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Predicting silver price by applying a coupled multiple linear regression (MLR) and imperialist competitive algorithm (ICA)

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Abstract. This paper seeks to estimate and predict the global price of silver as a strategic metal using a combined multiple linear regression (MLR) and imperialist competitive algorithm (ICA). For this purpose, the global silver, copper, and aluminum prices were studied during 2009-2019. Then, the global prices of silver, copper, and aluminum were considered each as one of the input parameters, and, in return, the silver price was chosen as the target parameter. Using the Table Curve 2D & 3D software, the comprehensive statistical relationships between the input and output parameters were specified and suggested. Subsequently, the SPSS v25 software and the stepwise method were used to suggest the best nonlinear regression relationship with the 85% confidence level. Eventually, the optimal coefficients of the proposed statistical relation were determined by applying the ICA, which resulted in the improving results and also the reducing prediction error up to 1%.

Keywords: metal price; forecasting; statistical analyses; imperialist competitive algorithm

1. Introduction

The price of a product is the most significant and influential parameter for evaluating different projects. Today, it is of particular importance for the public and private policymakers to predict the fluctuations of economic variables in order to regulate the economic relations, so that it is felt that some tools and methods are required to forecast the variables with the least error. Indeed, predicting price plays a significant role in optimizing production and marketing strategies. Therefore, knowing the price variations can contribute towards making the right decisions to apply various managerial options in order to develop or restrict the activities by the managers and shareholders.

Prediction is applied to various branches of science including the supply chain, transportation planning, economics, telecommunications, production, weather forecasting, atmospheric conditions, earthquakes, and performance of players and sports teams (Rescher 1998, Festic *et al*. 2010, Wu 2015, Chen *et al*. 2018). The prediction is raised in the problems that are divided into two groups: first, the problems where the prediction is made aiming to classify the inputs and determine what class each input belongs to, and the output here is a nominal variable, and second,

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Fig. 1 Silver price changes between 2000 and 2019 (www.investing.com)

the problems that predict a continuous variable, such as determining the future price, by the estimation or regression, and the output here is a numerical variable (Statsoft 2002). Another crucial parameter in the prediction is “prediction accuracy”. In recent years, several studies have been conducted to evaluate the prediction accuracy. The intrinsic characteristics, such as the nature of prediction variable, prediction horizon, predictor ideology, and used technology, are among the factors influencing the prediction accuracy (Collopy and Armstrong 1992). Hence, many tools and software are used to predict the variables and indicators, which sometimes provide long-term predictions and sometimes the short-term ones. Due to the high sensitivity of the projects to the price, the price estimation with high accuracy can help the decision-making on selecting projects.

Since 2002 the prices of metals traded in the world markets have set high records. It means that uncertainty plays a vital role in this matter (Chen 2010). In 2009 the most influential economies in the world saw the global recession, which was by far most in-depth over the past seven decades. As a result, many businesses were struggling to survive, while if they had a long-term prediction with a low error rate of the global economic situation of the rates related to their jobs, they would have been less troubled by the recession or the bankruptcy. The drastic price fluctuations have triggered the classical tools for price estimation not to be able to predict the prices (Shahriar and Erkan 2010). Fig. 1 shows the silver price changes between 2000 and 2019 (www.investing.com).

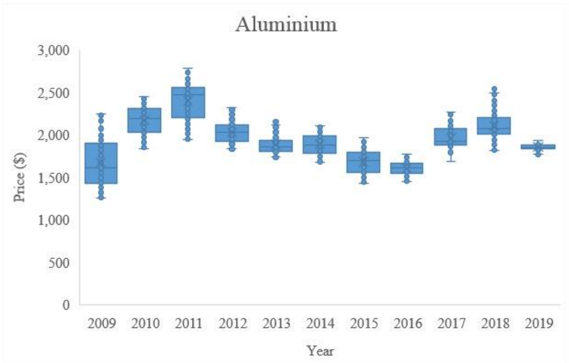
Given the considerable price changes in recent years, many researchers have attempted to predict the prices using intelligent methods. Xie *et al*. (2006) employed the monthly crude oil price between 1970 and 2003 to predict the crude oil price using the support vector machine (SVM) model. Then, they compared the proposed model with those generated by the artificial neural network (ANN) and genetic algorithm (GA). The obtained results showed that the SVM method, like the other two methods, had an excellent ability to estimate the crude oil price (Xie *et al*. 2006). Dunis and Nathani (2007) predicted the daily price of gold and silver with the advanced regressions by the linear and nonlinear models by using the daily price of gold and silver between

2000 and 2006, where the primary goal was to find a quantitative daily business strategy. Khaemasunun (2007) developed Thailand's gold price prediction using two multiple regression and autoregressive integrated moving average (ARIMA) models. The data from this study is related to an 8-year period, and the necessary code was implemented in Matlab. Shambora and Rossiter (2007) used the artificial neural network with the moving average crossover inputs to predict the price of crude oil in the upcoming market. Hadavandi *et al*. (2010) combined the time series and particle swarm optimization (PSO) algorithms to predict the changes in the gold price and the exchange rates. The mean absolute error (MAE) in the proposed model was obtained as 0.047.

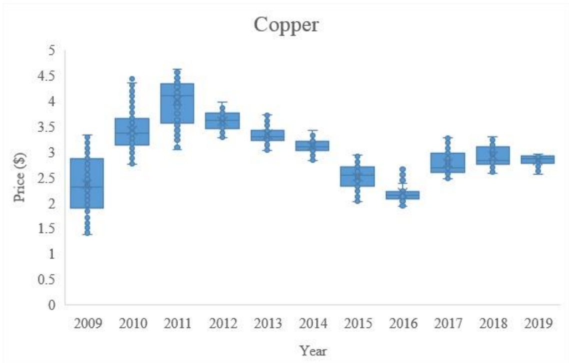
Soleimani and Jodeiri (2015) defined a production trend in the Iranian chromite mining section. For this, they used a dynamic panel estimation technique was employed using relevant data from chromite producing countries. The lifetime of reserves, chromite production, Hubert curve, the curve of the metal price, the intensity of use factors, supply and demand, and finally, the socio-economic changes were selected as decision-making criteria. These parameters were optimized by the CCD method. The results from the panel regressions reveal that Iran should reach the goals of sustainable developments in this section by four steps. Chen *et al*. (2016) estimated the aluminum and nickel prices using the aluminum and nickel prices between 2006 and 2015 and utilizing the gray wave prediction method. Olayiwola (2016) conducted research work that addressed the aforementioned gaps by presenting a knowledge discovery methodology applied to the development of (open-box) decision tree models in the forecast of copper spot prices, thereby revealing the prime predictor variables for the metal. The accuracy of the decision tree model is further also contrasted with a developed ARIMA model. Liu and Li (2017) predicted the gold price changes with the 99% precision using the gold price data between 1988 and 2015 and the random forest algorithm. Dehghani and Bogdanovic (2018) predicted the copper prices with the root mean square error (RMSE) of 0.132 based on the copper price data between 2009 and 2016 using the bat algorithm. Celic and Basarir (2017) predicted precious metal prices such as gold, silver, platinum, and palladium prices via ANN by using RapidMiner data mining software. Their study concentrated on data which includes gold, silver, palladium, platinum, Brent petrol, natural gas prices, thirty years' bond, ten years' bond, five years' bond, S&P 500, Nasdaq, Dow Jones, FTSE100, DAX, CAC40, SMI, NIKKEI, HANH, SENG and Euro/USD within the period of 4th of January 2010 to 14th of December 2015. The prices in the last quarter of 2015 were used for forecasting and validation. The results showed that error rates are accurate in order to foresee market trends. Sami and Junejo predicted future gold rates based on 22 market variables by applying machine learning (ML) approaches. They could predict the daily gold rates very accurately. Cortez *et al*. (2018) applied Chaos theory (CT) and ML techniques for estimating mineral commodities. In 2019, Zhou *et al*. used deep learning approaches to predict precious metals. They proposed a regularization self-attention regression model called RSAR, which consisted of a convolutional neural network (CNN) component and long short-term memory neural networks (LSTM) component. The model could extract both spatial and temporal features from precious metal price data. Given the impact of silver prices on the world markets, it is of great importance to predict the price of this strategic metal. However, the review of previous literature suggests that the silver price has not yet been conducted considering the price of other strategic metals using the smart methods. Therefore, in this paper, the silver prices were first collected in the ten years (2009-2019). Then, the best relations between the various parameters (copper, silver, and aluminum prices) were proposed using the statistical methods. Afterward, the coefficients obtained from the relations were optimized using the ICA.

Table 1 Input and output parameters

Parameter	Symbol	Price range ($)	Type of parameter
Copper Price	Co	1.381-4.623	Input data
Aluminum Price	Al	1261-2790	Input data
Silver Price	S	10.42-48.584	Input data
Forecasting The silver price	FS		Output data



(a)



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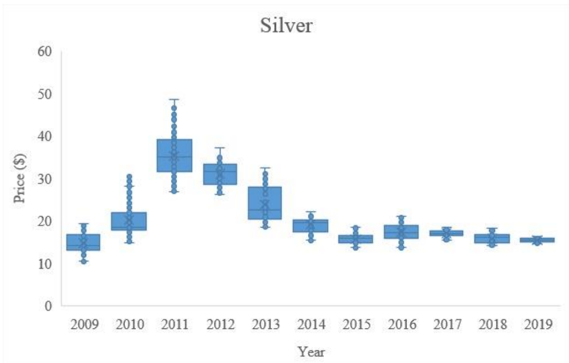


(c)

Fig. 2 Mean values and the standard deviation limits of (a) the aluminum (b) copper and (c) silver prices between 2009 and 2019 (www.investing.com)

2. Research methodology

2.1 Data presentation

After the relevant studies, the historical data for silver between 2009 and 2019 (www.investing.com) was used to develop a model for predicting the silver prices. The copper, silver, and aluminum prices were considered as the main parameters between 2009 and 2019. A total of 2672 datasets were used, consisting of 3 parameters (Table 1). Fig. 2 shows the box plot for each of the metals.

In the next step, the data were divided into two parts: model generation data and validation data. The data from 2009 to 2018 was considered for the model generation, and the data in 2019 was considered for validation purposes.

2.2 Multiple linear regression models

A multiple linear regression model (MLR) is a regression model in which more than one regression variable is used. In general, the response variable (future silver price) may depend on n variables (x). Eq. (1) presents an MLR prediction model with n regression variables (Jodeiri Shokri *et al*. 2014, 2016 and 2019, Shakeri *et al*. 2020)

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \quad (1)$$

where:
y: dependent variable;
x: independent variable;
ε: model error rate;
β_j, j = 0,1, ..., n is called the regression coefficients.

In fact, the process of predicting this model is a hyperplane in the n-dimensional space of the regression variables x_j. However, the prediction models with a more complex (nonlinear) structure relative to Eq. (1) can also be considered by this method. For example, in the following model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2^3 + \beta_3 e^{x_3} + \beta_4 x_1 x_2 + \varepsilon \quad (2)$$

To make it easier to analyze the above equation, which is a nonlinear relation, it is sufficient to replace the used variables used with the linear variables. In Eq. (2), assuming $z_1 = x_1$; $z_2 = x_2^3$; $z_3 = e^{x_3}$; $z_4 = x_1 x_2$, then Eq. (2) converts to Eq. (3)

$$y = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \beta_4 z_4 + \varepsilon \quad (3)$$

Which is, in fact, a linear regression model (Montgomery 1992).

2.2.1 Model goodness of fit criteria

The following assumptions that should be made for the errors:
• Error term ε has a zero mean.
• Error term has a constant σ^2 variance.
• Errors should be uncorrelated (error pattern is random).
• Errors have a normal distribution.

It should be noted that the last assumption is necessary for the hypothesis test to obtain the confidence interval. In the goodness of fit test of the final model, note that the validity of the assumptions should first be questioned, and then, the analysis is directed so that the model goodness of fit could be tested. The strong deviations from these assumptions may ultimately lead to model instability. These deviations are not typically determined using the standard summary statistics such as t, F, or R^2 criteria. They are the general properties of the model and, thus, will not guarantee the goodness of fit of the final model (Montgomery 1992).

To predict the silver price using the MLR, the residual analysis is used to measure the goodness of fit of the model. As noted in the previous sections, the residuals are defined as Eq. (4)

$$e_i = T_i - y_i \qquad ; \qquad i = 1; 2; \dots ; n \tag{4}$$

where:

T_i is the observation value,

y_i is the corresponding fitted value.

The value of residuals can be considered the known values of error. Therefore, any deviation from the assumptions on the errors should be specified in the residuals. The data where the absolute value of its residuals is significantly larger than the rest is called the outlier data, which are usually not the same as other data; therefore, if possible, these data should be modified or removed from the model data set. However, in the least square method, the fitted equations will be drawn towards the outlier points when the sum of the residual squares is minimized. Hence, in such cases, it is evident that the removal of wrong values from other data should be taken into account (Montgomery 1992).

2.3 Imperialist competitive algorithm

The process of finding the right solution for solving many engineering problems is difficult and inevitable. For this reason, a large number of search algorithms have been presented to find the appropriate solution for solving the problems. The evolutionary algorithms are an essential group of search algorithms that use the evolutionary laws in nature to find the right solution. They include the genetic algorithms (inspired by the evolution of creatures), ant colony optimization (based on the motion of ants), and particle swarm optimization (inspired by the collective movement of birds and fish) (Atashpaz and Lucas 2007).

The ICA was firstly presented by Atashpaz, Gargari, and Lucas in 2007. The ICA provides a robust algorithm for optimizing with the mathematical model of the socio-political phenomena (Atashpaz and Lucas 2007, Biabangard *et al*. 2009).

In the ICA, several countries are first considered as the primary population. The selection of the primary population of countries is a random process. Given the value of the cost function, aiming to minimize the cost function, the existing countries are divided into two categories: imperialist and colony. Then, the countries with more power are chosen as the imperialists, and the rest are chosen as the colony. After identifying the imperialists concerning their power, other countries are randomly attributed to one of the imperialists. The collection of each imperialist and its respective colonies is called the “empire”. Another way of dividing colonies into each imperialist is dependent on their normalized cost, which is calculated from Eq. (5) (Atashpaz and Lucas 2007).

$$C_n = max_i\{c_i\} - c_n \tag{5}$$

Where:

c_n: is the cost of nth imperialist;

$max_i\{c_i\}$: is the highest cost among the imperialists;

C_n is the normalized cost.

The relative normalized power of each imperialist, which is the ratio between the colonies of that imperialist to the entire colony countries, is calculated as Eq. (6). The initial number of colonies in an empire is also calculated according to Eq. (7).

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{6}$$

$$N.C._n = round\{P_n . N_{col}\} \tag{7}$$

$$T.C._n = Cost(imperialist_n) + \ \xi \times mean\{Cost(colonies\ \ of\ \ empire_n)\} \tag{8}$$

Where:

N_{col} is the total number of colony countries existing in the population of the primary countries.

Given $N.C._n$ for each empire, some primary colony countries are randomly selected and given to the nth imperialist. In the next step, it is tried to close the colony countries to the imperialist countries to analyze the culture and social structure of colonies in various political and social contexts. The colonies are then moved towards the imperialist country (Atashpaz and Lucas 2007).

It should be noted that during the algorithm implementation, some colonies may reach the points in the cost function, which have the cost less than the value of the cost function at the imperialist position. In this case, the colony and imperialist countries are replaced, and the algorithm will continue with the imperialist country in the new position. This time the new imperialist country will begin to apply the assimilation policies to its colonies. To calculate the cost function, the total cost of the empires is calculated as Eq. (8) (Atashpaz and Lucas 2007):

3. Results

3.1 Statistical analyses

All the required parameters were collected to provide the mathematical relation for the prediction of the silver price using the MLR methods and the ICA. Then, the relation between the parameters and the dependent variable was calculated by the Table Curve v5.01. In the next step, these relations entered the IBM SPSS v25 software, and the regression equation was obtained to predict the price of silver. The equation obtained for optimizing the prediction accuracy entered the ICA. The steps for performing the research are shown in Fig. 3.

After dividing the data and providing the data in the next step, the relationships of each of these parameters on each other, as well as the relationship of each of them on the silver price should be specified as a separate regression variable that will be used in the model. For this purpose, the two-dimensional and three-dimensional Table Curve v5.01 software was used. However, there may be a very high number of relationships mentioned between the parameters. The best relationships should be selected among all possible relationships between the parameters as the variable used in the model for finding a proper model. Also, the comparison of determination coefficients and the modified determination coefficients were used. In some cases, these coefficients may be very close to each other; then, since the goal is a desirable presentation, all of these cases are considered.

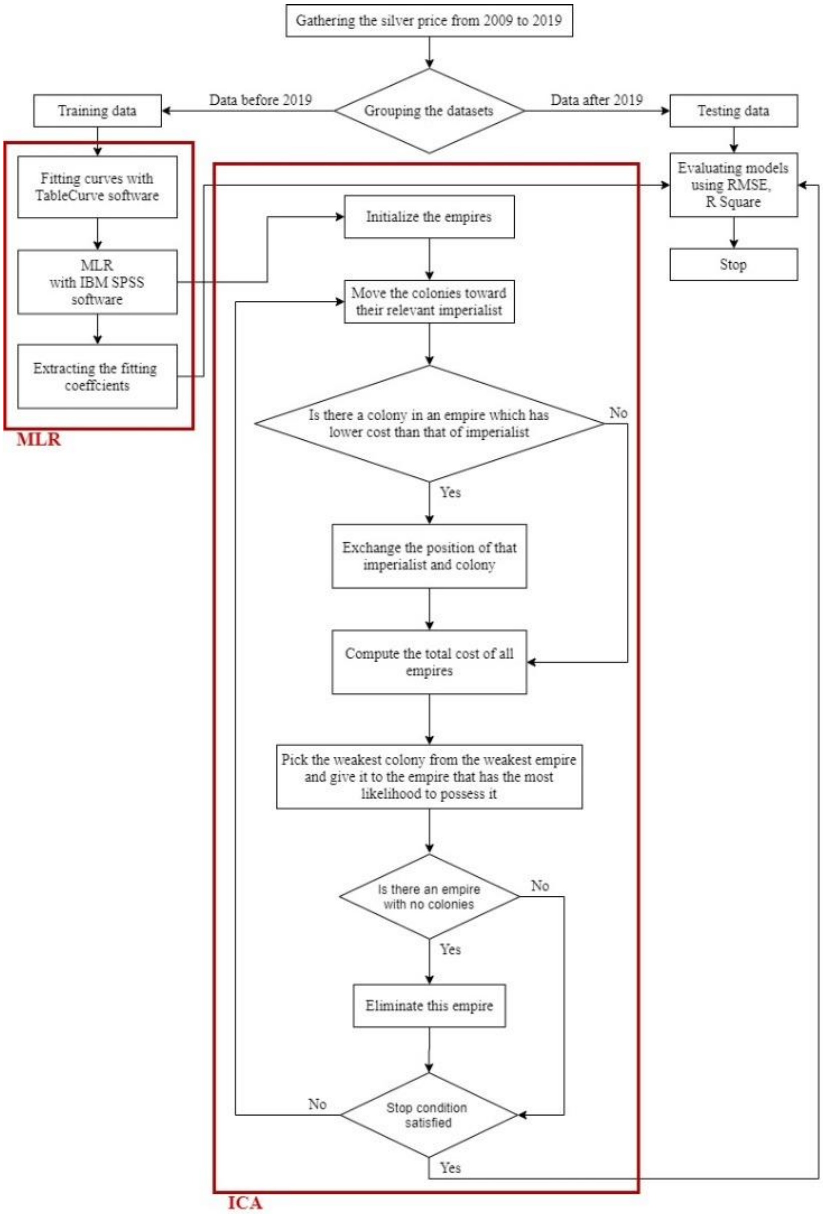


Fig 3 The Flowchart of silver price prediction

Finally, the variables used in the model are given in Table 2.

3.1.1 Model generation

After obtaining the best relationships, the next step was to find the best MLR relationships between the variables by the step-by-step method using the IBM SPSS v25 software. The results of the linear regression analysis are shown in Table 3.

By comparing the models, model 3 was chosen as the best model according to the lower

Table 2 Suggested relationships between input and output parameters

x_i	Relationship between	Suggested relationship
x_1	$FS \propto f(Co)$	$FS = Co^3$
x_2	$FS \propto f(Co; S)$	$FS = Co^3 + S$
x_3	$FS \propto f(S)$	$FS = S$
x_4	$FS \propto f(Al)$	$FS = Al^3$
x_5	$FS \propto f(Co; Al)$	$FS = C^3 + Al$
x_6	$FS \propto f(S; Al)$	$FS = S \times \ln(S) + Al^{1.5}$

Table 3 Results of statistical analyses for the linear regression

Model No.	R	R-Squared	Adjusted R- Squared	Std. The error of the Estimate
1	0.998	0.995	0.995	0.4942
2	0.998	0.995	0.995	0.4927
3	0.998	0.995	0.995	0.4923

Table 4 The best coefficients of the suggested statistical relationship

C_0	C_1	C_2	C_3
-0.003	0.020	0.990	-0.010

prediction error rate with R^2 and modified R^2 equal to 0.998 and 0.995, respectively (Eq. 9)

$$SF = C_0 + C_1x_3 + C_2x_1 + C_3x_4 \tag{9}$$

C_0 to C_3 are the constant values whose values are shown in Table 4.

Finally, Eq. (10) is proposed to predict the price of silver as a function of copper, silver, and aluminum prices.

$$SF = -0.003 + 0.020 \times S + 0.990 \times Co^3 - 0.010 \times Al^3 \tag{10}$$

Fig. 4 shows the relationship between the validation data of the statistical model and the measured data. Fig. 4 shows the error analysis histogram of the proposed model. The normal distribution of the error shows that the proposed model is appropriately selected.

3.2 Optimization using the ICA

According to Eq. (6), the mathematical relation of silver price prediction was presented using the ICA. In the algorithm, the following function was considered as the objective function

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{11}$$

Where:

O: number of data,

P_i: estimated data,
O_i: real data.

In the model generated in MATLAB 2017b, the number of unknowns was 6, the number of countries was 120, the number of imperialists and the number of repetitions were considered 15 and 100 respectively. Reducing the RMSE error value during the implementation of the ICA in Fig. 5 as well as the empires created with their colony, are shown in Fig. 6. Relationship (12) would be suggested for predicting the silver prices by using the ICA.

$$SF = 0.042 + (0.9981 \times S) - (1.4885 \times Co^{-9}) - (10.4218 \times Al^{-1.2924}) \quad (12)$$

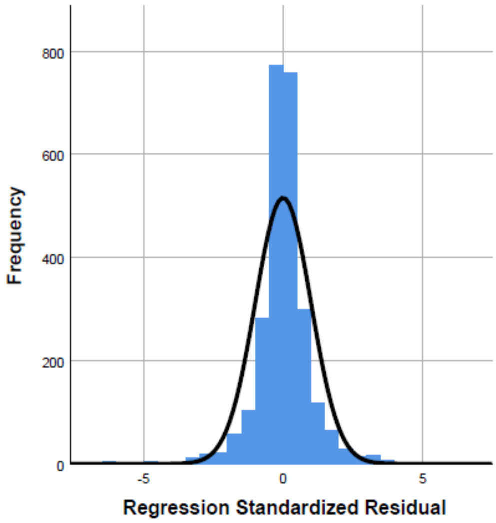


Fig. 4 The error analysis histogram of the proposed model

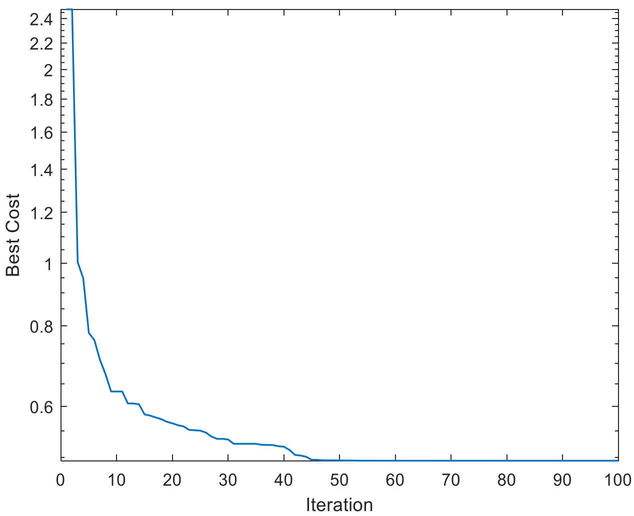


Fig. 5 RMSE error during the implementation of the ICA

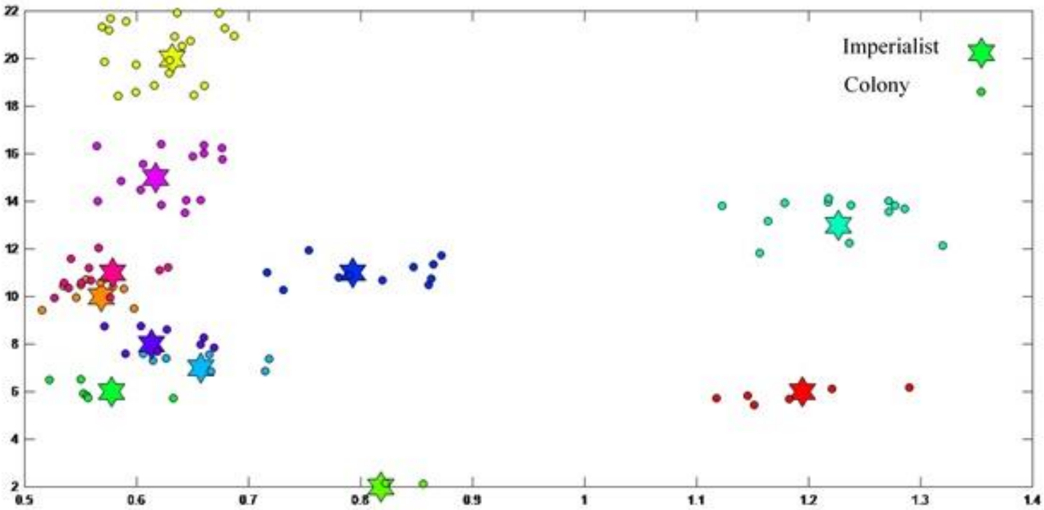
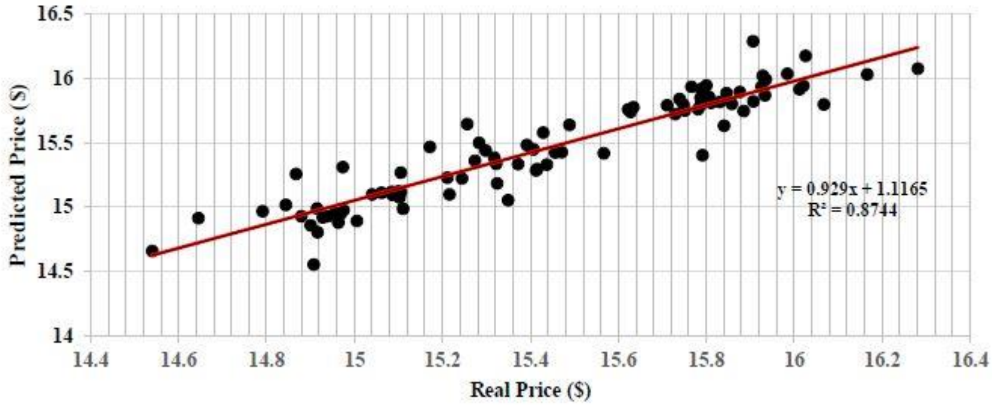
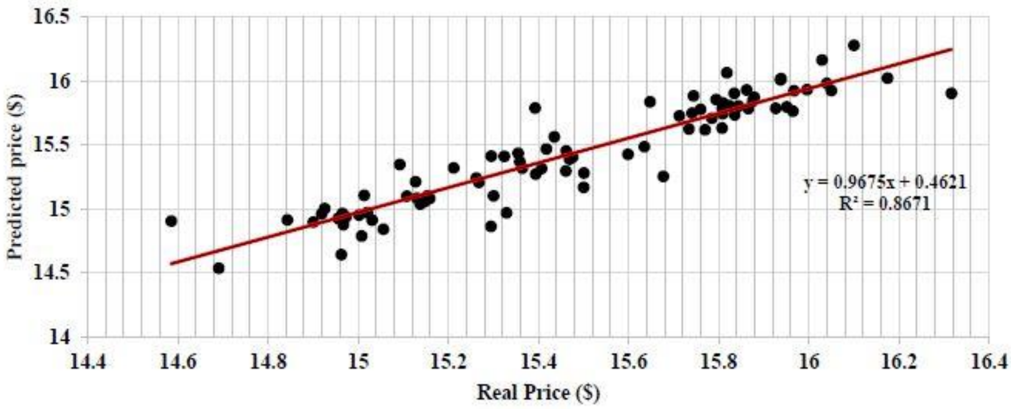


Fig. 6 The empires created with their colony



(a)



(b)

Fig. 7 The results of (a) the ICA and (b) the MLR in comparison to actual data

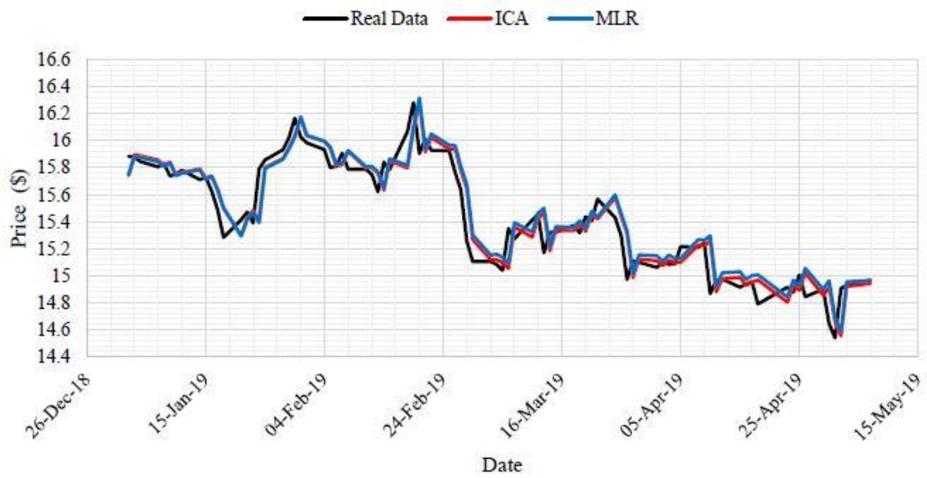


Fig. 8 The actual data diagram vs. the prediction of the silver price diagram by the ICA and MLR

4. Conclusions

In this paper, the development of a new model was suggested for predicting the silver prices using copper, silver, and aluminum prices. For this, the relationships among the copper, silver, and aluminum prices were firstly proposed using Table Curve v5 software. Subsequently, using the ICA and the MLR, the best relationships were presented for predicting the silver prices. The relationships among the input parameters were first created by using the global price data from 2009 to 2018 for presenting the relationships, and then, the price of silver was predicted in 2019. Afterward, the coefficients of the obtained relationships were calculated using both the ICA and the MLR. The results were compared using the coefficient of determination (R^2) and the root mean squared error (RMSE). The ICA and the MLR had determination coefficients of 87.44% and 86.71%, respectively, as compared to the actual data (Fig. 7), while the RMSE of the ICA and the MLR models were obtained as 0.148 and 0.155, respectively. Hence, the results showed that the ICA model had a more accurate prediction than the MLR. Fig. 8 shows the actual data diagram, along with the silver price diagrams predicted by the ICA and the MLR.

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References

Atashpaz, E. and Lucas, C (2007), “Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition”, *In 2007 IEEE Congress on Evolutionary Computation*, Ieee.

Biabangard, A. Atashpaz-Gargari, E. Soltani, N. and Lucas, C. (2009), “Application of imperialist competitive algorithm for materials property characterization from sharp indentation test”, *Int. J. Eng.*

Simul., **10**(1), 11-12.
Celic, U. and Basarir, C. (2017), "The prediction of precious metal prices via artificial neural network by using RapidMiner", *Alphanumeric J*., **5**(1), 45-54. http://dx.doi.org/10.17093/alphanumeric.290381.
Chen, M. (2010). "Understanding world metals prices - Returns, volatility and diversification", *Resources Policy*, **35**(3), 127-140. https://doi.org/10.1016/j.resourpol.2010.01.001.
Chen, Y., He, K. and Zhang, C. (2016), "A novel grey wave forecasting method for predicting metal prices. *Resources Policy*. **49**, 323-331. https://doi.org/10.1016/j.resourpol.2016.06.012.
Chen, Y., Li, W. and Jin, X. (2018), "Volatility spillovers between crude oil prices and new energy stock price in China", *Roman. J. Economic Forecast*., **21**(2), 43-62.
Collopy, F. and Armstrong, J.S. (1992), "Error measures for generalizing about forecasting methods: empirical comparisons", *Int. J. Forecast*., **8**(1), 69-10. https://doi.org/10.1016/0169-2070(92)90008-W.
Cortez, T., Saydam, S., Coulton, J. and Sammut, C. (2018), "Alternative techniques for forecasting mineral commodity prices", *Int. J. Mining Sci. Technol*., **28**(2), 309-322. https://doi.org/10.1016/j.ijmst.2017.09.001.
Dehghani, H. and Bogdanovic, D. (2018), "Copper price estimation using bat algorithm", *Resources Policy*, **55**, 55-61. https://doi.org/10.1016/j.resourpol.2017.10.015.
Dunis, C.L. and Nathani, A. (2007), "Quantitative trading of gold and silver using nonlinear models", *Neural Network World*, **17**(2), 93-111.
Festic, M., Repina, S. and Volcjak, R. (2010), "Estimating coal price dynamics with the principal components method", *Roman. J. Economic Forecast*., **2**, 188-212.
Hadavandi, E. Ghanbari, A. and Abbasian, S. (2010), "Developing a time series model based on particle swarm optimization for gold price forecasting", *In 2020 the Third International Conference on Business Intelligence and Financial Engineering*.
Jodeiri Shokri, B. Doulati Ardejani, F. and Karimpouli, S. (2016), "Prediction of remained pyrite fraction within a coal waste pile with using of multivariate regression method", *J. Environ. Sci. Technol*., **18**(3), 37-52.
Jodeiri Shokri, B., Naghadehi, M., Hadadi, F. and Doulati Ardejani, F. (2019), "Probabilistic prediction of pyrite oxidation process within Anjir Tangeh coal wastes pile", *Iran. J. Mining Eng*., **14**(44), 55-68.
Jodeiri Shokri, B., Ramazi, H.R., Doulati Ardejani, F. and Moradzadeh, A. (2014), "A statistical model to relate pyrite oxidation and oxygen transport within a coal waste pile: case study, Alborz Sharghi, northeast of Iran", *Environ. Earth Sci*., **71**(11), 4693-4702. https://doi.org/10.1007/s12665-013-2859-0.
Khaemasunun, P. (2007), *Forecasting Thai Gold Prices*, College of Innovation, Thammasat University, Thailand.
Liu, D. and Li, Z. (2017), "Gold price forecasting and related influence factors analysis based on random forest", *Proceedings of the Tenth International Conference on Management Science and Engineering Management*. *Advan. Intell. Syst. Comput*., Springer.
Montgomery, D.C. and Peck. E.A. (1992), *Introduction to Linear Regression Analysis*, John Wiley & Sons.
Olayiwola, A. (2016), "*Forecasting copper spot prices: A knowledge-discovery Approach*", Master Dissertation, University of Manchester, Manchester.
Rescher, N. (1998), *Predicting the future: An introduction to the theory of forecasting*, State University of New York Press.
Sami, I.U. and Junejo, K.N. (2017), "Predicting future gold rates using machine learning approach", *Int. J. Advan. Comput. Sci. Appl*., **8**(12), 92-99.
Shahriar, S. and Erkan, T. (2010), "An overview of global gold market and gold price forecasting", *Resources Policy*, **35**(3), 178-189. https://doi.org/10.1016/j.resourpol.2010.05.004.
Shakeri, J. Jodeiri Shokri, B. and Dehghani, H. (2020), "Prediction of blast-induced ground vibration using gene expression programming (GEP), Artificial Neural Networks (ANNs), and Linear Multivariate Regression (LMR)"., *Archiv. Min. Sci*., **65**(2), 317-335. http://10.24425/ams.2020.133195.
Shambora, W.E. and Rossiter, R. (2007), "Are there exploitable inefficiencies in the futures market for oil?", *Energy Economics*, **29**, 18- 27. https://doi.org/10.1016/j.eneco.2005.09.004.
Soleimani, M. and Jodeiri Shokri, B. (2015) "Defining chromite ore production trend by CCD method to

reach sustainable development goals in mining sector, Iran”, *Mineral Economics*., **28**(3), 103-115. https://doi.org/10.1007/s13563-015-0066-z.

Statsoft (2002), Electronic Statistics Textbook, Tulsa, OK: Statsoft. http://www.statsoft.com/textbook/stathome.html.

Wu, M.C., Lin, I.C., Huang, Y.T. and Lu, C.R. (2015), “Forecasting prices of presale houses: A real option approach”, *Roman. J. Economic Forecast*., **18**(1), 143-158.

Xie, W., Yu, L., Xu, S. and Wang, S. (2006), “A new method for crude oil price forecasting based on support vector machines”, *In International Conference on Computational*. Springer, Berlin, Heidelberg.

Zhou, J., He, Z., Song, Y.N., Wang, H., Yang, X., Lian, W. and Dai, H.N. (2019), “Precious metal price prediction based on deep regularization self-attention regression”, *IEEE Access*, **8**, 2178-2187. https://doi.org/10.1109/ACCESS.2019.2962202.

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