Resources Policy 73 (2021) 102195

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Proposing two novel hybrid intelligence models for forecasting copper price based on extreme learning machine and meta-heuristic algorithms

Hong Zhang [a], Hoang Nguyen [b,c,*], Xuan-Nam Bui [b,c], Biswajeet Pradhan [d,e], Ngoc-Luan Mai [f], Diep-Anh Vu [g]

[a] Department of Economics and Management, Changsha University, Changsha, China
[b] Department of Surface Mining, Mining Faculty, Hanoi University of Mining and Geology, 18 Vien Street, Duc Thang Ward, Bac Tu Liem District, Hanoi, 100000, Vietnam
[c] Center for Mining, Electro-Mechanical Research, Hanoi University of Mining and Geology, 18 Vien Street, Duc Thang Ward, Bac Tu Liem District, Hanoi, 100000, Vietnam
[d] The Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), University of Technology, Sydney, NSW, 2007, Australia
[e] Department of Energy and Mineral Resources Engineering, Sejong University, Choongmu-gwan, 209 Neungdong-ro, Gwangjingu, Seoul, 05006, South Korea
[f] Visagio Australia, 6/189 St Georges Terrace, Perth, Australia
[g] Basic Economics Department, Faculty of Economics and Business Administration, Hanoi University of Mining and Geology, 18 Vien Street, Duc Thang Ward, Bac Tu Liem District, Hanoi, 100000, Vietnam

ARTICLE INFO

Keywords:
Copper price
Forecasting price
Natural resources
Extreme learning machine
Optimization algorithms
Hybrid models

ABSTRACT

The focus of this study aims at developing two novel hybrid intelligence models for forecasting copper prices in the future with high accuracy based on the extreme learning machine (ELM) and two meta-heuristic algorithms (i.e., particle swarm optimization (PSO) and genetic algorithm (GA)), named as PSO-ELM and GA-ELM models. Accordingly, the time series datasets of the copper price for thirty years were collected based on the influencing parameters, such as crude oil, iron ore, gold, silver, and natural gas prices. Furthermore, the exchange rate of the four largest countries in copper-producing, including Chile (USD/CLP), China (USD/CNY), Peru (USD/PEN), and Australia (USD/AUD), were also considered to evaluate the copper prices. The GA and PSO algorithms then optimized the weights and biases of the ELM model to reduce the error of the ELM model for forecasting copper price. The traditional ELM model (without optimization), and artificial neural networks (ANN) were also developed as the comparative models for resulting in convincing experimental results in the proposed PSO-ELM and GA-ELM models. The results indicated that the proposed hybrid PSO-ELM and GA-ELM models could forecast copper price with higher accuracy and reliability over the traditional ELM and ANN models. Of those, the PSO-ELM yielded the most dominant accuracy with a root-mean-squared error (RMSE) of 304.943, mean absolute error (MAE) of 241.946, mean absolute percentage error (MAPE) of 0.037, and mean absolute scaled error (MASE) of 0.933. The *t*-test and Wilcoxon test also demonstrated the statistical significance of the proposed models and the best 95% confident interval of the PSO-ELM model with the range of $177.046 to $67.054 with p-value = 2.589e-05. Whereas, the GA-ELM model provided the forecasted copper price higher $137.233 than the actual copper price, and the 95% confidence interval is from $189.672 to $84.793 with p-value = 1.027e-06.

1. Introduction

In recent years, artificial intelligence (AI) applications in forecasting commodity prices are rapidly growing. Recent advances of AI have been observed in different application and research areas (Aggarwal et al., 2009; Armaghani and Asteris, 2021; Khandelwal et al., 2017; Nowotarski and Weron, 2018; Wang et al., 2017a; Weron, 2014; Yang et al., 2021; Zhao et al., 2017). Generally, the explanation for the thrive of AI applications is three-fold: 1) Robust ability to model underlying patterns of data with limited or even none domain knowledge input; 2)

* Corresponding author. Department of Surface Mining, Mining Faculty, Hanoi University of Mining and Geology, 18 Vien street, Duc Thang ward, Bac Tu Liem district, Hanoi, 100000, Vietnam.
E-mail addresses: zhcsu@tom.com (H. Zhang), nguyenhoang@humg.edu.vn (H. Nguyen), buixuannam@humg.edu.vn (X.-N. Bui), Biswajeet.Pradhan@uts.edu.au (B. Pradhan), vudiepanh@humg.edu.vn (D.-A. Vu).

https://doi.org/10.1016/j.resourpol.2021.102195
Received 19 September 2020; Received in revised form 10 June 2021; Accepted 10 June 2021
Available online 25 June 2021

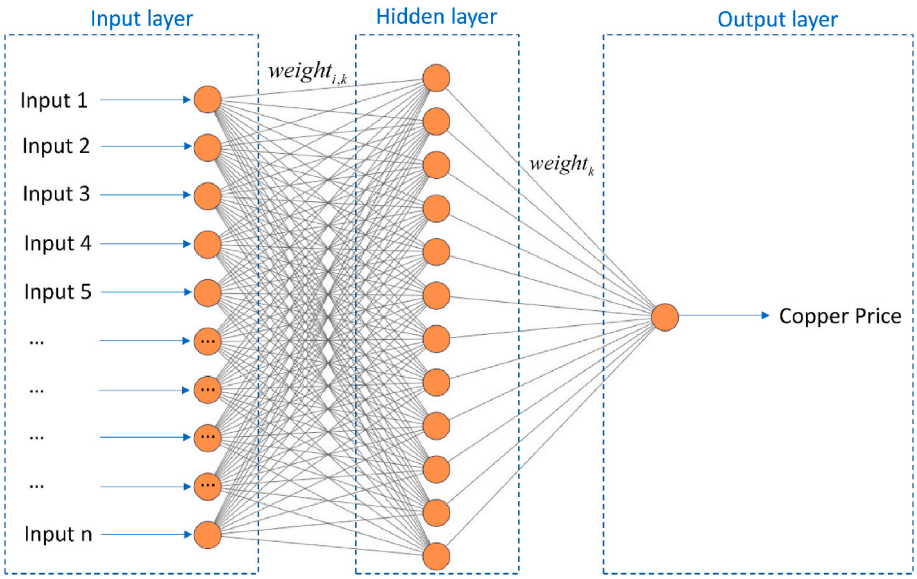


Fig. 1. Structure of an ELM model for forecasting copper price.

Availability of data and hardware as they work with AI in a spiral loop fashion: AI, particularly deep learning models, become practical and valuable because of high-performance hardware and large data collections, then, in turn, more data is collected, and better hardware is created to support unlocking even further potentials of AI. 3) Democratization of AI technology: learning materials, open-source programming packages, deployment platforms. The three ingredients make a perfect recipe for a booming of AI applications as we are witnessing nowadays (Asteris et al., 2019; Bui et al., 2019a, 2019c; Fang et al., 2019; Guo et al., 2019a; Ke et al., 2021a, 2021b; Yu et al., 2021; Zhou et al., 2012, 2016; Manoj et al., 2017).

In strategic mine planning, the feasibility and efficiency of a mining project are commonly evaluated through Net Present Value (NPV), where the economic values of mining blocks are discounted by time variables (Mai et al., 2016; Nguyen et al., 2020; Nguyen and Hoang, 2020). Besides, a realistic commodity price forecast is of utmost importance to assess the reliability and robustness of the estimated NPV score (Nguyen and Nguyen, 2020). Over the past five years, plenty of work has been done on this topic (Le, 2020). In the scope of this study, we focus on forecasting copper prices in the world. In this regard, Buncic and Moretto (2015) proposed a framework of dynamic model averaging and selection (DMA/DMS) for forecasting monthly copper prices from May 2002 to June 2014. The horizon and resolution of these models were also indicated in their study for one and six months. In another study, Seguel et al. (2015) applied two meta-heuristic algorithms (i.e., simulated annealing (SA) and genetic algorithm (GA)) for forecasting copper prices based on the dataset from October 2013 to August 2014. Based on their obtained results, the GA was introduced as the best model for forecasting copper price in their study. Liu et al. (2017) used decision tree learning for forecasting copper prices in both short and long terms. A promising result of mean absolute error (MAPE) was reported in their study with MAPE<4%. Using gene expression programming (GEP) model, Dehghani (2018) forecasted copper price with an acceptable result (i.e., RMSE = 0.17, R^2 = 0.64). The multivariate regression model provided lower accuracy based on the same dataset of the GEP model (RMSE = 0.18 and R^2 = 0.40). Dehghani and Bogdanovic (2018) claimed that artificial algorithms could forecast metal prices (i.e., copper price) with high reliability. Accordingly, they successfully developed a novel model based on combining the BAT algorithm and time series functions for this aim. Finally, they found that their proposed model can forecast copper price with higher accuracy than those of the classic estimation methods (i.e., RMSE = 0.132). In another study, Alameer et al. (2019) developed a novel hybrid AI model based on the GA and adaptive neuro-fuzzy inference system (ANFIS) model for forecasting copper price (i.e., GA-ANFIS). A variety of different comparative AI models were also used to compare with and evaluate the GA-ANFIS model, such as generalized autoregressive conditional heteroscedasticity (GARCH), autoregressive integrated moving average (ARIMA), ANFIS (without optimization), and support vector machine (SVM) models. Ultimately, they concluded that the GA-ANFIS model could forecast copper prices better than the other models. In another study, Astudillo et al. (2020) also applied the SVM model to consider different trend-cycle characteristics to forecast copper prices at the London Metal Exchange in the next 5 days, 10 days, 15 days, 20 days and one month. Their results showed good errors with RMSE values in the range of 0.034–0.075. It is worth noting that these errors were normalized within the range of 0–1. Díaz et al. (2020) considered the random walk model to make the best copper price forecasts through various decision tree models (e.g., random forest, regression tree, and gradient boosting tree). Different horizons were also investigated in their study to understand the accuracy of the models, and finally, they claimed that short-term forecasts provided higher accuracies than long-term forecasts. Based on machine learning approaches and deep learning, Hu et al. (2020) developed a novel intelligent model based on ANN (artificial neural network), (LSTM) long short-term memory, and GARCH methods for forecasting copper price volatility. Positive results were provided in their study with the support of the GARCH method and the improvement of the LSTM and ANN models in this regard. In spite the fact that long-term forecasts provided lower accuracies as recommended by Díaz et al. (2020); however, Tapia et al. (2020) used entropy to evaluate the dynamic behavior of copper price in long-terms and they concluded that long-term copper prices were not generated by stochastic process. This finding can demonstrated for the random walk model with low accuracy in a long-term of Díaz et al. (2020).

A literature review showed that extreme learning machines (ELM) had not been applied to forecast the copper price. Furthermore, hybrid models based on the ELM neural network and optimization algorithms have not been investigated to forecast copper prices. In data mining, many optimization algorithms can be applied for optimizing the ELM model (Kochenderfer and Wheeler, 2019). However, their role is similar (i.e., optimizing the ELM's parameters), and their performance may differ slightly. Therefore, in this study, GA and particle swarm optimization (PSO) were selected as the typical optimization algorithms for optimizing the ELM model as per recommendations of previous

```
Algorithm: Genetic algorithm
Set parameters
Choose encode method
Generate the initial population
Evaluate the fitness of population
while i < MaxIteration and Bestfitness < Maxfitness do
        Compute the fitness of each population
        Order the population, compute evaluation value
        Selection
        Crossover
        Mutation
        Update the population for the next generation
end while
Decode the individual with maximum Fitness
return the best solution
```

Fig. 2. Pseudo-code of the GA for optimization problems.

researchers (Alameer et al., 2019; Lalwani et al., 2019; Luan et al., 2019; Mirjalili et al., 2020). Accordingly, two novel hybrid AI models, namely GA-ELM and PSO-ELM, are developed and proposed in order to predict world copper prices. A review of the published papers shows that the GA-ELM and PSO-ELM models were also investigated and proposed for regression problems (Cao et al., 2015; Chu et al., 2018; Figueiredo and Ludermir, 2014; Pahuja and Nagabhushan, 2016; Wang et al., 2017b). Nevertheless, they have not been developed and proposed for forecasting copper prices. Alameer et al. (2019); Seguel et al. (2015) also applied GA for forecasting copper price as mentioned above; however, it has not been used to optimize the ELM model for this aim. Furthermore, it is worth mentioning that the previously proposed models for other problems cannot apply for forecasting copper price since the difference of variables, as well as the properties of the dataset used. Therefore, the GA-ELM and PSO-ELM models seem to be novel models in forecasting copper price as far as the authors know, and they are investigated and proposed in this study for forcasting copper price. In addition, the traditional ELM, and ANN models were also considered and developed to forecast copper price and compared with the GA-ELM and PSO-ELM models. A large dataset was collected on monthly copper prices and relevant predictors, such as other commodity prices and exchange rates, from 1990 to 2019.

2. Methodology

As mentioned above, this study forecasts copper prices using four AI models (i.e., ANN, ELM, GA-ELM, and PSO-ELM). Since the background of ANN was presented in many published papers and literature (Bui et al., 2021; Guo et al., 2019b; Livingstone, 2008; Nguyen et al., 2021b; Rosa et al., 2020; Zhang et al., 2020a). Therefore, they are not presented in this section. This study aims to propose two novel hybrid models (i.e., GA-ELM and PSO-ELM) for forecasting copper price; therefore, the principle of ELM, GA and PSO, and the framework of the hybrid models will be presented in this section.

2.1. Extreme learning machine

The ELM is one of the training algorithms for ANN models with one hidden layer. If the backpropagation (BP) algorithm is considered as an effective training algorithm for ANN models with the weight and bias are determined by the nature of tuning, its disadvantages, such as slow learning speed and tendency to converge to local minima, are overcome by the ELM (Sattar et al., 2019). Also, designing the structure of ANN is also challenging with the hidden layers as well as neurons (Nguyen et al., 2018, 2019). Meanwhile, the ELM consists of only one hidden layer in its structure (Fig. 1). These layers are thoroughly linked to generating a forward network with a single hidden layer. In the input layer of the ELM model, weights are assigned randomly. Whereas linear algebra computes them in the output layer as a pre-defined training procedure (Ertugrul, 2016; Ye and Qin, 2015). Therefore, the training stage (learning speed) is extremely fast with high generalization capacity (Huang et al., 2006, 2011a, 2011b). Finally, the output of the ELM network is computed as follows:

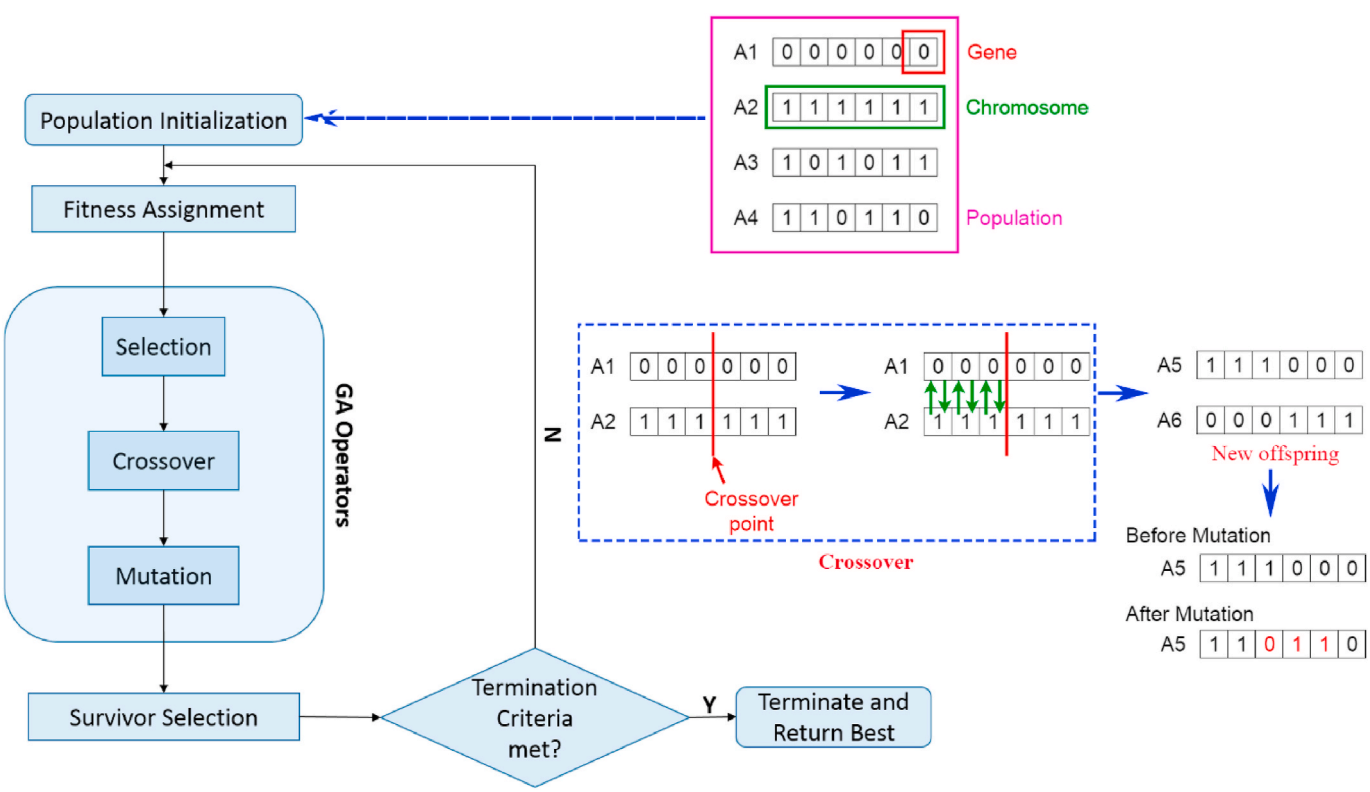


Fig. 3. Flowchart of the GA for optimal solution (Le et al., 2019).

Algorithm: Particle swarm optimization (PSO)

```
for each particle i
    for each dimention d
        Initialize position x_id randomly within permissible range
        Initialize velocity v_id randomly within permissible range
    end for
end for
Iteration k = 1
do
    for each particle i
        Calculate fitness value
        if the fitness value is better than p_best_id in history
            Set current fitness value as the p_best_id
        end if
    end for
    Choose the particle having the best fitness value as the g_best_id
    for each particle i
        for each dimention d
            Calculate velocity according to the equation
$v_j^{i+1} = wv_j^{(i)} + (c_1 \times r_1 \times (local\,best_j - x_j^{(i)})) + (c_2 \times r_2 \times (\text{global}\,best_j - x_j^{(i)})), v_{\min} \le v_j^{(i)} \le v_{\max}$
            Update particle position according to the equation
$x_j^{i+1} = x_j^{(i)} + v_j^{(i+1)}; j = 1, 2, ..., n$
        end for
    end for
k = k+1
while maximum iterations or minimum error criteria are not attained
```

Fig. 4. Pseudo-code of the PSO algorithm for optimization problems (Kulkarni and Venayagamoorthy, 2007).

$$y_{predict} = \sum_{k=1}^{m} \delta_k f_a \left(\sum_{i=1}^{n} weight_{i,k} x_i + bias_k \right) \tag{1}$$

where $y_{predict}$ is the output of the network (i.e., copper price); x denotes the inputs of the model; n and m are the number of input variables and neurons in the hidden layer, respectively; δ_k is the weight of the kth neuron in the output layer; $weight_{i,k}$ is the weight between ith and kth neurons in the hidden layer; $bias_k$ is the biases of the hidden neurons; f_a denotes the activation function used in the ELM.

2.2. Genetic algorithm

The GA is one of the evolutionary theory-inspired algorithms that can be used to find a suitable solution among potential solutions of a population (Haupt and Haupt, 1998). One of the outstanding advantages of GA is the ability to search for a suitable solution in an ample searching space (Armaghani et al., 2018; Fang et al., 2020). A procedure with three stages is applied for the GA in searching: selection → crossover → mutation. The pseudo-code of the GA is described in Fig. 2, and its flowchart is illustrated in Fig. 3. Besides, the GA also has a problem with its weak structures that is very slow in the global optimum (Mohammadpour et al., 2019; Danial et al., 2018). As the best review of the authors, the GA has been widely applied in terms of optimization (Armaghani et al., 2018; Chen et al., 2019; Fang et al., 2020; Faradonbeh et al., 2016a; Liu et al., 2020; Mohamad et al., 2016; Shi and Zhou, 2012). It was recommended as one of the robust optimization algorithms for real-life problems, as well as commodity price issues. More details of the GA can be referred to in the following literature (Faradonbeh et al., 2016b; Kumar et al., 2010; Mukhopadhyay et al., 2009; Sivaraj and Ravichandran, 2011; Umbarkar and Sheth, 2015; Vose, 1999; Whitley, 1994; Armaghani et al., 2018).

2.3. Particle swarm optimization

PSO is one of the swarm theory-based algorithms which was proposed by Eberhart and Kennedy (1995). It is developed based on the inspiration of swarm's social communication and interaction (e.g., birds, fishes) (Kennedy, 2010; Poli et al., 2007). Accordingly, the social behavior of sharing information of the swarm is applied to improve real-life problems (Gordan et al., 2016; Hajihassani et al., 2015; Jahed Armaghani et al., 2020; Danial et al., 2020). Each individual in the herd acts as a particle, and they fly around the searching space to seek the foods with a given velocity (Bui et al., 2019b; Zhang et al., 2020c). Their velocity can be continuously updated to share their experiences aiming

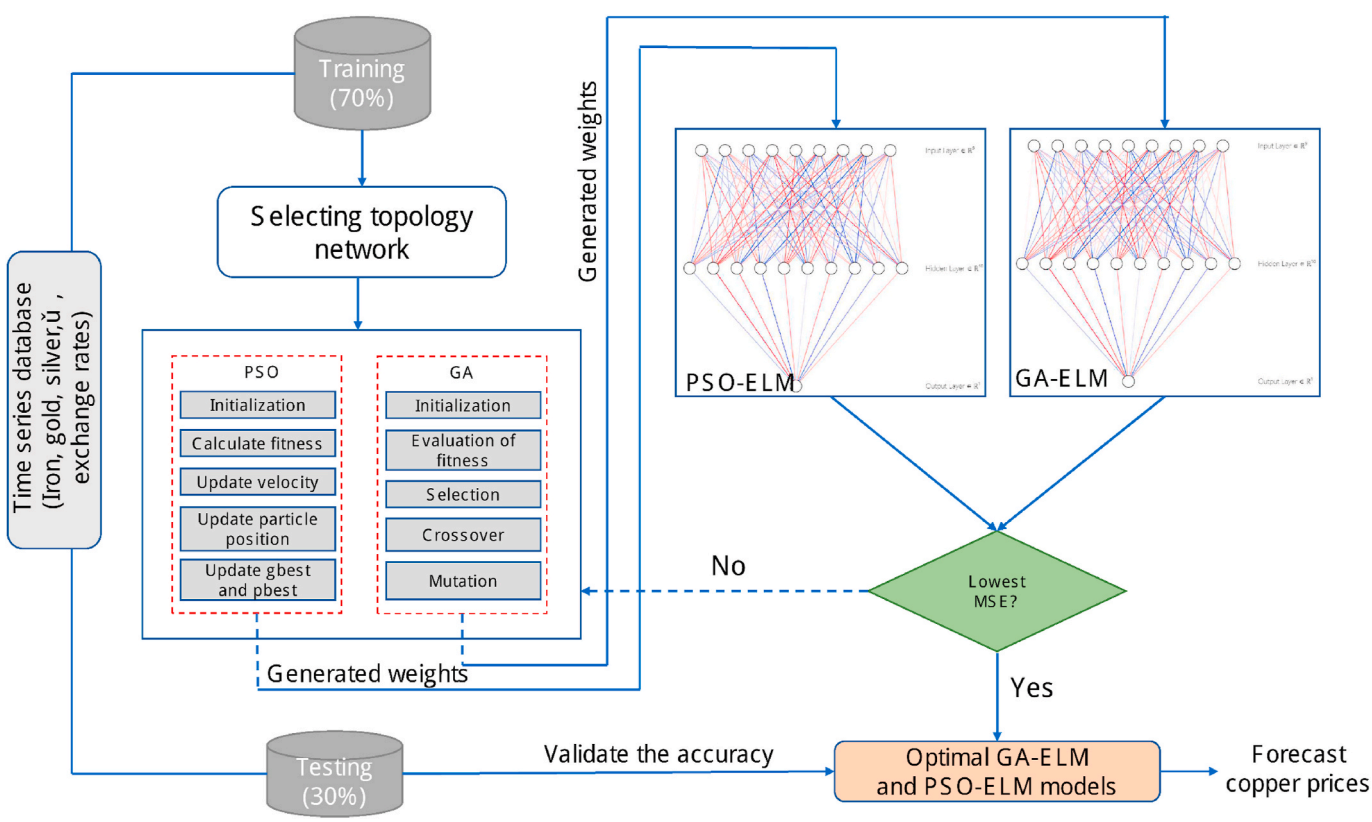


Fig. 5. Proposing the framework of the optimization intelligence models for forecasting copper prices.

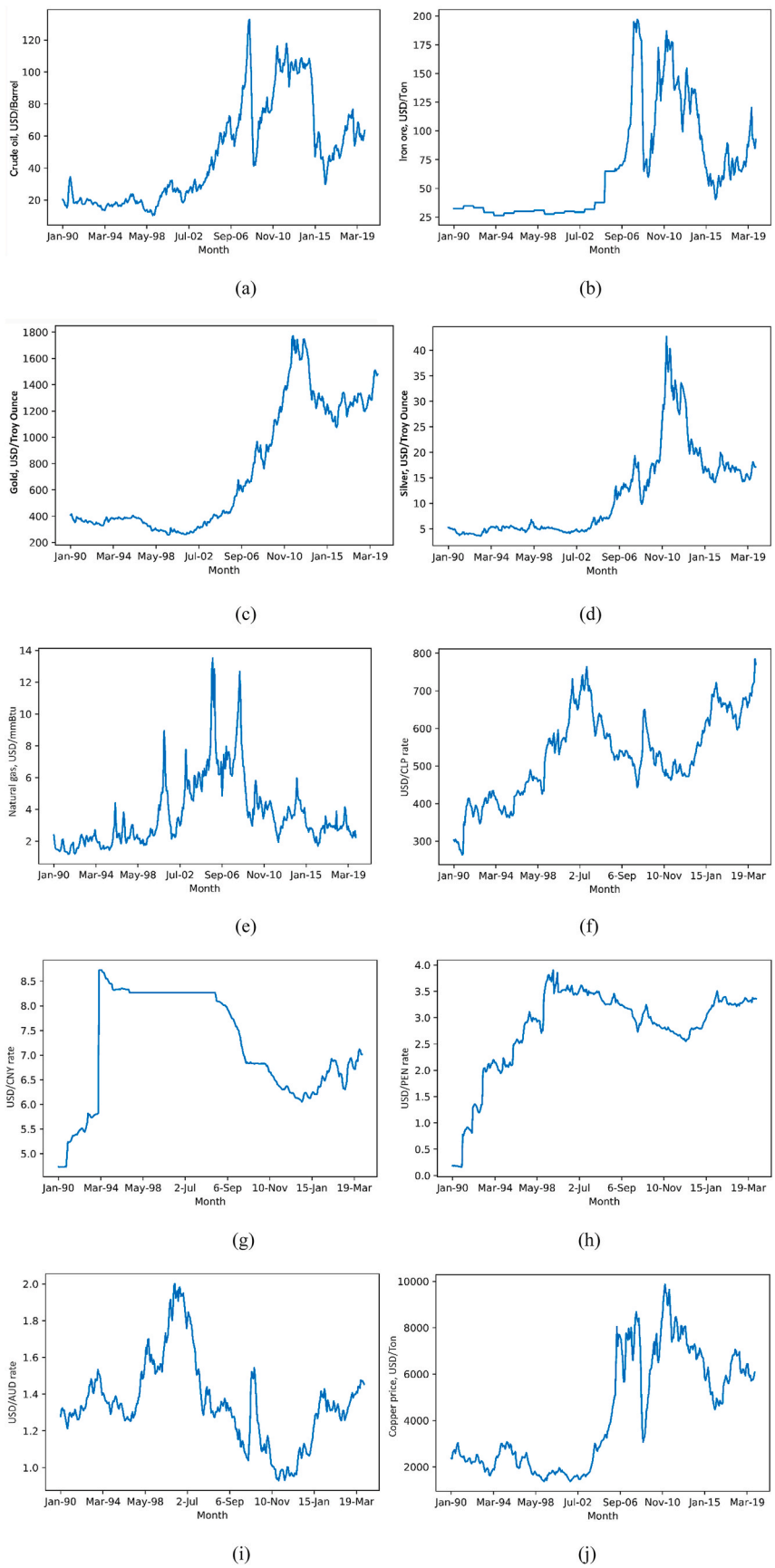


Fig. 6. Historical data used in this study for forecasting copper prices. Fig. 6. (Cont.). (a) Crude oil price; (b) Iron ore price; (c) Gold price; (d) Silver price; (e) Natural gas price; (f) Exchange rate between USD and CLP; (g) Exchange rate between USD and CNY; (h) Exchange rate between USD and PEN; (i) Exchange rate between USD and AUD; (j) Copper price.. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Summary of the monthly copper prices.

Category	Variables									
	Crude oil	Iron	Gold	Silver	Natural gas	USD vs CLP	USD vs CNY	USD vs PEN	USD vs AUD	Copper
count	360	360	360	360	360	360	360	360	360	360
mean	47.93653	65.94594	740.0569	11.57222	3.724611	529.8813	7.185217	2.80025	1.351106	4302.208
std	31.41344	46.07452	469.3777	8.441636	2.179986	112.2586	1.09137	0.816568	0.231239	2450.098
min	10.41	26.47	256.08	3.65	1.19	263.97	4.731	0.163	0.929	1377.28
25%	19.3925	30.03	353.6125	4.9275	2.22	446.6813	6.322	2.59975	1.25475	2054.638
50%	39.895	39.2	423.69	7.06	2.96	529.918	6.922	2.999	1.3265	3134.125
75%	68.605	87.005	1228.165	16.8	4.58	622.026	8.27	3.337	1.451	6684.913
max	132.83	197.12	1772.14	42.7	13.52	785.118	8.726	3.906	2.001	9867.6

Fig. 7. Splitting the time-series copper dataset.

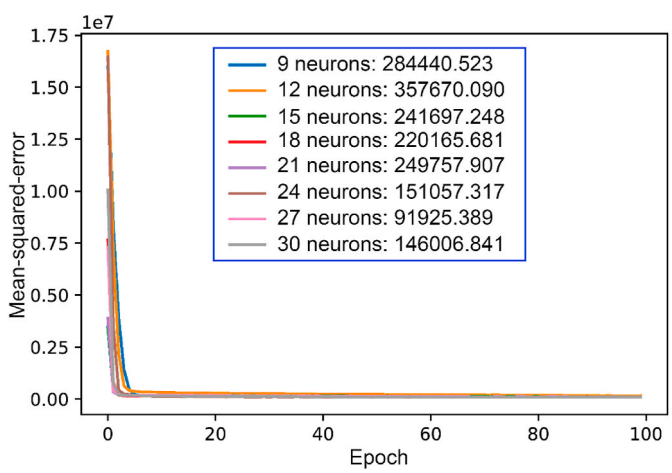


Fig. 8. Performance of the ELM model with the different number of neurons.

to reach better positions. Many iterations can be used to improve the accuracy of searching (Wang et al., 2020; Zhang et al., 2020b). At each iteration, the best position (best value of fitness) is recorded as the local best of the PSO. Also, the best positions at all the iterations are recorded as the global best of the PSO (Zhang et al., 2019, 2020b). Eventually, the best position is selected as the best solution for the swarm. The pseudo-code and the detail of the calculation of the PSO algorithm are presented in Fig. 4.

2.4. PSO-ELM and GA-ELM models

As stated above, the focus of this study is proposing novel intelligence models for forecasting copper prices with high accuracy based on machine learning and optimization algorithms. The combination of the ELM and GA and PSO to generate two novel models, i.e., GA-ELM and PSO-ELM, respectively, is the primary purpose of this study. For this aim, 70% of the copper price database was used to develop an initial ELM model. Subsequently, the GA and PSO algorithms were used to find and calculate the weights of the ELM model instead of the random weights of the traditional ELM model. Mean square error (MSE) was used as an objective function to evaluate the performance of the PSO-ELM and GA-ELM models. The best PSO-ELM and GA-ELM models are corresponding to the lowest MSE values. The framework of this approach is proposed in Fig. 5.

3. Statistical criteria for model assessment

In the present study, the ELM, ANN, ARIMA, GA-ELM, and PSO-ELM models are evaluated through a variety of statistical criteria, as described in equations (2)–(5), including mean absolute percentage error (MAPE), root-mean-squared error (RMSE), mean absolute scaled error (MASE), and mean absolute error (MAE).

$$\mathrm{MAPE} = \frac{100\%}{cp} \sum_{copper=1}^{cp} \left| \frac{y_{copper} - \hat{y}_{copper}}{y_{copper}} \right| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{cp} \sum_{copper=1}^{cp} \left(y_{copper} - \hat{y}_{copper} \right)^2} \tag{3}$$

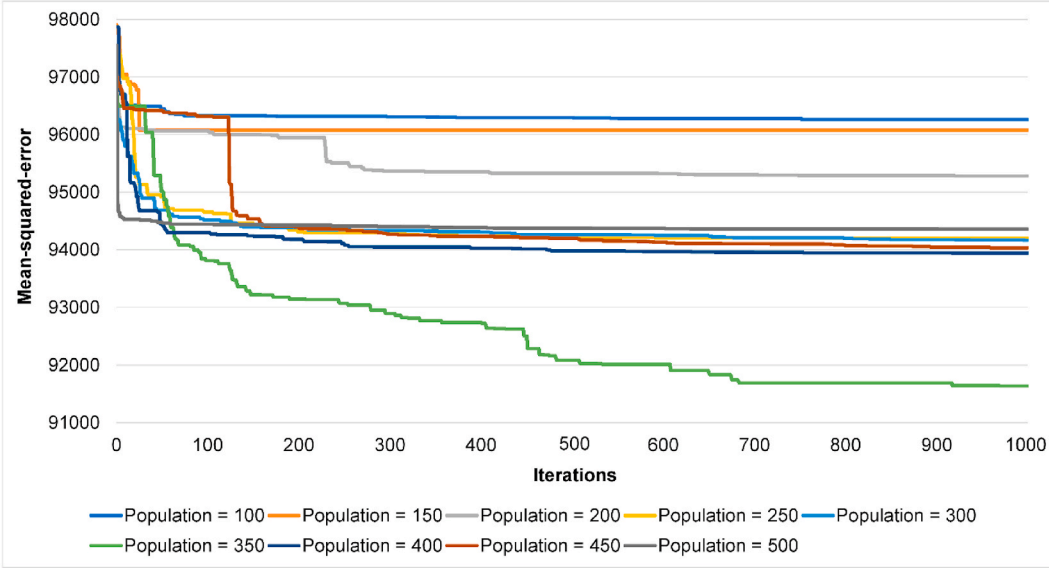
$$\mathrm{MASE} = \frac{1}{cp} \sum_{copper=1}^{cp} \left(\frac{\left| y_{copper} - \hat{y}_{copper} \right|}{\frac{1}{cp-1} \sum_{copper=1}^{cp} \left| y_{copper} - \hat{y}_{copper} - 1 \right|} \right) \tag{4}$$

$$\mathrm{MAE} = \frac{1}{cp} \sum_{copper=1}^{cp} \left| y_{copper} - \hat{y}_{copper} \right| \tag{5}$$

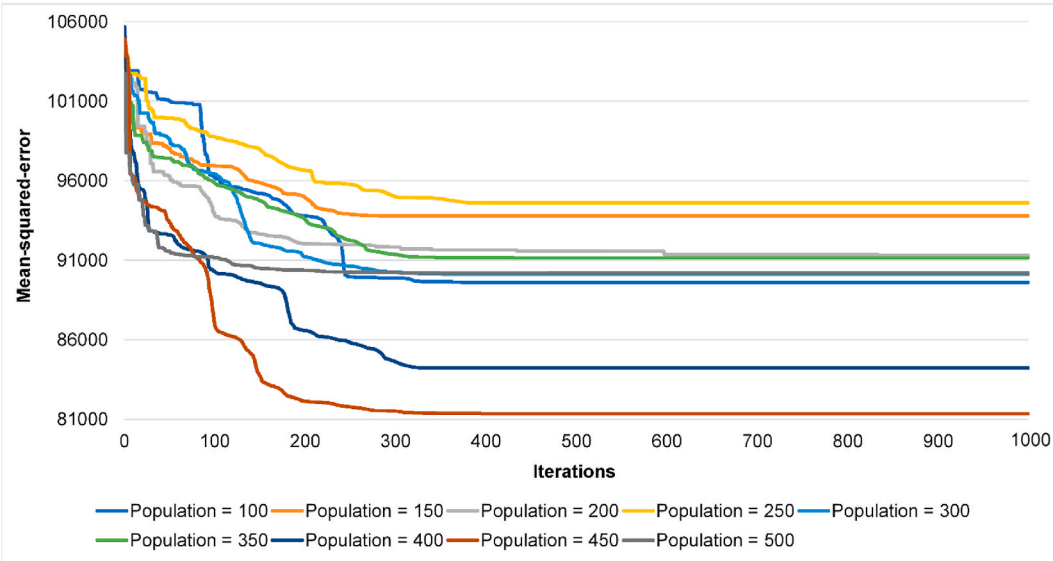
where cp is the samples of the copper price (monthly); y_{copper}, and $\hat{y}_{copper}$ are the actual and forecast of the copper price (monthly).

4. Dataset used

In this study, the dataset involves 360 months of the copper price in the world (in USD/ton), i.e., from January 1990 to December 2019. The time-series data of the relevant parameters were also collected for forecasting copper prices, such as crude oil (USD/barrel), iron ore (USD/ton), gold (USD/troy ounce), silver (USD/troy ounce), natural gas (USD/mmBtu), and the exchange rate of four largest countries in copper-producing, including Chile (USD/CLP), China (USD/CNY), Peru (USD/PEN), and Australia (USD/AUD). It is a fact that copper prices worldwide are highly dependent on the countries in copper-producing, especially large countries in copper-producing due to a large amount of copper being exported worldwide from these countries. The scarcity of



(a)



(b)

Fig. 9. Training performance with various populations of the GA-ELM and PSO-ELM models. (a) GA-ELM model; (b) PSO-ELM model.

copper supplies can drastically change the price of copper around the world. Therefore, we have selected the four largest countries in copper-producing as four of the input variables for forecasting monthly copper prices in this study. The details of the dataset used are illustrated in Fig. 6. It is worth noting that the dataset is available on https://www.indexmundi.com/commodities/and https://fxtop.com/en/historical-exchange-rates.php?MA=0&TR=1. The dataset was summarized in Table 1, and the original dataset was added to the supplementary material.

5. Results and discussion

To develop the forecast models in this study, the time-series dataset (with nine inputs and one output) was divided into two parts: 70% for in-sample (training) and 30% for out-of-sample (testing) (Nguyen et al., 2021a), as illustrated in Fig. 7. The MinMax scale method was applied to avoid over-fitting the models with the scale intervals [0,1]. A "trial-error" technique with different lag times was employed to define the step(s) for the forecast models. Finally, multi-step forecasting models with two steps (i.e., t-1, t-2) were applied for forecasting copper prices in the future. In other words, *t-1* and *t-2* are used as the input variables to forecast *t*.

As mentioned above, the structure of ELM consists of only one hidden layer; therefore, the number of neurons in the hidden layers is the only thing that needs to be selected in the ELM structure. A "trial-error" procedure with different neurons was conducted to determine the optimal number of neurons for the ELM neural network, as shown in Fig. 8. In conclusion, the ELM model with 27 neurons provided the lowest MSE (i.e., 91925.389). Therefore, the optimal structure of the ELM for forecasting copper price should be the ELM 9-27-1 model.

Once the optimal structure of the ELM was defined, GA and PSO algorithms were embedded to optimize the weights of the ELM neural network. The parameters of the GA and PSO algorithms are necessary

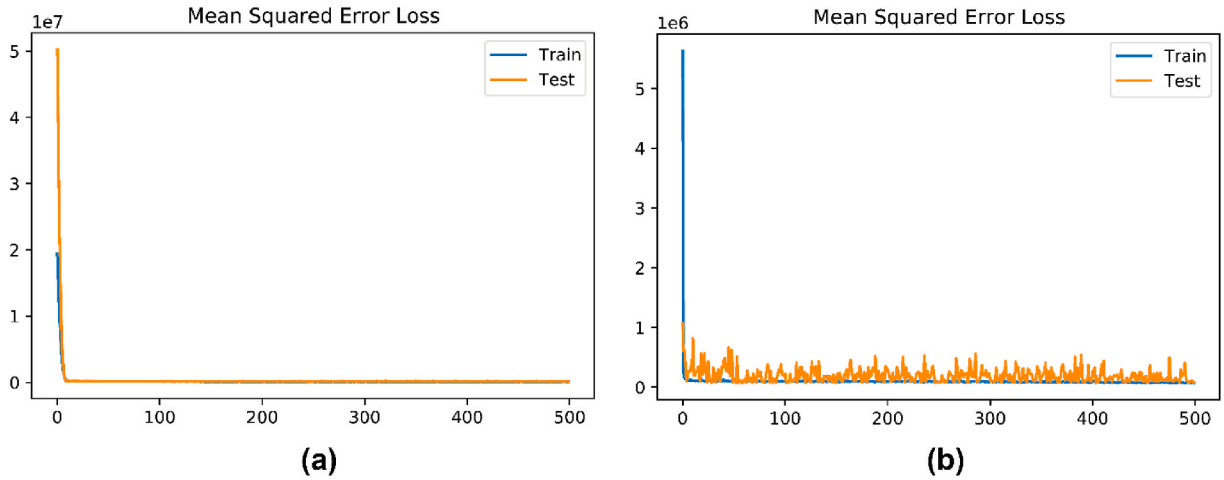


Fig. 10. Mean squared error loss of the selected ANN models. (a) The ANN 9-27-1 model; (b) The ANN 9-20-16-10-1 model.

Table 2
The accuracy of the ANN, ELM and hybrid ELM-based models.

Model	Training				Testing			
	RMSE	MAE	MAPE	MASE	RMSE	MAE	MAPE	MASE
ELM (9-27-1)	303.192	167.842	0.044	0.755	315.268	251.009	0.038	0.892
GA-ELM	292.717	160.005	0.043	0.763	310.581	252.947	0.039	0.919
PSO-ELM	285.236	152.496	0.042	0.772	304.943	241.946	0.037	0.933
ANN 9-27-1	306.618	173.821	0.045	0.758	316.684	262.061	0.039	0.826
ANN 9-20-16-10-1	306.102	208.567	0.062	0.842	313.012	245.692	0.037	0.836

before optimizing the ELM neural network. They were set up as follow:

- GA's parameters: p_m (mutation probability) = 0.025; p_c (crossover probability) = 0.95.
- PSO's parameters: $V_{\max}$ (maximum particle's velocity) = 2; c_i (individual cognitive) = 1.2; c_g (group cognitive) = 1.2; w (weight of bird) = 0.85.

To investigate the performance of the PSO-ELM and GA-ELM models under different number of populations (p_{size}), the p_{size} were assigned as 100, 150, 200, 250, 300, 350, 400, 450, and 500. To meet the stopping condition (i.e., lowest MSE), 1000 iterations were set up for both PSO-ELM and GA-ELM models. The training performance of the PSO-ELM and GA-ELM models is shown in Fig. 9. Finally, the optimal parameters of the PSO-ELM and GA-ELM were defined as follows:

- GA-ELM model: $p_m = 0.025$; $p_c = 0.95$; $p_{size} = 350$; $iteration = 918$.
- PSO-ELM model: $V_{\max} = 2$; $c_i = 1.2$; $c_g = 1.2$; $w = 0.85$; $p_{size} = 450$; $iteration = 423$.

In order to forecast copper price by ANN, two ANN models with one and multiple hidden layers were taken into account. The main rationale for selecting these two ANN models is to compare them with the ELM model in forecasting copper prices. Accordingly, an ANN model with the same structure as the ELM model (i.e., 9-27-1) was developed as the first ANN model. Another ANN model with multiple hidden layers was also developed to compare with the ELM model regarding the hidden layers. A trial and error procedure was applied to design the ANN model with multiple hidden layers, and the ANN 9-20-16-10 model was selected and developed for this aim. Finally, two ANN models were developed for forecasting copper price, including ANN 9-27-1 and ANN 9-20-16-10-1. In order to train these ANN models, the BP algorithm was used. Also, the MinMax scale method with the range of 0–1 was applied to avoid overfitting the ANN models (Zhang et al., 2021). The performance of the selected ANN models is shown in Fig. 10.

Once the ELM neural network was well-adjusted by the GA and PSO algorithms, the performance of the PSO-ELM and GA-ELM models were evaluated based on the in-sample and out-of-sample. The traditional ELM model (without optimization) and ANN models were also compared with the PSO-ELM and GA-ELM models to clarify the improvement of the ELM-based models proposed. Table 2 shows the performance and results of the mentioned models on the in-sample (training dataset) and out-of-sample (testing dataset).

As shown in Table 2, we can see that all forecast models performed very well, with the errors are very low (MAPE ~ 4%). Considering the ELM and ANN models, it is obvious that the ELM model is more accurate than the ANN in forecasting cooper price even though the number of hidden layers of the ANN 9-20-16-10-1 model is higher ELM model (only one hidden layer). The ANN 9-27-1 model also provided lower performance in the same structure than those of the ELM model. Remarkably, the ELM model with optimizing the GA and PSO algorithms improved the ELM model's accuracy, and the accuracy of the proposed PSO-ELM and GA-ELM models is higher than the traditional ELM model and ANN models. Among the two proposed hybrid models (i.e., PSO-ELM and GA-ELM models), the PSO-ELM model forecasted copper price more accurately than the GA-ELM model on both in-sample and out-of-sample through the statistical criteria. These findings interpret the critical role of the optimization algorithms in this study, especially in the coupling of the ELM model. In other words, the accuracy of the ELM models after optimizing (i.e., PSO-ELM and GA-ELM) is significantly higher than those of the ELM model without optimization. Further evaluation of the accuracy of the models is demonstrated in Fig. 11.

Observing Fig. 11, we can see that the performance and accuracy of the models on the training dataset are very high. The copper prices in the long-term were forecasted very close to the actual price. On the testing dataset, we can see that the trend of the models is similar to the actual price. Of those, the forecasted copper price by the PSO-ELM model is closer to the actual price than those of the ELM, GA-ELM, and ANN models in the long term (107 months of the testing dataset).

A Taylor diagram was adopted to evaluate the stability of the copper

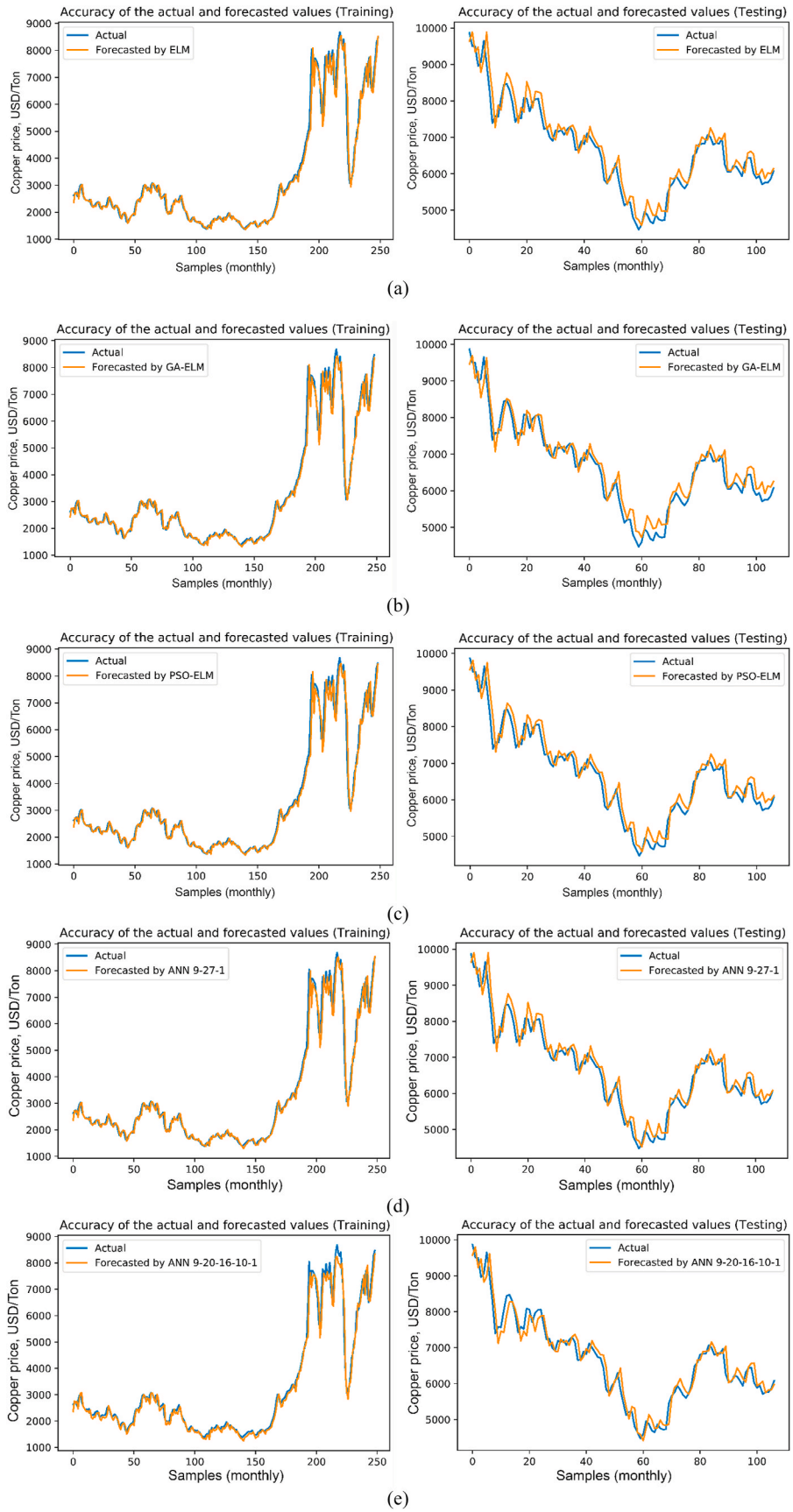


Fig. 11. Actual copper price versus predicted copper price by the individual models. (a) ELM model; (b) GA-ELM model; (c) PSO-ELM model; (d) ANN 9-27-1 model; (e) ANN 9-20-16-10-1 model.

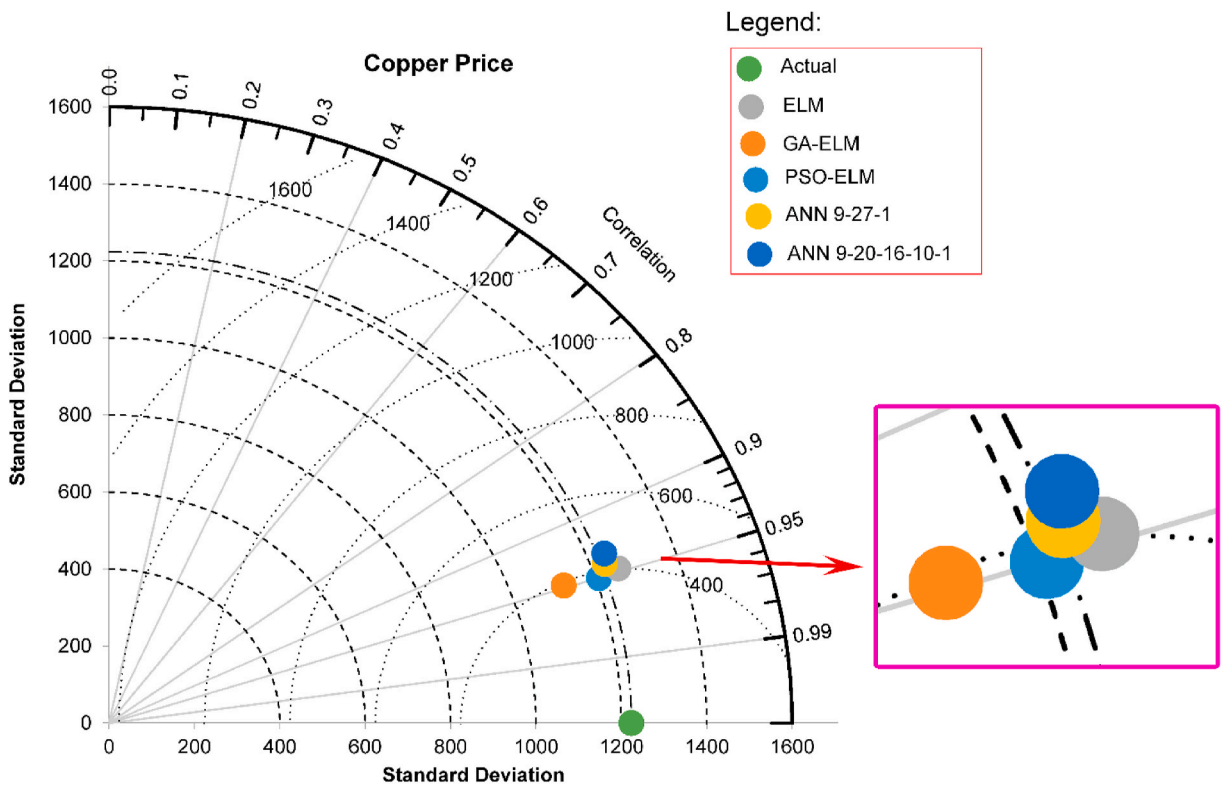


Fig. 12. Taylor diagram for the evaluation of the copper price forecast models.

Table 3
Statistical analysis of the models based on *t*-test and Wilcoxon test.

Model	*t*-test					Wilcoxon test	
	t	df	p-value	95% confident interval	Mean of the differences	V	p-value
ELM	−5.741	107	9.072e-08	[-206.556, −100.507]	−153.532	1247	3.364e-07
GA-ELM	−5.188	107	1.027e-06	[-189.672, −84.793]	−137.233	1353	1.821e-06
PSO-ELM	−4.400	107	2.589e-05	[-177.046, −67.054]	−122.050	1504	1.685e-05
ANN 9-27-1	−3.855	107	0.000199	[-208.165, −103.945]	−161.055	1223	0.000292
ANN 9-20-16-10-1	−1.339	107	0.1836	[-210.129, −109.417]	−160.356	1284	0.1169

price forecast models, as shown in Fig. 12. Herein, the stability of the models was evaluated through the standard deviation and correlation. Note that the Taylor diagram was conducted on the out-of-sample dataset to test the stability of the model in actuality. As can be seen, the GA-ELM model provided the lowest standard deviation, and its standard deviation is lower than the standard deviation of the actual model. However, a closer looking at Fig. 11, we can see that the PSO-ELM model seems to be more stable than the GA-ELM model since the standard deviation of the PSO-ELM and the actual models are not too dissimilar. Furthermore, the correlation of the PSO-ELM model is slightly higher than the GA-ELM model. In comparison, the traditional ELM model provided lower stability nor correlation than those of the GA-ELM and PSO-ELM models. It is important to note that the ANN models provided the lowest stability and accuracy since its standard deviation is higher than the actual model even though the structure of the ANN 9-27-1 model is the same as the ELM model.

Through the analysis described above, it can be seen that the models with the contributions of the optimization algorithms (i.e., GA and PSO) provided better accuracy than the single ELM and ANN models. The question is whether the results obtained are sufficient to conclude that the GA and PSO algorithms effectively improve the accuracy of the ELM model, or are they caused by random factors? Two test methods were employed to answer this question, namely *t*-test and Wilcoxon-test (Blair and Higgins, 1985; Bridge and Sawilowsky, 1999; Sawilowsky, 2005). The test results of the models are listed in Table 3.

The analytical results in Table 3 showed that the forecasted copper price by the PSO-ELM model is higher $122.05 than the actual copper price, and the 95% confidence interval is from $177.046 to $67.054 with p-value = 2.589e-05. Whereas, the GA-ELM model provided the forecasted copper price higher $137.233 than the actual copper price, and the 95% confidence interval is from $189.672 to $84.793 with p-value = 1.027e-06. Without optimization, the ELM model provided the forecasted copper price higher $153.532 than the actual copper price, and the 95% confidence interval is from $206.556 to $100.507 with p-value = 9.072e-08. Meanwhile, the ANN models provided a higher mean of the differences (e.g., $161 for the ANN 9-27-1 model and $160 for the ANN 9-20-16-10-1 model). These statistical indices are even higher than those of the ELM model. Remarkable, the p-value of the ANN 9-20-16-10-1 model is higher than 0.05. In other words, the ANN 9-20-16-10-1 model is not statistically significant, and it should not be used to forecast the copper price.

The test results from the Wilcoxon test method are similar to the *t*-test method. Thus, it can conclude that the developed models are statistically significant except the ANN 9-20-16-10-1 model. Although the statistical significance and the error of the models are different; however, based on the obtained results in Table 2 and Figs. 11 and 12, it can be concluded that the PSO- ELM is the best model for forecasting copper price in this study.

6. Conclusion

Forecasting copper prices with high accuracy and reliability are vital for investors and businesses. Investigation results showed that copper prices have complicated movements from 1990 to 2019, and accurate forecasting fluctuations in copper prices is a challenge. This study developed and proposed two novel machine learning models for forecasting monthly copper prices with high accuracy and reliability, i.e., PSO-ELM and GA-ELM. Also, the traditional ELM model (without optimization) and ANN models were developed and evaluated to forecast copper prices in this study. The results showed that the ELM neural network is a state-of-the-art model with a simple structure and high performance. Furthermore, its performance was significant improved by the GA and PSO algorithms in forecasting copper price (i.e., GA-ELM and PSO-ELM models). Of those, the PSO-ELM model was introduced as the best machine learning model for forecasting copper price with the highest accuracy, reliability, and stability in actual (i.e., RMSE = 304.943, MAE = 241.946, MAPE = 0.037, and MASE = 0.933). It can be used to evaluate and take into account the copper price in the future for the investment of the relevant fields.

Although the obtained results in this work are favorable; however, some limitations need to be considered in future works. For example, the forecast of daily copper prices is necessary instead of the monthly copper price as forecasted in this study; the feasibility of other intelligent methods and optimization algorithms in forecasting copper prices. Furthermore, most previous studies as well as this study, performed the forecast of copper prices based on multivariate models. Therefore, taking the univariate models into account for forecasting copper prices might provide simpler models in this regard.

Acknowledgments

The authors would like to thank the Center for Mining and Electro-Mechanical Research, Hanoi University of Mining and Geology (HUMG), Hanoi, Vietnam, and the Innovations for Sustainable and Responsible Mining (ISRM) research group of HUMG, for their supports.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2021.102195.

References

Aggarwal, S.K., Saini, L.M., Kumar, A., 2009. Electricity price forecasting in deregulated markets: a review and evaluation. Int. J. Electr. Power Energy Syst. 31, 13–22.
Alameer, Z., Elaziz, M.A., Ewees, A.A., Ye, H., Jianhua, Z., 2019. Forecasting copper prices using hybrid adaptive neuro-fuzzy inference system and genetic algorithms. Nat. Resour. Res. 28, 1385–1401.
Armaghani, D.J., Asteris, P.G., 2021. A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength. Neural Comput. Appl. 33, 4501–4532.
Armaghani, D.J., Hasanipanah, M., Mahdiyar, A., Majid, M.Z.A., Amnieh, H.B., Tahir, M. M., 2018. Airblast prediction through a hybrid genetic algorithm-ANN model. Neural Comput. Appl. 29, 619–629.
Asteris, P.G., Ashrafian, A., Rezaie-Balf, M., 2019. Prediction of the compressive strength of self-compacting concrete using surrogate models. Comput. Concr. 24, 137–150.
Astudillo, G., Carrasco, R., Fernández-Campusano, C., Chacón, M., 2020. Copper price prediction using support vector regression technique. Appl. Sci. 10, 6648.
Blair, R.C., Higgins, J.J., 1985. Comparison of the power of the paired samples t test to that of Wilcoxon's signed-ranks test under various population shapes. Psychol. Bull. 97, 119.
Bridge, P.D., Sawilowsky, S.S., 1999. Increasing physicians' awareness of the impact of statistics on research outcomes: comparative power of the t-test and Wilcoxon rank-sum test in small samples applied research. J. Clin. Epidemiol. 52, 229–235.
Bui, H.-B., Nguyen, H., Choi, Y., Bui, X.-N., Nguyen-Thoi, T., Zandi, Y., 2019a. A novel artificial intelligence technique to estimate the gross calorific value of coal based on meta-heuristic and support vector regression algorithms. Appl. Sci. 9, 4868.
Bui, X.-N., Jaroonpattanapong, P., Nguyen, H., Tran, Q.-H., Long, N.Q., 2019b. A novel hybrid model for predicting blast-induced ground vibration based on k-nearest neighbors and particle swarm optimization. Sci. Rep. 9, 1–14.
Bui, XN., Muazu, M.A., Nguyen, H., 2020. Optimizing Levenberg–Marquardt backpropagation technique in predicting factor of safety of slopes after two-dimensional OptumG2 analysis. Eng. Comput. 36, 941–952. https://doi.org/10.1007/s00366-019-00741-0.
Bui, X.-N., Nguyen, H., Tran, Q.-H., Nguyen, D.-A., Bui, H.-B., 2021. Predicting ground vibrations due to mine blasting using a novel artificial neural network-based cuckoo search optimization. Nat. Resour. Res. 30, 2663–2685.
Buncic, D., Moretto, C., 2015. Forecasting copper prices with dynamic averaging and selection models. N. Am. J. Econ. Finance 33, 1–38.
Cao, Z., Xia, J., Zhang, M., Jin, J., Deng, L., Wang, X., Qu, J., 2015. Optimization of gear blank preforms based on a new R-GPLVM model utilizing GA-ELM. Knowl. Base Syst. 83, 66–80.
Chen, W., Sarir, P., Bui, XN., et al., 2020. Neuro-genetic, neuro-imperialism and genetic programing models in predicting ultimate bearing capacity of pile. Eng. Comput. 36, 1101–1115. https://doi.org/10.1007/s00366-019-00752-x.
Chu, Z., Ma, Y., Cui, J., 2018. Adaptive reactionless control strategy via the PSO-ELM algorithm for free-floating space robots during manipulation of unknown objects. Nonlinear Dynam. 91, 1321–1335.
Danial Jahed, Armaghani, Mahdi, Hasanipanah, Amir, Mahdiyar, Muhd Zaimi Abd, Majid, Hassan Bakhshandeh, Aminieh, Mahmood M. D., Tahir, 2018. Airblast prediction through a hybrid genetic algorithm-ANN model. Neural Comput. Appl. 29, 619–629. https://doi.org/10.1007/s00521-016-2598-8.
Danial Jahed, Armaghani, Panagiotis G., Asteris, Seyed Alireza, Fatemi, Mahdi, Hasanipanah, Reza, Tarinejad, Ahmad Safuan A., Rashid, Van Van, Huynh, 2020. On the Use of Neuro-Swarm System to Forecast the Pile Settlement. Appl. Sci. 10 (6) https://doi.org/10.3390/app10061904.
Dehghani, H., 2018. Forecasting copper price using gene expression programming. Journal of Mining and Environment 9, 349–360.
Dehghani, H., Bogdanovic, D., 2018. Copper price estimation using bat algorithm. Resour. Pol. 55, 55–61.
Díaz, J.D., Hansen, E., Cabrera, G., 2020. A random walk through the trees: forecasting copper prices using decision learning methods. Resour. Pol. 69, 101859.
Eberhart, Kennedy, J., 1995. A new optimizer using particle swarm theory, MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science. IEEE, pp. 39–43.
Ertugrul, Ö.F., 2016. Forecasting electricity load by a novel recurrent extreme learning machines approach. Int. J. Electr. Power Energy Syst. 78, 429–435.
Fang, Q., Nguyen, H., Bui, X.-N., Nguyen-Thoi, T., 2019. Prediction of blast-induced ground vibration in open-pit mines using a new technique based on imperialist competitive algorithm and M5Rules. Nat. Resour. Res. 29, 791–806.
Fang, Q., Nguyen, H., Bui, X.-N., Tran, Q.-H., 2020. Estimation of blast-induced air overpressure in quarry mines using cubist-based genetic algorithm. Nat. Resour. Res. 29, 593–607.
Faradonbeh, R.S., Armaghani, D.J., Monjezi, M., 2016a. Development of a new model for predicting flyrock distance in quarry blasting: a genetic programming technique. Bull. Eng. Geol. Environ. 75, 993–1006.
Faradonbeh, R.S., Armaghani, D.J., Monjezi, M., Mohamad, E.T., 2016b. Genetic programming and gene expression programming for flyrock assessment due to mine blasting. Int. J. Rock Mech. Min. Sci. 88, 254–264.
Figueiredo, E.M., Ludermir, T.B., 2014. Investigating the use of alternative topologies on performance of the PSO-ELM. Neurocomputing 127, 4–12.
Gordan, B., Armaghani, D.J., Hajihassani, M., Monjezi, M., 2016. Prediction of seismic slope stability through combination of particle swarm optimization and neural network. Eng. Comput. 32, 85–97.
Guo, H., Nguyen, H., Bui, XN., et al., 2021. A new technique to predict fly-rock in bench blasting based on an ensemble of support vector regression and GLMNET. Eng. Comput. 37, 421–435. https://doi.org/10.1007/s00366-019-00833-x.
Guo, H., Nguyen, H., Vu, D.-A., Bui, X.-N., 2019b. Forecasting mining capital cost for open-pit mining projects based on artificial neural network approach. Resour. Pol. 101474.
Hajihassani, M., Armaghani, D.J., Monjezi, M., Mohamad, E.T., Marto, A., 2015. Blast-induced air and ground vibration prediction: a particle swarm optimization-based artificial neural network approach. Environmental Earth Sciences 74, 2799–2817.
Haupt, R., Haupt, S., 1998. Practical Genetic Algorithms. 2ndEdn. lohn Wiley and Sons Inc., New York.
Hu, Y., Ni, J., Wen, L., 2020. A hybrid deep learning approach by integrating LSTM-ANN networks with GARCH model for copper price volatility prediction. Phys. Stat. Mech. Appl. 557, 124907.
Huang, G.-B., Wang, D.H., Lan, Y., 2011a. Extreme learning machines: a survey. International journal of machine learning and cybernetics 2, 107–122.
Huang, G.-B., Zhou, H., Ding, X., Zhang, R., 2011b. Extreme learning machine for regression and multiclass classification. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 42, 513–529.
Huang, G.-B., Zhu, Q.-Y., Siew, C.-K., 2006. Extreme learning machine: theory and applications. Neurocomputing 70, 489–501.
Jahed Armaghani, D., Kumar, D., Samui, P., Hasanipanah, M., Roy, B., 2020. A novel approach for forecasting of ground vibrations resulting from blasting: modified particle swarm optimization coupled extreme learning machine. Eng. Comput. https://doi.org/10.1007/s00366-020-00997-x.
Ke, B., Nguyen, H., Bui, X.-N., Bui, H.-B., Choi, Y., Zhou, J., Moayedi, H., Costache, R., Nguyen-Trang, T., 2021a. Predicting the sorption efficiency of heavy metal based on the biochar characteristics, metal sources, and environmental conditions using various novel hybrid machine learning models. Chemosphere 276, 130204.
Ke, B., Nguyen, H., Bui, X.-N., Bui, H.-B., Nguyen-Thoi, T., 2021b. Prediction of the sorption efficiency of heavy metal onto biochar using a robust combination of fuzzy

C-means clustering and back-propagation neural network. J. Environ. Manag. 293, 112808.
Kennedy, J., 2010. Particle swarm optimization. In: Sammut, C., Webb, G.I. (Eds.), Encyclopedia of Machine Learning. Springer US, Boston, MA, pp. 760–766.
Khandelwal, M., Armaghani, D.J., Faradonbeh, R.S., Yellishetty, M., Majid, M.Z.A., Monjezi, M., 2017. Classification and regression tree technique in estimating peak particle velocity caused by blasting. Eng. Comput. 33, 45–53.
Kochenderfer, M.J., Wheeler, T.A., 2019. Algorithms for Optimization. Mit Press.
Kulkarni, R.V., Venayagamoorthy, G.K., 2007. An Estimation of Distribution Improved Particle Swarm Optimization Algorithm, 2007 3rd International Conference on Intelligent Sensors. Sensor Networks and Information. IEEE, pp. 539–544.
Kumar, M., Husain, M., Upreti, N., Gupta, D., 2010. Genetic Algorithm: Review and Application. Available at: SSRN 3529843.
Lalwani, S., Sharma, H., Satapathy, S.C., Deep, K., Bansal, J.C., 2019. A survey on parallel particle swarm optimization algorithms. Arabian J. Sci. Eng. 44, 2899–2923.
Le Minh, Thong, 2020. Overview of energy forecasting models - the possibility of applying the POLES forecasting model for Vietnam in the current context. J. Min. Earth Sci. 61 (5), 118–124. https://doi.org/10.46326/JMES.KTQTKD2020.16.
Le, L.T., Nguyen, H., Dou, J., Zhou, J., 2019. A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning. Appl. Sci. 9, 2630.
Liu, C., Hu, Z., Li, Y., Liu, S., 2017. Forecasting copper prices by decision tree learning. Resour. Pol. 52, 427–434.
Liu, L., Moayedi, H., Rashid, A.S.A., Rahman, S.S.A., Nguyen, H., 2020. Optimizing an ANN model with genetic algorithm (GA) predicting load-settlement behaviours of eco-friendly raft-pile foundation (ERP) system. Eng. Comput. 36, 421–433. https://doi.org/10.1007/s00366-019-00767-4.
Livingstone, D.J., 2008. Artificial Neural Networks: Methods and Applications. Springer.
Luan, J., Yao, Z., Zhao, F., Song, X., 2019. A novel method to solve supplier selection problem: hybrid algorithm of genetic algorithm and ant colony optimization. Math. Comput. Simulat. 156, 294–309.
Mai, N.L., Topal, E., Erten, O., Sommerville, B., 2016. Risk Reduction Strategy for the Iron Ore Production Scheduling Using Stochastic Integer Programming.
Manoj, Khandelwal, Danial Jahed, Armaghani, Roohollah Shirani, Faradonbeh, Mohan, Yellishetty, Muhd Zaimi Abd, Majid, Masoud, Monjezi, 2017. Classification and regression tree technique in estimating peak particle velocity caused by blasting. Engineering with Computers 33, 45–53. https://doi.org/10.1007/s00366-016-0455-0.
Mirjalili, S., Dong, J.S., Sadiq, A.S., Faris, H., 2020. Genetic Algorithm: Theory, Literature Review, and Application in Image Reconstruction, Nature-Inspired Optimizers. Springer, pp. 69–85.
Mohamad, E.T., Armaghani, D.J., Hasanipanah, M., Murlidhar, B.R., Alel, M.N.A., 2016. Estimation of air-overpressure produced by blasting operation through a neuro-genetic technique. Environmental Earth Sciences 75, 174.
Mohammadpour, T., Bidgoli, A.M., Enayatifar, R., Javadi, H.H.S., 2019. Efficient clustering in collaborative filtering recommender system: hybrid method based on genetic algorithm and gravitational emulation local search algorithm. Genomics 111, 1902–1912.
Mukhopadhyay, D.M., Balitanas, M.O., Farkhod, A., Jeon, S.-H., Bhattacharyya, D., 2009. Genetic algorithm: a tutorial review. International journal of grid and distributed computing 2, 25–32.
Nguyen, H., Bui, X.-N., Bui, H.-B., Mai, N.-L., 2018. A comparative study of artificial neural networks in predicting blast-induced air-blast overpressure at Deo Nai open-pit coal mine. Vietnam. Neural Computing and Applications 32, 3939–3955.
Nguyen, H., Bui, X.-N., Tran, Q.-H., 2021a. Estimating air over-pressure resulting from blasting in quarries based on a novel ensemble model (GLMNETs–MLPNN). Nat. Resour. Res. 30, 2629–2646.
Nguyen, H., Bui, X.-N., Tran, Q.-H., Nguyen, H.A., Nguyen, D.-A., Le, Q.-T., 2021b. Prediction of ground vibration intensity in mine blasting using the novel hybrid MARS–PSO–MLP model. Eng. Comput. 1–19.
Nguyen, H., Drebenstedt, C., Bui, X.-N., Bui, D.T., 2019. Prediction of blast-induced ground vibration in an open-pit mine by a novel hybrid model based on clustering and artificial neural network. Nat. Resour. Res. 29, 691–709.
Nguyen Thi Kim, Ngan, Hoang Thi, Phuong, 2020. Potential and trends of use clean energy in Vietnam. J. Min. Earth Sci. 61 (5), 1–8. https://doi.org/10.46326/JMES.KTQTKD2020.01.
Nguyen Cong, Tan, Luu Thi Thu, Ha, Dong Thi, Bich, 2020. Coal pricing mechanism of some countries in the world and lessons learned for Vietnam national Coal – Mineral industries holding corporation limited. J. Min. Earth Sci. 61 (5), 60–67. https://doi.org/10.46326/JMES.KTQTKD2020.09.
Nguyen Thi Huyen, Trang, Nguyen Thi Tuyet, Mai, 2020. Effeciency of using the business capital: realistic vision in Mong Duong Coal Joint Stock Company – Vinacomin. J. Min. Earth Sci. 61 (5), 18–25. https://doi.org/10.46326/JMES.KTQTKD2020.03.
Nowotarski, J., Weron, R., 2018. Recent advances in electricity price forecasting: a review of probabilistic forecasting. Renew. Sustain. Energy Rev. 81, 1548–1568.
Pahuja, G., Nagabhushan, T., 2016. A Novel GA-ELM Approach for Parkinson's Disease Detection Using Brain Structural T1-Weighted MRI Data, 2016 Second International Conference on Cognitive Computing and Information Processing (CCIP). IEEE, pp. 1–6.
Poli, R., Kennedy, J., Blackwell, T., 2007. Particle swarm optimization. Swarm intelligence 1, 33–57.
Rosa, J.P., Guerra, D.J., Horta, N.C., Martins, R.M., Lourenço, N.C., 2020. Overview of Artificial Neural Networks, Using Artificial Neural Networks for Analog Integrated Circuit Design Automation. Springer, pp. 21–44.
Sattar, A.M., Ertuğrul, Ö.F., Gharabaghi, B., McBean, E.A., Cao, J., 2019. Extreme learning machine model for water network management. Neural Comput. Appl. 31, 157–169.
Sawilowsky, S.S., 2005. Misconceptions Leading to Choosing the T Test over the Wilcoxon Mann-Whitney Test for Shift in Location Parameter.
Seguel, F., Carrasco, R., Adasme, P., Alfaro, M., Soto, I., 2015. A meta-heuristic approach for copper price forecasting. International Conference on Informatics and Semiotics in Organisations. Springer, pp. 156–165.
Shi, X., Zhou, J., 2012. Prediction residential house's damage effect near openpit against blasting vibration based on SVM with grid searching method/genetic algorithm. Adv. Sci. Lett. 11, 238–243.
Sivaraj, R., Ravichandran, T., 2011. A review of selection methods in genetic algorithm. Int. J. Eng. Sci. Technol. 3, 3792–3797.
Tapia, C., Coulton, J., Saydam, S., 2020. Using entropy to assess dynamic behaviour of long-term copper price. Resour. Pol. 66, 101597.
Umbarkar, A., Sheth, P., 2015. Crossover operators in genetic algorithms: a review. ICTACT journal on soft computing 6.
Vose, M.D., 1999. The Simple Genetic Algorithm: Foundations and Theory. MIT press.
Wang, D., Luo, H., Grunder, O., Lin, Y., Guo, H., 2017a. Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm. Appl. Energy 190, 390–407.
Wang, B., Moayedi, H., Nguyen, H., Foong, L.K., Rashid, A.S.A., 2020. Feasibility of a novel predictive technique based on artificial neural network optimized with particle swarm optimization estimating pullout bearing capacity of helical piles. Eng. Comput. 36, 1315–1324. https://doi.org/10.1007/s00366-019-00764-7.
Wang, X., Wang, C., Li, Q., 2017b. Short-term wind power prediction using GA-ELM. Open Electr. Electron. Eng. J. 11.
Weron, R., 2014. Electricity price forecasting: a review of the state-of-the-art with a look into the future. Int. J. Forecast. 30, 1030–1081.
Whitley, D., 1994. A genetic algorithm tutorial. Stat. Comput. 4, 65–85.
Yang, L., Nguyen, H., Bui, X.-N., Nguyen-Thoi, T., Zhou, J., Huang, J., 2021. Prediction of gas yield generated by energy recovery from municipal solid waste using deep neural network and moth-flame optimization algorithm. J. Clean. Prod. 127672.
Ye, Y., Qin, Y., 2015. QR factorization based Incremental Extreme Learning Machine with growth of hidden nodes. Pattern Recogn. Lett. 65, 177–183.
Yu, Z., Shi, X., Miao, X., Zhou, J., Khandelwal, M., Chen, X., Qiu, Y., 2021. Intelligent modeling of blast-induced rock movement prediction using dimensional analysis and optimized artificial neural network technique. Int. J. Rock Mech. Min. Sci. 143, 104794.
Zhang, H., Nguyen, H., Bui, X.-N., Nguyen-Thoi, T., Bui, T.-T., Nguyen, N., Vu, D.-A., Mahesh, V., Moayedi, H., 2020a. Developing a novel artificial intelligence model to estimate the capital cost of mining projects using deep neural network-based ant colony optimization algorithm. Resour. Pol. 66, 101604.
Zhang, H., Nguyen, H., Bui, X.-N., Pradhan, B., Asteris, P.G., Costache, R., Aryal, J., 2021. A generalized artificial intelligence model for estimating the friction angle of clays in evaluating slope stability using a deep neural network and Harris Hawks optimization algorithm. Eng. Comput. 1–14.
Zhang, X., Nguyen, H., Bui, X.-N., Le, H.A., Nguyen-Thoi, T., Moayedi, H., Mahesh, V., 2020b. Evaluating and predicting the stability of roadways in tunnelling and underground space using artificial neural network-based particle swarm optimization. Tunn. Undergr. Space Technol. 103, 103517.
Zhang, X., Nguyen, H., Bui, X.-N., Tran, Q.-H., Nguyen, D.-A., Bui, D.T., Moayedi, H., 2019. Novel soft computing model for predicting blast-induced ground vibration in open-pit mines based on particle swarm optimization and XGBoost. Nat. Resour. Res. 29, 711–721.
Zhang, X., Nguyen, H., Bui, X.-N., Tran, Q.-H., Nguyen, D.-A., Bui, D.T., Moayedi, H., 2020c. Novel soft computing model for predicting blast-induced ground vibration in open-pit mines based on particle swarm optimization and XGBoost. Nat. Resour. Res. 29, 711–721.
Zhao, Y., Li, J., Yu, L., 2017. A deep learning ensemble approach for crude oil price forecasting. Energy Econ. 66, 9–16.
Zhou, J., Li, X., Mitri, H.S., 2016. Classification of rockburst in underground projects: comparison of ten supervised learning methods. J. Comput. Civ. Eng. 30, 04016003.
Zhou, J., Li, X., Shi, X., 2012. Long-term prediction model of rockburst in underground openings using heuristic algorithms and support vector machines. Saf. Sci. 50, 629–644.