



Contents lists available at ScienceDirect

## Resources Policy

journal homepage: [www.elsevier.com/locate/resourpol](http://www.elsevier.com/locate/resourpol)

## Copper price estimation using bat algorithm

Hesam Dehghani<sup>a,\*</sup>, Dejan Bogdanovic<sup>b</sup><sup>a</sup> Mining Engineering Faculty, Hamedan University of Technology, Hamedan, Iran<sup>b</sup> Technical Faculty, University of Belgrade, Belgrade, Serbia

## ARTICLE INFO

## Keywords:

Copper price

Bat algorithm

Time series

Estimation

## ABSTRACT

The most effective parameter on the value of mining projects is metal price volatility. Therefore, knowing the metal price volatility can help the managers and shareholders of the mining projects to make the right decisions for extending or restricting the mining activities. Nowadays, classical estimation methods cannot correctly estimate the metal prices volatility due to their frequent variations in the past years. For solving this problem, it is necessary to use the artificial algorithms that have a good ability to predict the volatility of the various phenomena. In this paper, the Bat algorithm was used to predict the copper price volatility. Accordingly, Brownian motion with mean reversion (BMMR) was chosen as the most suitable time series function with the root mean square error (RMSE) of 0.449. Then, the estimation parameters of the equation were modified using Bat algorithm. Finally, it is concluded that the determined equation with 0.132 of RMSE can predict the copper price better than the classic estimation methods.

## 1. Introduction

Product price is the most important and effective parameter in various project evaluation. Mining projects are no exception and the value of the project is the most sensitive to changes in mineral prices. Therefore, knowing the mineral price changes may play an important role in making the right decisions for applying the administrative options for extending or restricting the mining activities via mining projects managers and shareholders. Significant volatilities in the minerals price, especially in recent years, have led that the classic prediction approaches do not have the ability to correctly estimate the price changes. Hence, numerous researchers have tried to predict the minerals price using artificial methods. Xie et al. (2006) proposed a new method for crude oil price prediction based on a support vector machine (SVM) model. They compared their model with other models, which were developed using artificial neural networks (ANN) and genetic algorithm (GA). The obtained results show that like ANN and GA, SVM is a capable method for forecasting the crude oil price. Hadavandi et al. (2010) developed a time series model for gold price and exchange rate forecasting based on particle swarm optimization (PSO). Dehghani and Ataee-pour (2012) predicted the copper price using binomial tree. Dehghani et al. (2014) estimated the price and operating cost in a copper mine using multidimensional binomial tree. Kriechbaumer et al. (2014) used an improved combined wavelet-autoregressive integrated moving average (ARIMA) to forecast monthly price of aluminum, copper, lead and zinc. Chen et al. (2016a), (2016b) investigated the

changes of the various metals price using grey wave forecasting method. Liu and Li (2017) forecasted the gold price and analyzed the related influence factors based on random forest. Li and Li (2015) studied the volatility of the copper price using time series functions. Lasheras et al. (2015) used the ARIMA and artificial neural networks methods for predicting the copper spot price in New York Commodity Exchange (COMEX). The results of this research show that the estimation error of the neural network is always less than time series model. Liu et al. (2017) predicted the copper price using decision tree learning. Their model forecast the copper price using price volatility of the several materials such as crude oil, gold, silver, etc. Table 1 shows some of the research-works in field of minerals price prediction.

Numerous studies on the mineral price prediction indicate the challenge and importance of this process.

Copper price plays vital roles in various aspects in today's economies. Copper price has a significant impact on gold and other precious metals' prices (Morales and Andreosso-O'Callaghan, 2011). Copper is strongly associated with many industries, such as electrical wiring, construction, and equipment manufacturing; and therefore, copper price has become a significant impact factor on the performance of related companies and economies (Lasheras et al., 2015). On the other hand, for some countries such as Chile and Zambia, whose economy relies extensively on copper production, fluctuations in copper price is very important (Lasheras et al., 2015).

Forecasting copper price is particularly important for policymakers and participants in the market. Budgeting is crucial for mining

\* Corresponding author.

E-mail addresses: [dehghani@hut.ac.ir](mailto:dehghani@hut.ac.ir) (H. Dehghani), [dnbogdanovic@yahoo.com](mailto:dnbogdanovic@yahoo.com) (D. Bogdanovic).<http://dx.doi.org/10.1016/j.resourpol.2017.10.015>Received 23 August 2017; Received in revised form 25 October 2017; Accepted 27 October 2017  
0301-4207/ © 2017 Elsevier Ltd. All rights reserved.

**Table 1**  
Minerals price prediction research works.

Author(s)	Commodity	Method
Feng, et al. (2009)	Coal	PSO and RBF neural network
Shafiee and Topal (2010)	Gold	Random walk theory
Zhang and Ma (2011)	Coal	Partial Least Squares
Deghani and Atae-pour (2012)	Copper	Regression Binomial tree
Deghani, et al. (2014)	Copper	Multidimensional binomial tree
Kriechbaumer, et al. (2014)	aluminum, copper, lead and zinc	wavelet-autoregressive integrated moving average
Sivalingam, et al. (2016)	Gold	Extreme Learning Machine
Guha and Bandyopadhyay (2016)	Gold	Autoregressive Integrated Moving Average Method
Liu and Li (2016)	Gold	Random forest algorithm
Chen, et al. (2016)	Nickel, Aluminum	Grey wave forecasting method
Mostafa and El-Masry (2016)	Oil	Gene expression programming and artificial neural networks
Chen, et al. (2016)	Oil	Grey Wave Forecasting Method
Sharma (2016)	Gold	Box Jenkins Autoregressive Integrated Moving Average Method
Liu, et al. (2017)	Copper	Decision tree learning



**Fig. 1.** Copper price from 1966 to 2017. All the data were available to public and were downloaded from <http://www.quandl.com>.

companies as the payback periods are typically long. Therefore, it requires a steady and reliable financial model to adequately evaluate and forecast the future revenue and cost to maintain a healthy cash flow along the project phase (Runge, 1998). Accordingly, changes in the price of copper have always been considered by economic activists. Fig. 1 shows the copper price changes from 1966 to 2017. Generally, the trend of copper price can be divided to four sections.

- **Stability era:** This period lasted from 1984 since to 2003. During this period, the price of copper has not changed much and ranged between \$ 900 and \$ 3500 per tonne. The main reason for this stability was the equilibrium of supply and demand.
- **Economic prosperity era:** This period has begun since 2003 and ended in 2008. During this period, rising global market demand has led to an impressive rise in copper price. For example, in 2004, China increased its global copper demand by as much as 95%. This growth in demand has surprised manufacturers and the copper price increased suddenly.
- **Depression era:** The US credit and housing market crisis that began in the second half of 2007 has involved the globe in the second half of 2008. On the one hand, the crisis has disturbed the supply and demand balance of this commodity to the surplus of supply and increase of inventories, and, on the other hand, led to capital flight

from the copper market. Therefore, the copper price has decreased from mid-2008 to early 2009, from \$ 8985 per tonne to around \$ 3000 per tonne. Because of this occurrence, many mines and smelting units were temporarily closed and many projects were canceled or deferred, too.

- **Return era:** China's positive performance as well as the supply of economic motive offers led that copper prices rising 140% to 7400 dollars per tonne. The highest copper price is equivalent to \$ 10,000 per tonne in 2011. During this period, the price fluctuations are very high and always tend to move to its average. The rise and fall of China's demand, the unrest in the Middle East and the exploitation of new copper reserves have been a major cause of these fluctuations.

According to the above mentioned points and importance of copper price volatility, the current research-work tries to estimate the copper price using novel methods i.e. a combination of time series and Bat algorithm. Using the abilities of time series functions and Bat algorithm such as accuracy, flexibility, consideration of interactions of various parameters, etc., the proposed model will be capable of predicting future copper prices accurately.

## 2. Methodology

In order to develop the copper price volatility estimation model, copper price historical datasets were gathered ([www.quandl.com](http://www.quandl.com), 2017). As described earlier, the current conditions of the global economy are such that copper prices are reluctant to comply with their previous conditions, *Stability era*, *Economic prosperity era*, *Depression era*. Therefore, the datasets were gathered from *Return era*, which is from 2009 to 2016. Datasets from 2009 to 2015 were used for training the models and the 2016 datasets were used for validating the models. For achieving this purpose, at the first stage, the best estimation model was selected using time series functions and then the calculated estimation coefficients were modified using the Bat algorithm. Fig. 2 shows the process of the model preparation.

### 2.1. Time series function

A time series is a sequence of observations taken sequentially in time. Many sets of data appear as time series: a monthly sequence of the quantity of metals shipped from a factory, a weekly series of the commodity prices, daily exchange rates, and so on. Examples of time series abound in fields such as economics, business, engineering and the natural sciences. An intrinsic feature of a time series is that, typically, adjacent observations are dependent. The nature of this dependence among observations of a time series is of considerable practical interest. Time series analysis is concerned with techniques for the analysis of this dependence. Autoregressive integrated moving average (ARIMA), moving average (MA), autoregressive moving average (ARMA), Brownian motion with mean reversion (BMMR), etc. are some of the most famous time series functions, which are described in Table 2.

where,  $\mu$  is the mean,  $\sigma$  is the variance,  $\alpha_1, \alpha_2$  are the autoregressive coefficients,  $b_1, b_2$  are the moving average coefficients,  $\lambda$  is the jump rate,  $\gamma$  is the speed of reversion parameter,  $\mu_j$  and  $\sigma_j$  are the normal parameters of jump size,  $\omega$  is the volatility parameter,  $c_1$  is the error coefficient,  $N_t$  is a sample from a Normal (0,1) distribution,  $K_t$  is a sample from a poisson ( $\lambda t$ ) distribution and  $Y$  is the value of time series variable at the time  $t$ .

### 2.2. Bat algorithm

Bat algorithm (BA) is a metaheuristic algorithm proposed by Yang in 2010. Bat algorithm is based on the echolocation capability of micro bats guiding them on their foraging behavior (Yang et al., 2010). Like many metaheuristic algorithms, BA has the advantage of simplicity and

Download English Version:

<https://daneshyari.com/en/article/7387592>

Download Persian Version:

<https://daneshyari.com/article/7387592>

[Daneshyari.com](https://daneshyari.com)