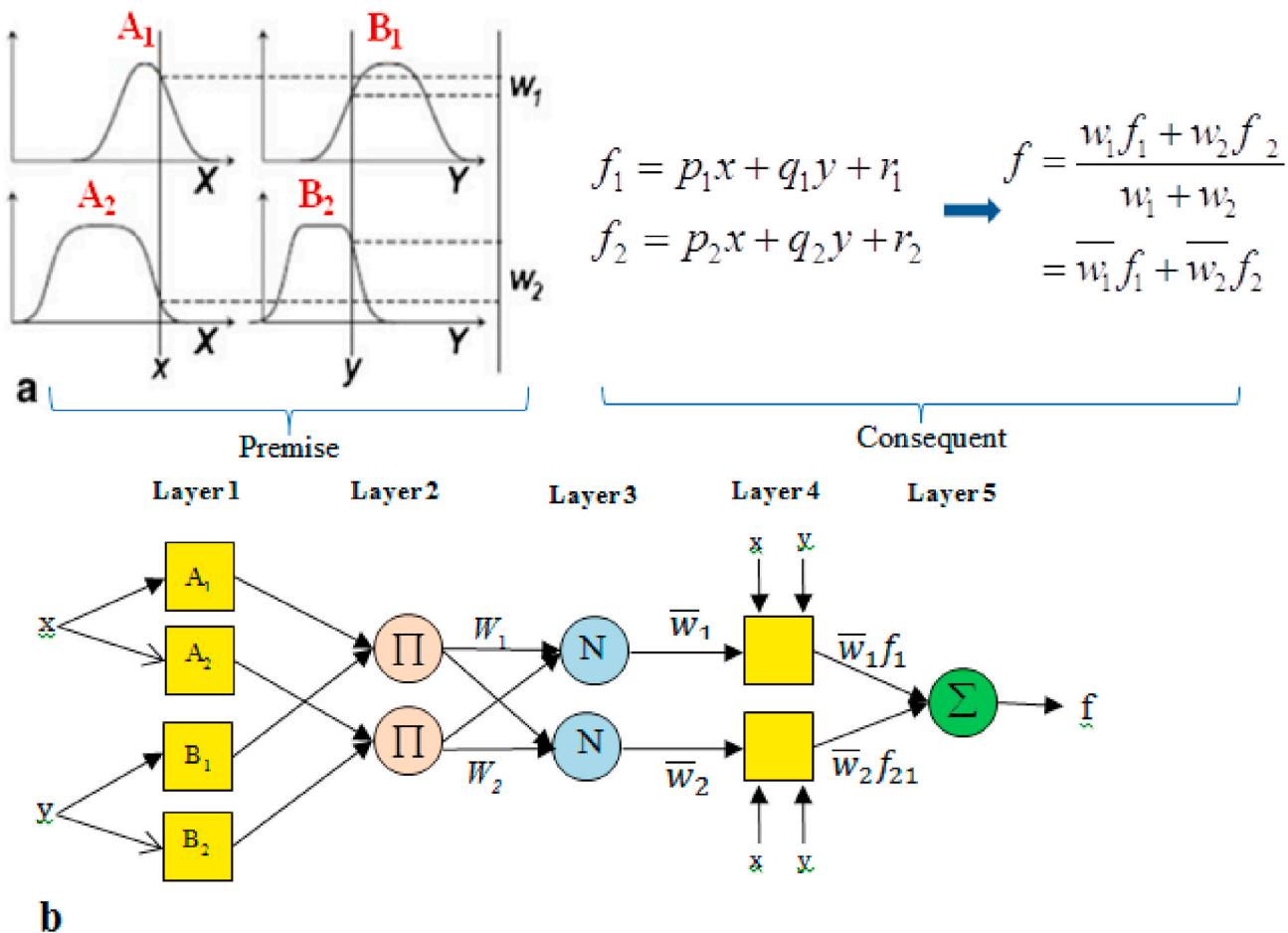


Fig. 2. (a) The schematic of the TSK fuzzy model and (b) The structure of the ANFIS model (Jang, 1993; Shojaeian and Asadizadeh, 2020).

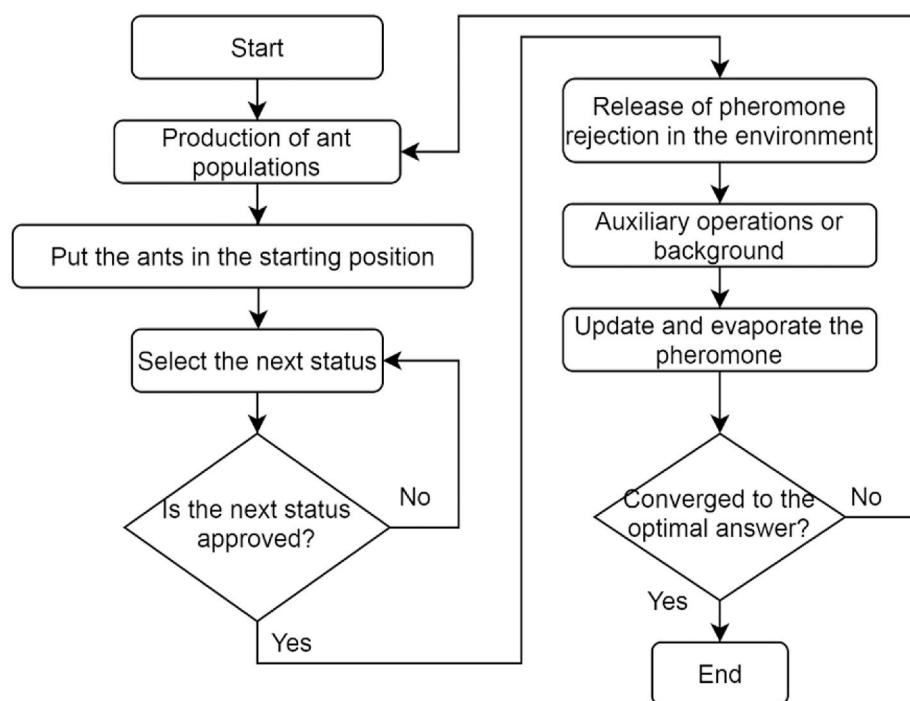


Fig. 3. The diagram of the ant colony algorithm (Adapted from Xu et al., 2012)

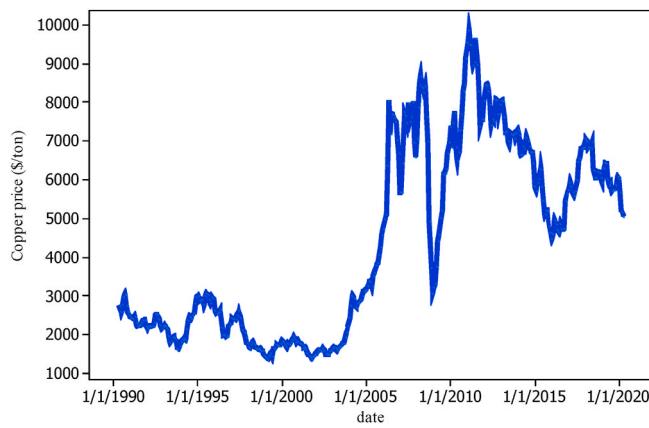


Fig. 4. The monthly changes in copper prices from 1990 to 2020.

Table 1
The input and output parameters (Available on www.indexmundi.com).

Type	Parameter	Symbol	Period	Min	Max
<i>Input</i>	coal (\$/ton)	C	Monthly	22.25	180
	Aluminum (\$/ton)	Al	Monthly	1039.81	3071.24
	Crude Oil (\$/barrel)	Cr	Monthly	10.41	132.83
	Gold (\$/ozt)	G	Monthly	256.08	1772.14
	Iron Ore (\$/ton)	I	Monthly	26.47	197.12
	Natural Gas (\$/per Million Metric British)	N	Monthly	1.19	13.52
	Nickel (\$/ozt)	Ni	Monthly	3871.93	52179.05
	Silver (\$/ozt)	S	Monthly	3.65	42.7
<i>Output</i>	Copper (\$/ton)	Cop	Monthly	1377.28	9867.6

2.1.3. Adaptive neuro-fuzzy inference system

Jang (1993) developed an adaptive network-based fuzzy (or neuro-fuzzy) inference system (ANFIS). ANFIS is a network based on the Takagi-Sugeno fuzzy inference system that trains FIS membership function parameters by the available data using the least-squares and the backpropagation gradient descent methods (Aqil et al., 2007; Jantzen et al., 2005; Zounemat-Kermani and Teshnehlab, 2008).

ANFIS architecture can be identified by two main parts (i.e., premise and consequence), each having five layers. A schematic view of ANFIS with two inputs is shown in Fig. 2. This model can be expressed by given rules as follows:

$$\begin{aligned} \text{Rule 1 : if } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then } (f_1 = p_1x + q_1y + r_1) \\ \text{Rule 2 : if } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then } (f_2 = p_2x + q_2y + r_2) \end{aligned} \quad (2)$$

where x and y are the inputs, A_i and B_i are membership functions for inputs, p_i , q_i , and r_i are the parameters of output function and f_i shows the outputs (Jang et al., 1997).

As shown in Fig. 2b, the first layer is known as the fuzzification layer, which fuzzifies the input values by appropriate membership functions. The second layer is known as the rule layer, in which the weights of each membership function are generated by multiplying the membership values calculated in the first layer.

The third layer is the normalization layer, which normalizes each rule's calculated weights (or firing strengths). The fourth layer is known as the defuzzification layer, in which the weighted values of rules are calculated. Finally, the five-layer is the output or summation layer, which calculates the output of the fuzzy system by summing up the outputs of the defuzzification layer (Akyildiz and Hudaverdi, 2020).

2.1.4. Ant colony optimization algorithm

This algorithm was developed by Dorigo (1992) to solve the traveling salesman problem with 75 cities, known as the basic model of the ant algorithm, which is based on the behavior of real ants looking for

food. Ants are capable of following the same path to find food, which is the shortest possible path. Along the path, each ant secretes a chemical called pheromone. All members of the colony feel this substance and move toward the path with different pheromones. In other words, the path with more pheromones will be more attractive for an ant's selection. In this optimization algorithm, a series of artificial ants create answers to find appropriate solutions utilizing innovative information and through artificial pheromones. Then, the amount of path pheromones is updated based on the quality of the produced response, thus establishing the communication between the ants (Dorigo and Gambardella, 1997).

Each artificial ant uses innovative information and memory and the characteristics of natural ants to record its former movements. Innovative information is defined based on the objective function of the problem representing the amount of improvement in the value of this function caused by the ants' movement along the path. Moreover, every movement made by an artificial ant is stored in memory to facilitate going back and correcting pheromone levels. More pheromone in a pathway increments the likelihood of ants following that pathway, and evaporation of pheromones reduces the probability of poor-quality solutions (Saghatforoush et al., 2016). The diagram of the ACO algorithm is represented in Fig. 3.

In the ACO procedure, the initial iteration starts with artificial ants randomly placed on the nodes that form the tours. The transition from node i to node j is randomly selected based on a possibility given by Eq. (3):

$$P_{ij}^k(t) = \frac{([\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta)}{\sum_{i \in N_i} [\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta} \quad (3)$$

where $\tau_{ij}(t)$ is the pheromones value from node i to node j on the considered path, η_{ij} is a heuristic value between edge (ij) assigned by a weighting function (called heuristic information, α and β are positive constant factors that control the influence of τ_{ij} and η_{ij} , respectively, and N_i shows the set of the node points (Bonabeau et al., 1999).

The following iterations are repeated based on the updated pheromone. The pheromone update causes increasing the amount of pheromone related to good paths or solutions and decreasing those related to bad ones. According to Eq. (4), pheromone levels can be increased by considering a certain value of $\Delta\tau_{ij}$ and increasing the amount of pheromone evaporation (Manderick and Moyson, 1988).

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij} \quad (4)$$

where ρ is the evaporate rate of pheromone ($\rho \in (0, 1]$), $\Delta\tau_{ij}$ is the pheromone value on edge (i, j) that is calculated by Eq. (5).

$$\Delta\tau_{ij} = \sum_{k=1}^m \Delta\tau_{ij}^k \quad (5)$$

where m is equal to the number of ants and $\Delta\tau_{ij}^k$ is the pheromone value associated with ant k on edge (i, j) (Dorigo et al., 2006; Selma and Chouraqui, 2020).

2.2. Database and inputs selection

Studies on forecasting metal prices have shown the role of many factors in fluctuating copper prices. The copper price is likely to depend upon the energy costs of crude oil, coal, and natural gas due to their association with copper production (Joseph and Kundig, 1999). Moreover, the copper price may relate to other metal prices in the market as alternatives. For instance, when other metal prices decline, the copper price is likely to follow the same trend (Charlot and Marimoutou, 2014). Based on the above reasoning and previous studies on forecasting copper price (Liu et al., 2017; Dehghani, 2018; Diaz et al., 2020; Alameer et al., 2020) and the subject of data availability, we investigated the

Table 2

Pearson's correlation matrix of the input and output variables.

Correlations	Coal	Aluminum	Crude Oil	Gold	Iron Ore	Natural Gas	Nickel	Silver	Copper
<i>Coal</i>	1	0.702 ^a	0.842 ^a	0.807 ^a	0.861 ^a	0.280 ^a	0.558 ^a	0.818 ^a	0.870 ^a
<i>Aluminum</i>	0.702 ^a	1	0.705 ^a	0.490 ^a	0.736 ^a	0.573 ^a	0.855 ^a	0.597 ^a	0.815 ^a
<i>Crude Oil</i>	0.842 ^a	0.705 ^a	1	0.814 ^a	0.886 ^a	0.412 ^a	0.655 ^a	0.858 ^a	0.901 ^a
<i>Gold</i>	0.807 ^a	0.490 ^a	0.814 ^a	1	0.750 ^a	0.011	0.446 ^a	0.927 ^a	0.863 ^a
<i>Iron Ore</i>	0.861 ^a	0.736 ^a	0.886 ^a	0.750 ^a	1	0.394 ^a	0.719 ^a	0.839 ^a	0.891 ^a
<i>Natural Gas</i>	0.280 ^a	0.573 ^a	0.412 ^a	0.011 ^b	0.394 ^a	1	0.546 ^a	0.118 ^b	0.309 ^a
<i>Nickel</i>	0.558 ^a	0.855 ^a	0.655 ^a	0.446 ^a	0.719 ^a	0.546 ^a	1	0.560 ^a	0.763 ^a
<i>Silver</i>	0.818 ^a	0.597 ^a	0.858 ^a	0.927 ^a	0.839 ^a	0.118	0.560 ^a	1	0.891 ^a
<i>Copper</i>	0.870 ^a	0.815 ^a	0.901 ^a	0.863 ^a	0.891 ^a	0.309 ^a	0.763 ^a	0.891 ^a	1

^a Correlation is significant at the 0.01 level (2-tailed).^b Correlation is significant at the 0.05 level (2-tailed).**Table 3**

The values of the parameters used for the GEP model for copper price prediction.

GEP Parameter	Value		
	Number of model		
	1	2	3
Fitness function	RMSE	MAE	MSE
Inversion rate	0.00546	0.00546	0.00546
IS transportation rate	0.00546	0.00546	0.00546
RIS transportation rate	0.00546	0.00546	0.00546
One-point recombination rate	0.00277	0.00277	0.00277
Two-point recombination rate	0.00277	0.00277	0.00277
Gene size	17	17	15
Head size	8	8	7
Tail size	9	9	8
Mutation rate	0.00138	0.00138	0.00138
Number of Chromosome	30	30	35
Number of genes	3	4	3
Gene recombination rate	0.00277	0.00277	0.00277
Gene transportation rate	0.00277	0.00277	0.00277
Training	70%	70%	70%
Validation	30%	30%	30%
Number of generations	5000	5000	5000

Table 4

Optimal performance of applied GEP models.

Methods	Test			
	R^2	RMSE	R^2	RMSE
GEP-RMSE	0.967	440.090	0.966	452.220
GEP-MSE	0.942	597.220	0.930	630.650
GEP-MAE	0.959	515.408	0.948	574.980

parameters affecting the copper price volatilities. Accordingly, we considered them in two major groups, i.e., energy price (crude oil, coal, and natural gas) and metal price (aluminum, gold, iron ore, nickel, and silver).

The price data of considered input parameters and copper price fluctuations were gathered from 1990 to 2020 (copper price fluctuations are illustrated in Fig. 4). The entire data were downloaded from www.indexmundi.com. Index Mundi is a data portal that gathers facts and statistics from multiple sources and turns them into easy-to-use visuals. These data are presented through user-friendly maps, charts, and tables that facilitate understanding complex information.

Fig. 4 represents the changes in copper prices during this period, and Table 1 provides the range of price changes of input and output parameters. It is worth noting that the total number of data is 360 datasets, of which 70% of the data (252 data) were randomly used for training, and 30% (108 data) were used for validation and testing of the model.

The Pearson cross-correlation coefficients were applied to determine

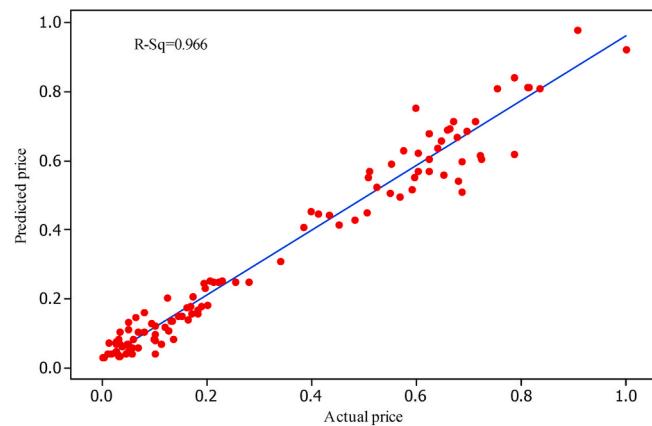


Fig. 5. The correlation between the values obtained for the test data in the GEP model.

the significant relationships between considered inputs and copper price. This statistical test was applied to measure the linear correlation between two data sets by a linear dependence degree ranging from -1 to 1. The values -1, 0, and 1 imply a negative correlation, no correlation, and positive correlation, respectively (Pearson, 1895; Dehghani, 2018). The Pearson cross-correlation coefficient ($r_{i,c}$) between parameters $i(P_i)$ and copper price (P_c) is measured as follows:

$$r_{i,c} = \frac{\text{cov}(P_i, P_c)}{\sigma_{P_c} \times \sigma_{P_i}} \quad (6)$$

where σ_{P_i} and σ_{P_c} stand for the values of standard deviations of the input parameter i and copper price, respectively. In this equation, $\text{cov}(P_i, P_c)$ is the covariance between the value of the input parameter i and the copper price is achieved by Eq. (7):

$$\text{cov}(P_i, P_c) = \frac{1}{n} \sum_{j=1}^n (P_{cj} - \bar{P}_c)(P_{ij} - \bar{P}_i) \quad (7)$$

where P_{cj} is the copper price in month j , P_{ij} is the value of input parameter in month j , \bar{P}_c is the average value of the copper prices, \bar{P}_i is the average value of each input parameter, and n is equal to the dataset number. Pearson's correlation matrix of the considered inputs and copper price presented in Table 2 indicates the significant correlations with a P-value < 0.01.

3. Performance assessment of the applied models

3.1. GEP for copper price prediction

In the present study, the GEP algorithm software was used to obtain

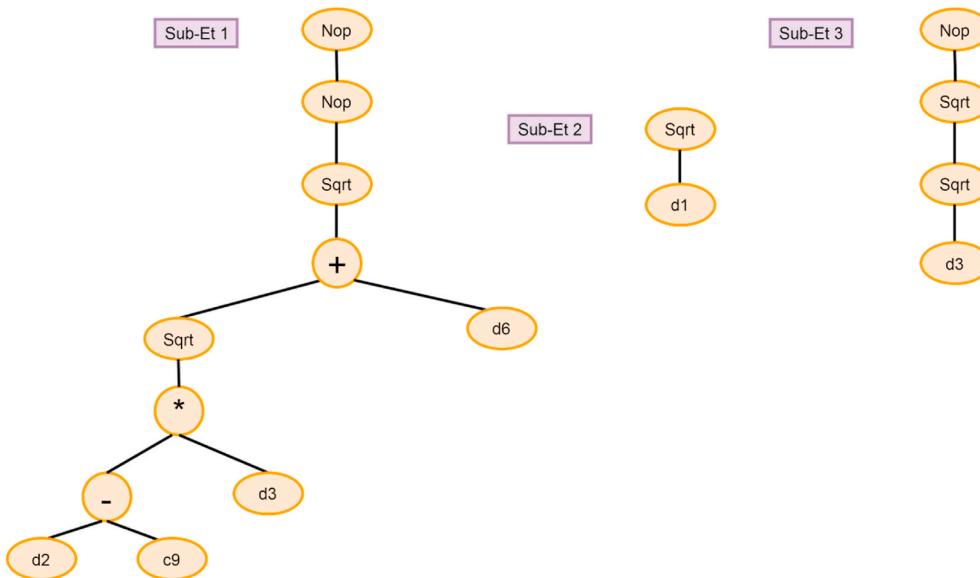


Fig. 6. The expression tree for the GEP model in copper price forecasting.

the ultimate relationship between the initial and copper prices. It includes various software tools and soft calculations for analysis. There are five main steps in GEP modeling. The first step is to select the fit function. RMSE, MSE, and MAE fitness functions were used in the present work to predict copper prices. Among these functions, the RMSE fit function yielded the best results for copper price predictions. The relationships of the considered fitness functions are as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_{ipred} - X_{imeas})^2} \quad (8)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_{ipred} - X_{imeas})^2 \quad (9)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |X_{ipred} - X_{imeas}| \quad (10)$$

where X_{ipred} is the predicted price of the copper and X_{imeas} denotes the measured copper price.

The second step includes choosing a set of terminals and a set of functions to generate chromosomes based on the inputs and outputs provided in Table 1. The most proper functions for obtaining the final equation were determined in the next step to obtain the best relation. The functions used in the model include $\{F = +, -, \times, /, x, x^2, x^3, x^{(1/3)}, 1/x, \exp(x), \log(x)\}$.

The chromosomal structure is selected in the third step, along with the fourth step includes selecting the type of linking function. Here, the multiplying function was used to predict the copper price in the final model. Ultimately, a set of genetic and rate operators have been considered to achieve the best results in the model. According to Shakeri et al. (2020) and Dehghani (2018), the fixed-rate values of the software lead to better results, so these rates were not changed, and various models were constructed based on the constant rate values. The parameters utilized to determine the best model based on the fitness functions among various tested models are presented in Table 3.

Based on Table 4, the GEP-RMSE model was selected as the best one among the three ultimate models built using GEP regarding its lower RMSE value and the higher R^2 . In this models, 252 datasets were randomly considered training data, and remain 108 datasets were selected as the validation data.

Using the GEP algorithm, the final relation was obtained for copper price forecast as an expression tree (Fig. 6), based on which the final

relation (Eq. (11)) was extracted. Hence, $C9$ is a numerical constant with a value of -0.35 .

$$\text{Copper price} = \left(\sqrt{\sqrt{(Cr + 0.35) \times G + Ni}} \right) \times \left(\sqrt{Al} \right) \times \left(\sqrt{4G} \right) \quad (11)$$

The correlation between the actual copper prices and values obtained for the test data in the GEP model is presented in Fig. 5.

3.2. ANN for copper price prediction

Possessing sufficient data for network training and utilizing a proper training algorithm, the neural network can learn the complex relationships between the inputs and outputs well. Normally, the data are classified into three categories of educational, validation, and test data with a ratio of 70, 15, and 15%, respectively. Regarding the input and output parameters of neural networks, it should be considered that the closer range of changes of these parameters leads to the better ability of the network to generalize and learn the relationship between these parameters. Only the numerical value of the parameters and not their measurement units are considered in the network. The best situation for most neural networks is when all the network's input and output data is between 0 and 1, which is determined as follows (Alameer et al., 2020):

$$X_{normalized} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \quad (12)$$

where x_i is the actual value and x_{min} and x_{max} are the minimum and maximum values of the original data, respectively.

In this study, a feedforward backpropagation multi-layer perceptron neural network was utilized to predict the copper price. According to the results of training and testing of neural networks with one and two concealed layers and the different number of neurons in each layer, it was found that the network with one hidden layer containing 13 neurons has the best performance to predict copper price using the prepared database. Since the number of inputs is 8 and the output is 1, the network with the 8-13-1 architecture (Fig. 7) was selected as the optimal network with the parameters provided in Table 5.

The correlation between real values of copper price and predicted values (normalized data) by ANN is presented in Fig. 8. This correlation and high neural network accuracy are better presented in copper price forecast using the considered parameters. Also, these results with non-

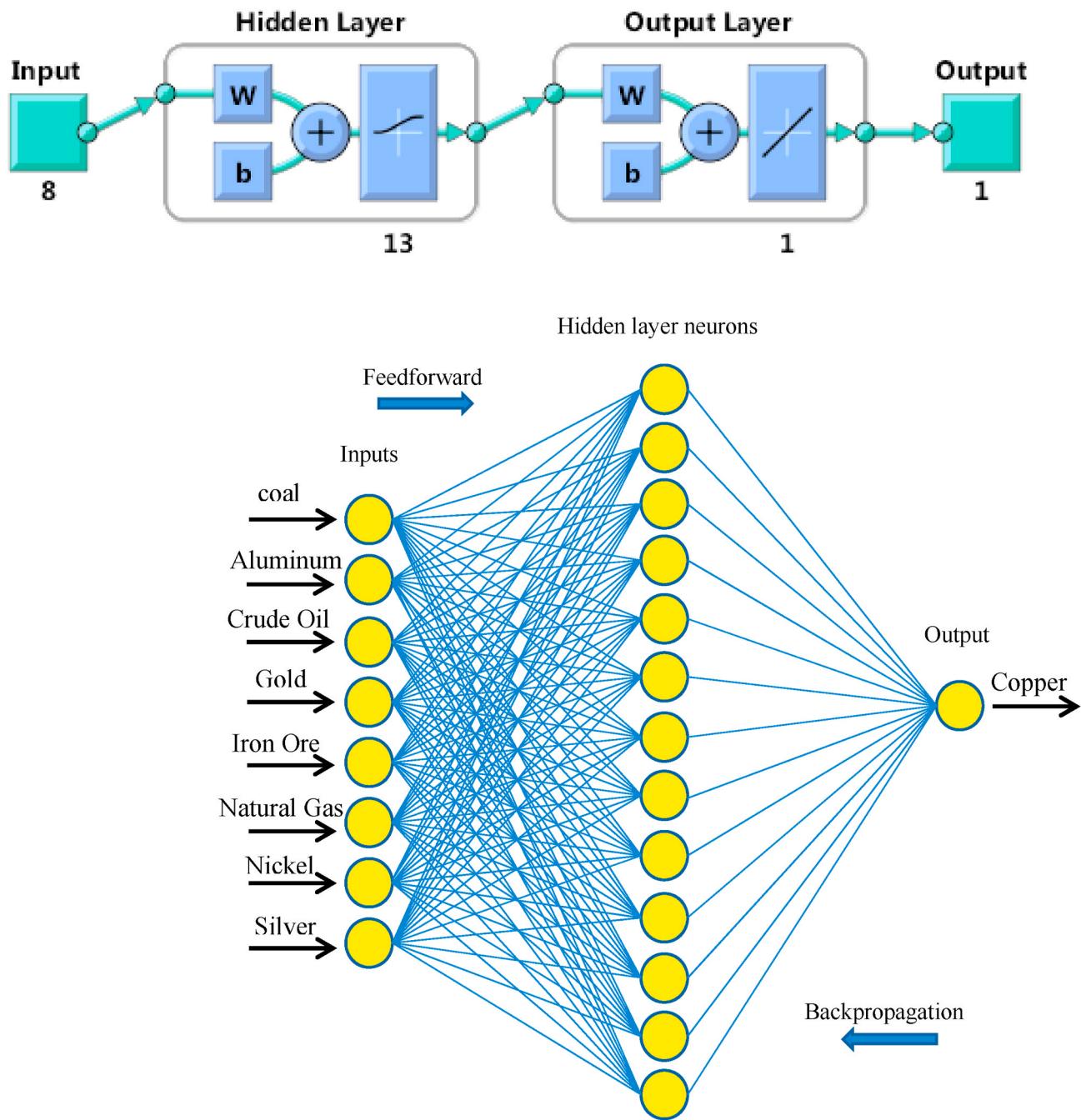


Fig. 7. The schematic structure of the obtained optimal neural network.

Table 5
The optimal neural network parameters for copper price prediction.

No. of Input layer neurons	8
No. of hidden layers	1
No. of hidden layer neurons	13 neurons
No. of Output layer neurons	1 neuron
Learning algorithm	Levenberg-Marquardt
Hidden layer transfer function	Log-Sigmoid (logsig)
Output layer transfer function	Purelin
No. of total data	360
No. of train data	252
No. of validation data	54
No. of test data	54
No. of epochs	200
Learning rate	0.05

normalized data are provided in Fig. 9. According to the findings, the ANN can predict the copper price with high accuracy by considering the definite parameters.

3.3. ANFIS and ANFIS-ACO algorithms for copper prices prediction

Two other innovative methods, ANFIS and ANFIS-ACO, are used here to predict copper prices and results compared to the ANN approach. The input parameters of the methods in this phase are similar to the previous methods. In the ANFIS-ACO approach, to train the ANFIS model, the learning algorithm was separately adopted to achieve good performance and high accuracy. The ACO algorithm obtains the optimal parameters of the ANFIS model in this regard. ACO-based ANFIS approaches are implemented through a Matlab code. Table 6 represents the optimal values of the parameters of the ANFIS model and the ANFIS model based

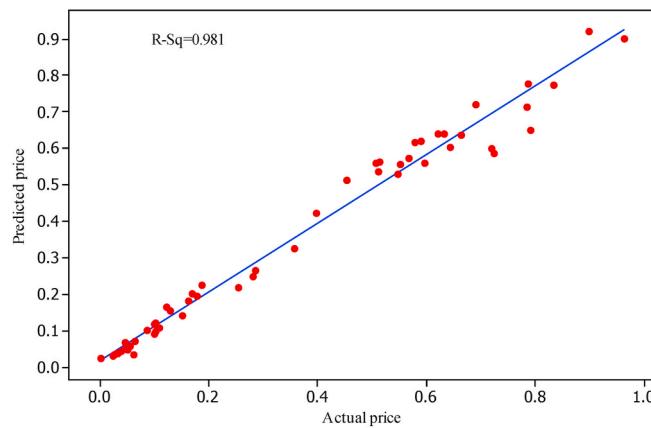


Fig. 8. The correlation between the real values of copper price and predicted values for normalized data.

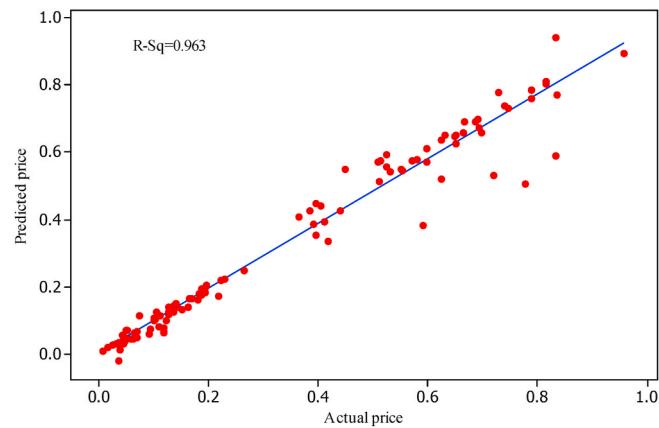


Fig. 10. The correlation between real values of copper price and ANFIS-predicted values.

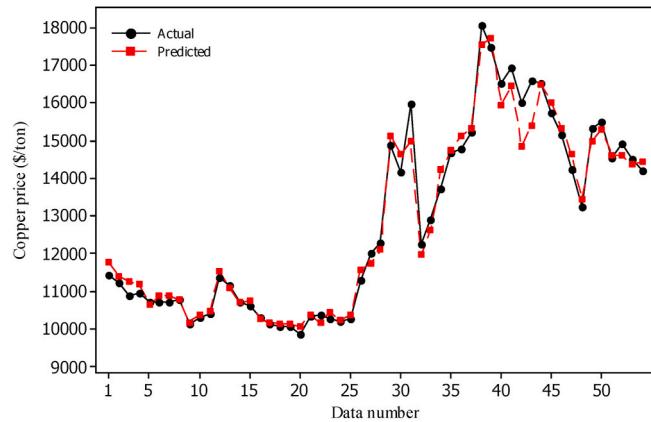


Fig. 9. The actual and predicted values of non-normalized data.

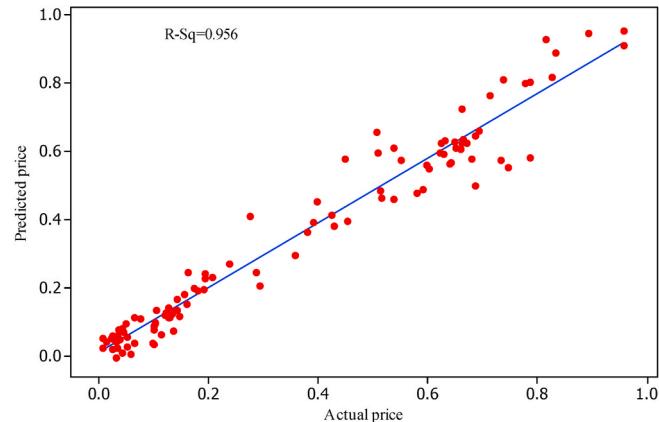


Fig. 11. The correlation between real values of copper price and ANFIS-ACO-predicted values.

Table 6
The optimal ANFIS and ANFIS-ACO values.

Parameter (ANFIS)	Description/value
Fuzzy structure	Sugeno-type
Type of membership function of the input	Gaussian ("gaussmf")
Type of membership function of the output	Linear
The center of the cluster influence	0.7
Input number	8
Output number	1
Optimization approach	ACO
Iteration number	1000
No. of data for train	252
No. of data for test	108
Initial step size	0.2
The step size of the decrease rate	0.8
The step size of the increase rate	1.4
Number of fuzzy rules	6
Parameter (ACO)	Description/value
Initial pheromone Matrix Value	0.001
Number of construction steps	80
Movement steps	700
Pheromone decay coefficient	0.5

on ACO for predicting the copper price.

The correlation between the actual and predicted values of copper price by ANFIS models is represented in Figs. 10 and 11.

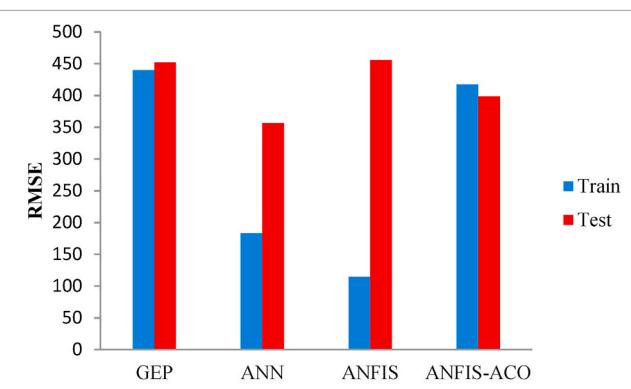


Fig. 12. RMSE values for training and testing data of the models used in this research for copper price prediction.

4. Discussion and conclusions

Artificial intelligence-based networks include a very higher power and efficiency for price prediction of ores such as copper. In this study, for the first time, four different methods of artificial intelligence (i.e., GEP, ANN, ANFIS, and ANFIS-ACO) were used to predict the copper price. By selecting appropriate affecting parameters and gathering sufficient datasets, most of artificial intelligence-based techniques have a

Table 7All predicted values of R^2 , RMSE, and MAPE for copper price forecast.

Methods	Train				Test			
	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE
GEP	0.967	440.090	331.340	9.590	0.966	452.220	327.352	9.730
ANN	0.997	183.134	331.399	2.110	0.980	356.510	239.105	5.700
ANFIS	0.998	114.811	63.571	1.990	0.963	455.520	239.614	5.560
ANFIS-ACO	0.971	417.476	323.225	9.249	0.956	398.370	377.415	9.810

higher capability in predicting complicated problems. In this research, based on previous studies and Pearson cross-correlation coefficients, we identified eight parameters affecting the copper price from 1990 to 2020. These parameters include changes in the prices of coal, aluminum, crude oil, gold, iron ore, natural gas, nickel, silver, and lead. Eventually, the copper price was predicted by applying AI techniques. The results indicated that these networks have a high potential for predicting the copper price. To evaluate the performance of the network, statistical criteria including R^2 , RMSE, MAE and Mean Absolute Percentage Error MAPE were considered and optimal networks were selected based on high values of R^2 and low values of the other criteria. The R^2 and MAPE were obtained using the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^N (X_{ipred} - X_{imeas})^2}{\sum_{i=1}^N (X_{mean-meas} - X_{imeas})^2} \leq 1 \quad (13)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{X_{ipred} - X_{imeas}}{X_{imeas}} \right| \quad (14)$$

where X_{ipred} and X_{imeas} are the predicted and measured price of the copper, respectively.

It is notable to mention that MAPE less than 10% refers to a highly accurate prediction performance (Lewis, 1982; Dehghani and Zangeneh, 2018).

Fig. 12 illustrates the performance of different optimal achieved models in this research based on RMSE for training and testing data. It is worth stating that the ANN model outperformed the other models in copper price prediction.

The overall performance of all optimal models used in this study is shown in Table 7. According to these results, the ANN with a hidden layer containing 13 neurons, and logsig and purelin activation functions for the hidden layer, and an output layer with RMSE of 356.51, MAE of 239.105 (\$/ton), MAPE of 5.70% and R^2 of 98.1% for the test data outperformed the other ones in copper price forecast. After the ANN model, the ANFIS model with RMSE, MAE, MAPE and R^2 values of 455.52, 239.614 (\$/ton), 5.56% and 95.6%, respectively, was ranked next, followed by ANFIS - ACO and GEP models. It is of note that all four AI methods used in this work had satisfactory performance in predicting copper prices.

Declaration of competing interest

The authors certify that they have no conflict of interest.

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