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MODEL EFFECT OF COPPER PRICE ON FREEPORT MCMORAN STOCK PRICE

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Abstract: The copper price in copper mining companies is an essential aspect in terms of profit, revenue, production targets, and hedging. This research aims to determine an alternative of copper price modeling and its causality relationship to Freeport McMoRan (FCX) stock price. The methods utilized in this research were Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), Genetic Algorithms (GA) and Granger Causality Test. Based on this research result, all modeling methods equally show excellent performance for modeling copper price. Another finding from this research is that the copper price positively affects the FCX stock price. Therefore, it can be concluded that the copper commodity price influences the value of a copper mining company. The results of this research can be utilized as a reference for company analysts as a part to estimate profit probability, estimate revenue, estimate production targets, and hedging strategies.

Keywords: ARIMA, causality, genetic algorithm, neural network, price model

Abstrak: *Harga tembaga pada perusahaan tambang tembaga merupakan aspek penting dalam hal keuntungan, pendapatan, target produksi dan lindung nilai. Penelitian ini bertujuan untuk menentukan alternatif pemodelan harga tembaga dan hubungan kausalitasnya terhadap harga saham FCX. Metode pemodelan harga tembaga yang digunakan dalam penelitian ini adalah Autoregressive Integrated Moving Average (ARIMA), Jaringan Syaraf Buatan (JSB), Algoritma Genetika (AG) dan Uji Kausalitas Granger. Berdasarkan hasil Penelitian ini, semua metode pemodelan menunjukkan kinerja yang sangat baik untuk pemodelan harga tembaga. Temuan lain dari penelitian ini adalah bahwa harga tembaga berpengaruh positif terhadap harga saham FCX. Dengan demikian dapat disimpulkan bahwa harga komoditas tembaga berpengaruh terhadap nilai suatu perusahaan pertambangan tembaga. Hasil penelitian ini dapat dijadikan acuan bagi analis perusahaan sebagai bagian untuk mengestimasi probabilitas laba, mengestimasi pendapatan, mengestimasi target produksi dan strategi hedging.*

Kata kunci: *ARIMA, kausalitas, algoritma genetika, jaringan syaraf, model harga*

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INTRODUCTION

Copper is a good conductor of electricity and is difficult to replace. Copper had become part of the development of human civilization, especially when electricity was first discovered (Pearce, 2019). The need for copper will increase along with the development of technology, electronic automation systems, and the growing need for Green Energy (Rötzer and Schmidt, 2020). Based on Schipper et al. (2018) research, trend of copper demand continues to increase from year to year (Figure 1).

Freeport-McMoRan Inc. (FCX) is one of the largest publicly traded copper mining company (Stowell, 2017), headquartered in Phoenix, Arizona, USA. FCX is included in the top 10 copper mining companies with the largest production globally (Table 1), based on Statista, processed based on the annual report in 2018. Therefore, FCX is an essential part of supporting advanced future technology (DBS, 2018; Maes and Nuzman, 2015).

The copper price is an essential component in terms of profit, revenue, production targets, and hedging for any copper mining company (Astudillo et al. 2020). In line with this, according to Gligoric et al. (2020), the difference between average copper price and cost of producing copper per pound is equal to profit possibility. Meanwhile, Figure 2 shows the possible profit per pound of copper obtained by FCX from 2006 to 2019.

Still, in line with Astudillo's previously stated, the copper price is an important part of a copper mining company's revenue. For FCX, copper is the dominant component in annual revenue, and Figure 3 shows FCX revenue from 2017 to 2019 with a range of around 70% - 75%. This inferred that FCX revenue is highly depend on copper price. In another words, volatility of copper price is positively influence FCX revenue.

According to the potential for copper demand that continues to increase, FCX estimates that the copper sales target will also increase in 2020-2022, 4.2 billion lbs in 2022. This is supported by the consolidated copper reserves of FCX (recoverable reserves), around 116 billion lbs and average sales through 3rd quarter 2020 of approximately 0.26 billion lbs per month.

In line with the research of Ahmad et al. (2017), FCX undertook to hedge to manage risks associated with changes or fluctuations in copper price. Figure 5 shows the lost and gained associated with FCX hedging, such as sales contract, forward contract, futures contract, and swap. Based on Adiwaskito (2011) research, the ARIMA result can be used as a basis for hedging decisions and maximizing the company's cash flow.

There were similarities in trend of copper prices and FCX stock prices. According to Vivekananda et al. (2019) research, there was positive correlation between commodity price and company stock price in non-LQ45 index. Therefore, as an initial hypothesis, copper price affects FCX stock price. Meanwhile for investors in stock valuation, company profits can be used to estimate dividend growth rate (Eldomiaty et al. 2015), also known as sustainable growth rate (Momcilovic et al. 2015).

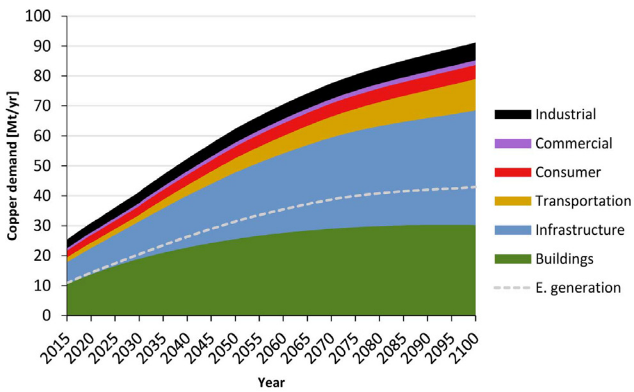


Figure 1. World copper demand prediction (Schipper et al. 2018)

Table 1. Top 10 world copper mining company in 2018

Company	Production (million metric tons)
Freeport-McMoRan	1.9
Codelco	1.7
BHP Billiton	1.7
Glencore	1.5
Southern Copper	0.88
Antofagasta	0.73
Rio Tinto	0.63
KGHM	0.63
First Quantum	0.61
Vale	0.4

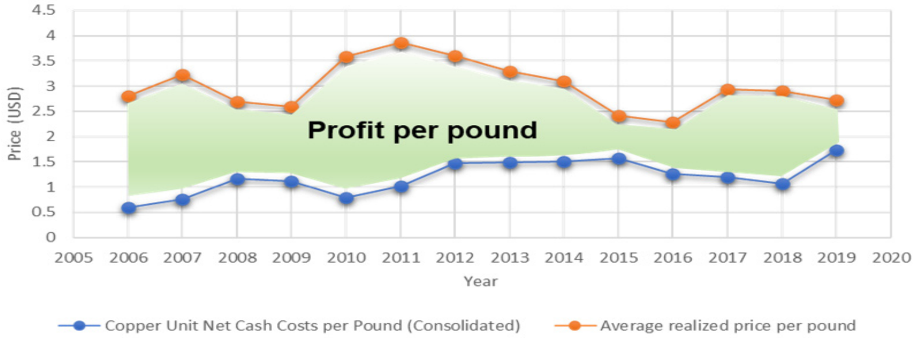


Figure 2. Copper profit probability per pound based on FCX Annual Report

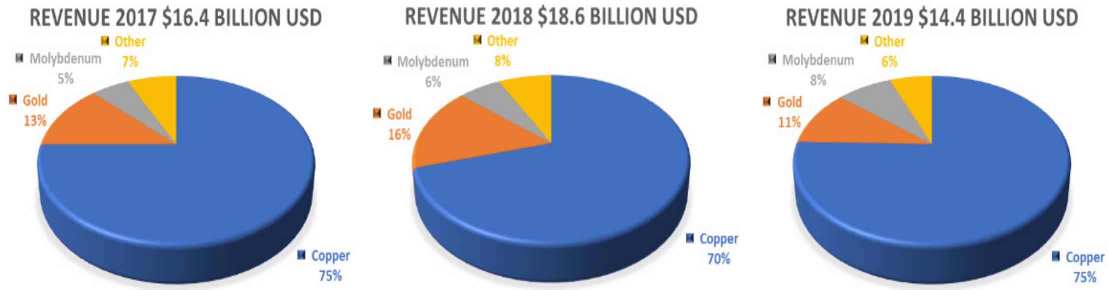


Figure 3. FCX revenue components based on FCX Annual Report 2019

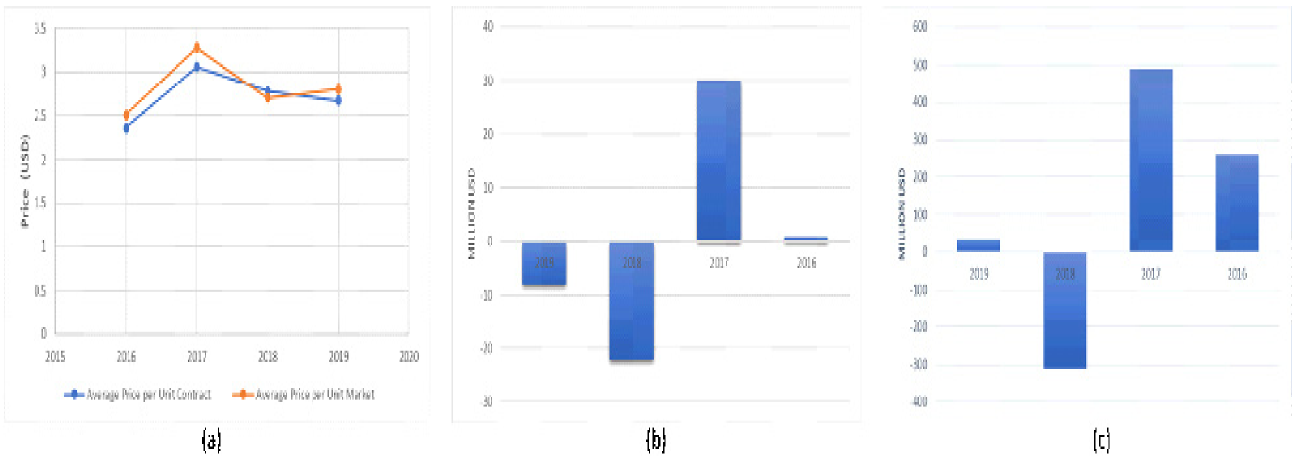


Figure 5. FCX hedging based on annual report (a) Sales contract (b) Future and swap contract (c) Forward contract

According to previous research from Carrasco et al. (2020), copper price modeling used a genetic algorithm produces an adequate prediction precision level, especially in his research for investment over 73 days. Seguel et al. (2015), in his research, genetic algorithm was proven to be useful in predicting copper price data in a time series. In line with previous researchers, Dehghani (2018) research revealed that genetic algorithm more precisely in predicting copper price compared to multivariate regression. Meanwhile, based on Banga (2017), the Neural Network was better than ARIMA, especially in RMS and prediction error. Carrasco et al. (2018) argued that neural network produced better modeling compared to linear modeling. The empirical result of Lasheras et al. (2015) research stated that Elman and Multilayer Neural Network both provide better modeling results compared to ARIMA. Meanwhile, Olayiwola (2016) argued that Neural Network was like a black box; only knew the input and output without knowing the process.

In previous research of copper price modeling, mostly only utilized single method and two methods comparison. Meanwhile in this research utilized three method comparison and analyzed its causality to FCX stock price. Also, in previous research, the authors saw discrimination when comparing ARIMA method with Artificial Neural Networks and Genetic Algorithms. This was identified when ARIMA only used input data only from the lag variable itself, while Artificial Neural Network and Genetic Algorithm used input data not only from the lag variable itself but also other variables such as opening price, the highest price, the lowest price, closing price, volume, and composite index. Therefore, what happens was Artificial Neural Network, and Genetic Algorithm were superior to ARIMA method.

As a problem-solving approach in this research, the author used equal data input for ARIMA, Artificial Neural Networks, and Genetic Algorithms. Therefore, the author hypothesizes that with equal data input, all methods will equal in performance. In addition, to analyze the causality relationship between copper price and FCX stock price. The Granger causality test is used to determine the lag in copper price, which affects the FCX stock price.

Based on research background explained, copper price is an essential aspect in terms of profit, revenue, production targets, and hedging for copper mining company. Therefore, the objectives of this research ware to determine the most suitable copper price model and modeling method. Furthermore, still according to research background explained, there were similarity trend between copper price and FCX stock price. Therefore, this research objective also to analyze causality relationship between copper price and FCX stock price.

METHODS

The data used was secondary data of copper prices and FCX stock prices from January 1997 to August 2020. The data was retrieved on August 24th, 2020 from Quandl and Macrotrends. Copper prices data were retrieved from Macrotrends. Meanwhile FCX stock prices were retrieved from Quandl.

The research method used quantitative methods using ARIMA (Autoregressive Integrated Moving Average), Artificial Neural Network, Genetic Algorithm, and Granger Causality test. ARIMA, Artificial Neural Network and Genetic Algorithm were utilized to determine copper price model. In the other hand, Granger Causality Test was implemented to determine relationship between copper price and FCX stock price. This research used Python programming in the Google Collaboratory cloud computing application.

ARIMA(p, d, q) is a non-stationary time series model that can be derived differencing by taking the difference to the d, which has an autoregressive p-order model and a q-order moving average model (Makridakis and Hibon, 1997; Junaid et al. 2020). ARIMA was chosen due to its simplicity in process and mathematical equation. Result of ARIMA model was applied as a base line model. In this research, ARIMA equation used was as follows:

$$Yt = c + \phi 1\ Yt\text{-}1 + et - \Theta 1\ et\text{-}1$$

Description: Y (copper price); c (constant); ϕ (autoregressive parameter); e (error term); Θ (moving average parameter)

Meanwhile, the steps to perform ARIMA modeling are as follows:

- Identify the corresponding p, d and q values by observing the correlogram (ACF) and partial correlogram (PACF).
- Estimating the autoregressive parameters and moving average that are included in the model.
- Testing ARIMA models that are more in line with the data using the Akaike Information Criterion (AIC) test.
- Make forecasts from the best ARIMA model equations obtained.

Artificial Neural Networks (ANN) are computational algorithms with the architecture and operation of how the human brain works (Goldberg, 2017). In this research, a feed-forward neural network type was used with the ReLU and Sigmoid activation functions. The artificial neural network architecture used was two input layers (Xt-1 and Xt-2), one output layer (Xt), and in between, there were 2 to 4 hidden layers, as shown in Figure 7. Artificial Neural Networks was used because of its ability to solve nonlinear problem using artificial intelligence algorithm. This method is very well known and widely used by researchers.

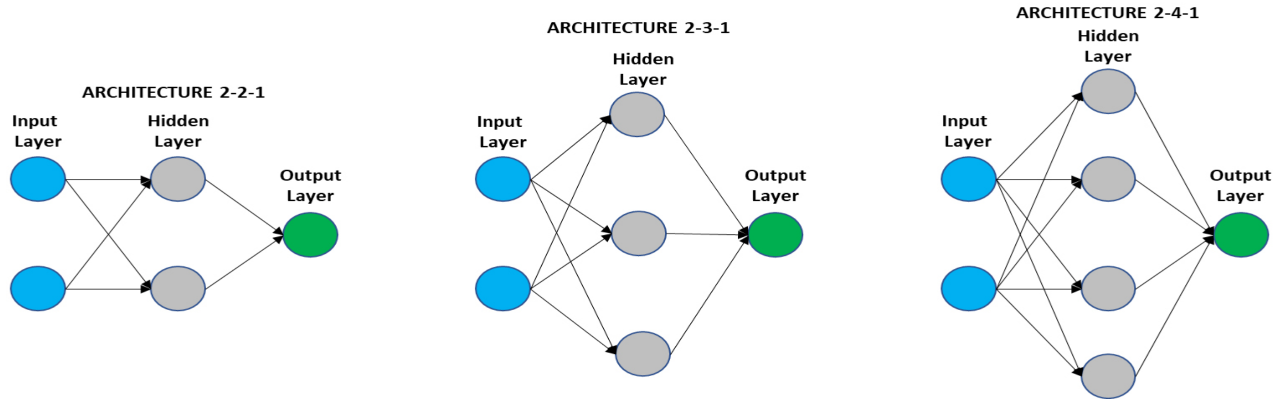


Figure 7. Artificial Neural Network architecture

The Genetic Algorithm (GA) is an optimization algorithm based on selection an individual who survives in the evolutionary process or Darwin's natural selection (Drachal and Pawłowski, 2021). This method utilized because of its unique characteristic to find optimize result of nonlinear problem. To carry out genetic algorithm modeling, what needs to determine the general equation that needs to be identified. In this case, the general ARIMA equation was used as the basic model. As shown in the equation below, variables a and b are the genetic algorithm's chromosome models that need to be identified the best fit value.

$$Xm = a + Xt\text{-}1 + b(Xt\text{-}1 - Xt\text{-}2)$$

Description: Xm (copper price model); Xt-1 (copper price one day before); Xt-2 (copper price two days before).

In the GA process, a fitness function is needed, which is a function to ensure that the chromosome model variables a and b get the best fit value. The fitness function equation used is as follows:

$$FF = \sum_{i=0}^{n} (X_t - X_m)^2$$

Description: Xt (actual copper price); Xm (copper price model); n (number of data (Xt)).

The Granger causality test is a statistical hypothesis test to determine whether a time series can cause or influence another time series (Granger, 1969). According to Gujarati and Porter (2009), in a time-series event, if the Xt-p event occurred before Yt, then maybe Xt-p caused Yt. Past events may affect the present but not vice versa. In this research, a two-variable autoregressive model causality test was used as in the equation below, which represents copper price (Xt) and FCX stock price (Yt). To test the hypothesis, p_value test was performed for each coefficient (a0 … a6). If p_value < 0,05 then the conclusion is right-hand side variable "Granger Cause" left-hand side variable. Before carrying out Granger Causality Test, as data preparation, both variables must be stationary. The data stationarity test can be done by performing Augmented Dickey Fuller (ADF) test. If the data is not stationary in level, then differentiate the data until it is stationary.

$$Yt = a0 + a1\ Xt\text{-}1 + a2\ Xt\text{-}2 + a3\ Xt\text{-}3 + a4\ Xt\text{-}4 + a5\ Xt\text{-}5 + a6\ Xt\text{-}6$$

Description: Y (FCX stock price (t, t-1 … t-6 are referred to lag number)); X (copper price (t, t-1 … t-6 are referred to lag number)); a (constant).

As it has been expressed briefly in the introduction. In previous research there was unequal input data between methods. It causes, significant difference of modeling performance between method. Due to that fact, in this research applied equal input data for all modeling methods. In another hand, Author said there was similarity trend between copper price and FCX stock price graphically. Therefore, hypothesizes for this research are as follow:

- If input data between method are equal, then the performance of modeling result also equal.
- Copper price influenced the movement of FCX stock price.

As shown in research framework in Figure 8, before determined copper price causality relationship to FCX stock price. ARIMA modeling analysis was carried out first until the best equation model was found. The next step was number of lags from the ARIMA model was used as an input layer in the Artificial Neural Network modeling. The final step of copper modeling was to use ARIMA equation model as the basic model in Genetic Algorithms model. Then Granger Causality test was utilized to analyze the causality relationship between copper price and FCX stock price.

RESULT

ARIMA(p,d,q) Model

Based on the comparison of the AIC value of each ARIMA model in Table 2, the best model was ARIMA model (1,1,0), with the smallest AIC value was -20859,437. This was in line with Tylkowski and Hojan (2019) research, also strengthened by Paul et al. (2013), they stated, the smallest AIC value indicate the best model of ARIMA. In the other hand, the ARIMA(1,1,0) model coefficient for the constant was 0,0003 and the coefficient for autoregressive parameter was -0,0577. So, the equation for the ARIMA(1,1,0) copper price model was as follows:

$$Xt = 0{,}0003 + Xt\text{-}1 – 0{,}0577\ (Xt\text{-}1 - Xt\text{-}2)$$

Description: Xt (actual copper price); Xt-1 (copper price one day before); Xt-2 (copper price two days before).

Using the ARIMA(1,1,0) equation, it can be calculated MSE, RMSE, MAPE, and R2 as shown in Table 3. The ARIMA(1,1,0) correlation coefficient was very significant close to one, and the RSME value was 0,041840437. In Figure 9, which is a plot of the overall comparison between the actual data, the model, and the error, the shape of the ARIMA(1,1,0) model was very close to the actual data. Based on this result, ARIMA produced very good performance to model copper price. This result was in line with Mahto et al. (2019), the results of his research related to commodity modeling using ARIMA also produced good modeling with MAPE 2,30%. Also based on Mahmood and Ali (2016), daily data modeling of gold prices with the ARIMA(1,1,0) model showed very good result with MAPE 0.82%.

Table 2 ARIMA model AIC comparison

MODEL	AIC	Constant	Coeff. AR1	Coeff. MA1
ARIMA(1,1,0)	-20859.437	0.0003	-0.0577	
ARIMA(0,1,1)	-20859.202	0.0003		-0.0569
ARIMA(1,1,1)	-20857.468	0.0003	-0.087	0.0294

Table 3. MSE, RMSE, MAPE dan R2 value of ARIMA(1,1,0) equation

MSE	RMSE	MAPE (%)	R-squared
0.001751	0.04184	1.1804255	0.99861175

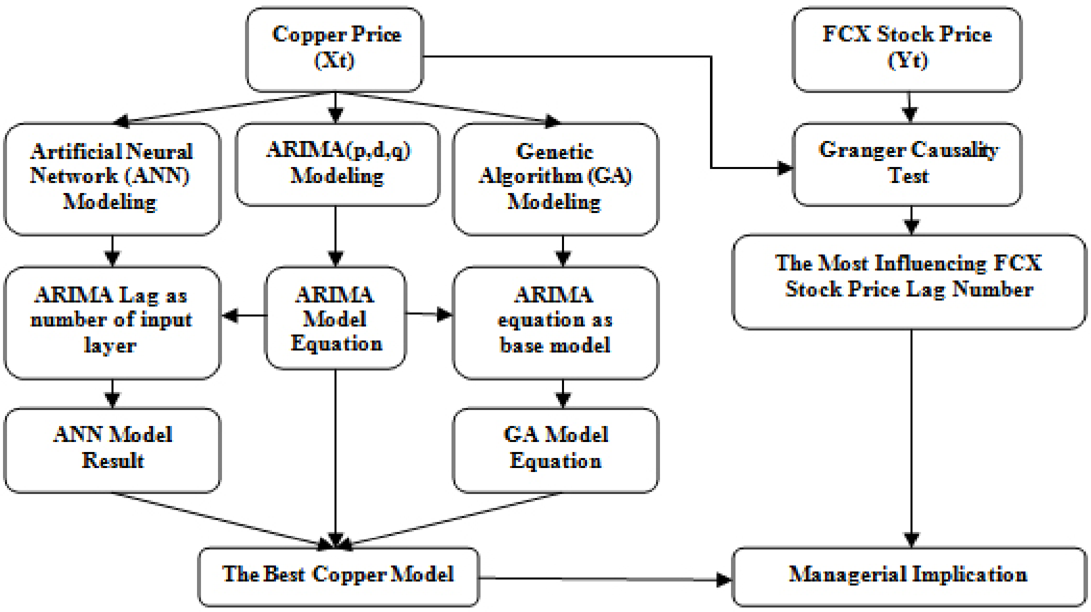


Figure 8. Research framework

Artificial Neural Network (ANN) Model

The ANN learning process used 1000 iterations or epochs for each activation and architecture. The ANN learning results were compared with the latest copper price (Xt), then calculated MSE, RMSE, MAPE & R2 as shown in Table 4 . Based on the results, almost all the architectures were similar in terms of MSE, RMSE, MAPE & R2 values. However, the sigmoid 2-4-1 architecture had the best MSE, RMSE & R2 than other ANN architectures.

Figure 10 shows the overall comparison between actual data, model, and error of ANN 2-4-1 sigmoid architecture. In this graph, ANN learning outcome model is very close to the actual data. In this research ANN 2-4-1 sigmoid architecture produced very good performance to model copper price. The result of this research was consistent with Mombeini and Yazdani-Chamzini (2015), ANN proved to be very good for modeling the gold price in their research with R2 equal to 0,989. Supporting the previous statement, research by Li et al. (2010) also stated that in their research to model agricultural commodities, ANN produced good modeling with MAPE less than 5%.

Table 4. MSE, RMSE, MAPE and R2 value of ANN model

Activation	Architecture	MSE	RMSE	MAPE (%)	R-squared
ReLU	2-2-1	0.001750176	0.041835109	1.185115964	0.9986121
ReLU	2-3-1	0.001758502	0.041934499	1.183513639	0.998605497
ReLU	2-4-1	0.001754415	0.041885741	1.195484291	0.998608738
Sigmoid	2-2-1	0.001756595	0.041911748	1.205244191	0.99860701
Sigmoid	2-3-1	0.001848169	0.042990339	1.275954867	0.998534391
Sigmoid	2-4-1	0.001749809	0.041830713	1.18026725	0.998612391

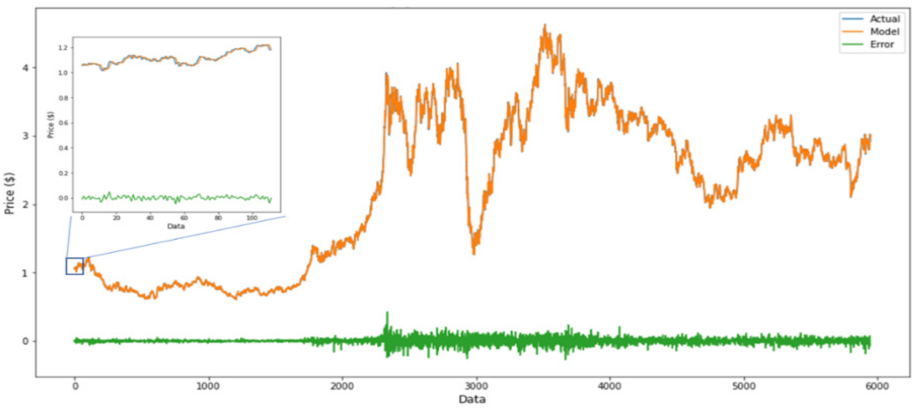
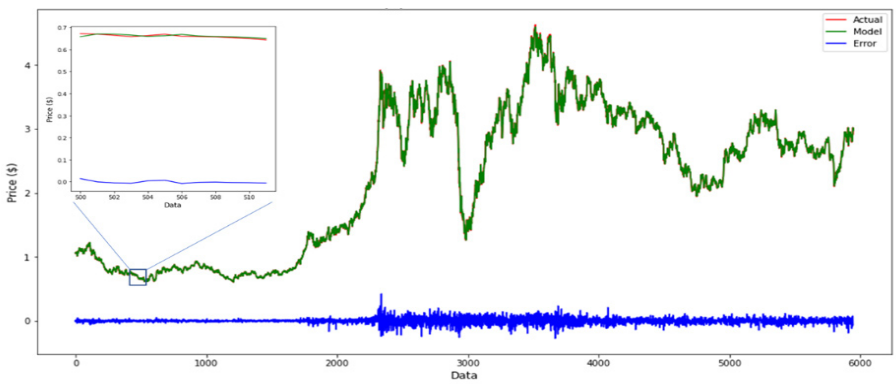


Figure 9. Plot of ARIMA(1,1,0) actual data, model and error



Gambar 10. Plot of ANN actual data, model and error

Genetic Algorithm (GA) Model

The genetic algorithm is a type of search algorithm. To obtain effective search results, the chromosome variable's value was limited to a specific value range, from -0,06 to 0,0004. Therefore, the best model was identified in 12 iterations experiment utilized specific given chromosome range, as listed in Table 5 . Based on experiment results with the best MSE, RMSE, and R2 values, obtained the most fit variable values were a = 0,00031861 and b = -0,05654089. Therefore, the equation for the copper price model based on genetic algorithm was as follows:

$$Xm = 0{,}00031861 + Xt\text{-}1 - 0{,}05654089(Xt\text{-}1 - Xt\text{-}2)$$

Description: Xm (actual copper price); Xt-1 (copper price one day before); Xt-2 (copper price two days before).

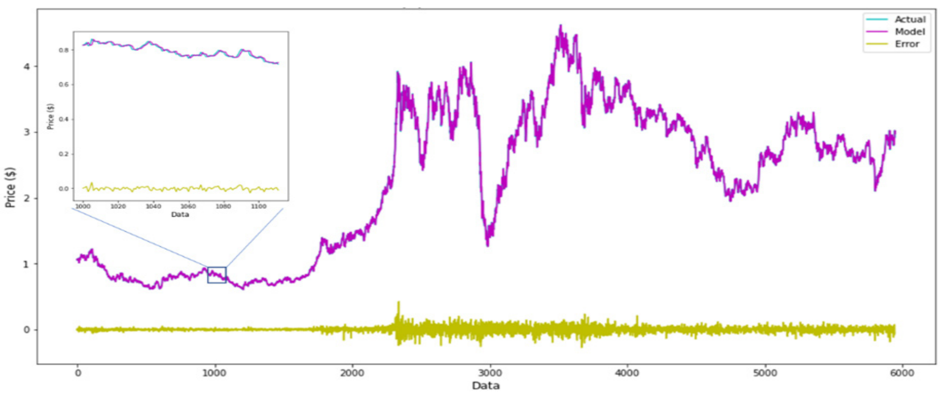
Figure 11 is the overall comparison plot between actual data, model, and error of the copper price equation model from the genetic algorithm search results. Like ARIMA and ANN results, Genetic Algorithm model was very close to the actual data. In this research Genetic Algorithm produced very good performance to model copper price. This research was in line with the research of Bonde and Khaled (2012), that in their research Genetic Algorithm was good enough to model stock prices with an accuracy of about 70%. Even based on Dharma et al. (2020) stated that Genetic Algorithm was effective method for modeling inflation rate in Indonesia with MSE of 0,1099.

Granger Causality Test

Based on the Granger causality test results in the first derivative, as shown in Table 6, with H0 rejection when the p-value $<\alpha = 0{,}05$. Obtained in lag three and lag four, there was a one-way effect; the copper price affected stock price, but not vice versa. In this research, the most proper interpretation is that the copper price affects stock price, and it is impossible to do the opposite way because FCX is not the price maker in the copper mining industry. This is in accordance with the introduction, more specifically, as shown in Table 1, that there are still many copper mining companies with a fairly large production as FCX competitor in copper mining industry.

Table 5. MSE, RMSE, MAPE and R2 value of GA model

Iteration	MSE	RMSE	MAPE (%)	R-squared	Variable a	Variable b
Auto	0.00175086	0.04184332	1.18026098	0.99861156	-0.00094729	-0.05387988
12	0.00175062	0.04184045	1.18049371	0.99861175	0.00031861	-0.05654089
24	0.00175098	0.04184471	1.17992252	0.99861146	-0.00026841	-0.0577389
36	0.00175071	0.04184151	1.18006268	0.99861168	0.00003053	-0.05674378



Gambar 11. Plot of GA actual data, model and error

Table 6. Granger causality test

H0 (Null Hypothesis)	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Copper Price "DOES NOT GRANGER CAUSE" FCX Stock Price	0.8251	0.0961	0.009	0.019	0.0091	0.0179
FCX Stock Price "DOES NOT GRANGER CAUSE" Copper Price	0.889	0.8943	0.5688	0.6256	0	0

This result was in line with Kang et al. (2013), which stated that the results of the Granger causality test showed that commodity prices affected the volatility of stock prices in China. Also, Zevallos et al. (2015), implied similar thing that metal influenced stock in Peru market. Still in line with this, according to Gunawan and Manurung (2008), based on the result of Granger causality test, copper price affected the volatility of stock prices in Indonesian market. Meanwhile, Wang et al. (2013) also inferred the similar thing with this research that metal commodity markets generally affect stock markets in China, India, Russia, South Korea, Taiwan, and Africa.

Managerial Implications

The modeling method in this research can be used as a reference for company analysts as an input for estimating the probability of profit, estimating revenue, estimating production targets, and hedging strategies. Related to speculator, the copper model of this research can be used as a reference or a way to gain profit or margin by making predictions on market movements and purchasing copper commodity in the future exchange. Meanwhile, for stock investors, the Granger causality test can be considered to estimate the stock price movement of base metal company based on base metal prices movement in certain lag.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This research indicated that the copper price modeling using ARIMA method, Artificial Neural Network, and Genetic Algorithm perform equally well for modeling the copper price. Therefore, this result support and confirm the author's hypothesis described in the introduction, which stated that if the input data are equally for all methods then the performance also equal. However, the author's recommendation to model copper price is sufficiently to use ARIMA because the process and mathematical calculations are simple and more practical. In addition to that, using Python programming language or others can enhance significantly in term of modeling processing time and can be directly connected to data provider server to perform modeling automatically even in real-time.

Meanwhile, Granger causality test in this research showed that copper price influenced FCX stock price at lag three and lag four. Therefore, the copper price has a positive effect on the FCX stock price. In other words, the value of a copper mining company is influenced by the price of the copper commodity itself, so that the results of this research support and confirm the author's hypothesis described in the introduction, which stated that copper price affects FCX stock price.

Recommendations

The results of copper price model in this research can be used to model the others mineral commodity prices such as tin, lead, and zinc. It is possible to test this in further research because these minerals have similarity in price trend, price index, and percentage change to the previous price. In the other hand, relationship between copper price and FCX stock price in this research can be used to estimate the stock price movements of downstream copper product companies such as copper smelting companies, copper pipe companies, and copper cable manufacturing companies. Therefore, it is feasible to be tested in further research.

REFERENCES

Adiwaskito MH. 2011. Analisis penerapan autoregressive integrated moving average sebagai dasar pengambilan keputusan hedging: Studi kasus pada PT. XYZ [tesis]. Jakarta: Universitas Indonesia.

Astudillo G, Carrasco R, Fernandez-Campusano C, Chacon M. 2020. Copper price prediction using support vector regression technique. *Applied Sciences* 10(19):6648. https://doi.org/10.3390/app10196648

Banga C. 2017. Forecasting volatility in copper prices using linear and non-linear models. *International Journal of System Modeling and Simulation* 2(1):22–26. https://doi.org/10.24178/

ijsms.2017.2.1.22

Bonde G, Khaled R. 2012. Stock price prediction using genetic algorithms and evolution strategies. *Proceedings of the 2012 International Conference on Genetic and Evolutionary Methods* 2012:10–15.

Carrasco R, Vargas M, Soto I, Fuentealba D, Banguera L. 2018. Chaotic time series for copper's price forecast. *IFIP Advances in Information and Communication Technology* 527:278–288. https://doi.org/10.1007/978-3-319-94541-5_28

Carrasco R, Fernández-Campusano C, Soto I, Lagos C, Krommenacker N, Banguera L, Durán C. 2020. Copper price variation forecasts using genetic algorithms. *Communications in Computer and Information Science* 1194:284-296. https://doi.org/10.1007/978-3-030-42520-3_23

[DBS] Development Bank of Singapore. 2018. Copper and its electrifying future. https://www.dbs.com.hk. [12 August 2020].

Dehghani H. 2018. Forecasting copper price using gene expression programming. *Journal of Mining and Environment* 9:349–360.

Dharma F, Shabrina Noviana A, Tahir M, Hendrastuty N, Wahyono. 2020. Prediction of Indonesian inflation rate using regression model based on genetic algorithms. *Jurnal Online Informatika* 5(1):45–52.

Drachal K, Pawłowski M. 2021. A review of the applications of genetic algorithms to forecasting prices of commodities. *Economies* 9(1):6–27. https://doi.org/10.3390/economies9010006

Eldomiaty T, Attia O, Mostafa W, Kamal M. 2015. How do managers manage dividend growth rates?. *Research in Finance* 31:105–134. https://doi.org/10.1108/S0196-382120150000031005

[FCX] Freeport McMoran Inc. 2019. Annual report 2019. https://investors.fcx.com. [12 January 2021].

[FCX] Freeport McMoran Inc. 2020. Conference call presentation. https://investors.fcx.com. [12 January 2021].

Gligoric Z, Gligoric M, Dimitrijevic B, Grozdanovic I, Milutinovic A, Ganic A, Gojkovic Z. 2020. Model of room and pillar production planning in small scale underground mines with metal price and operating cost uncertainty. *Resources Policy* 65:1–9. https://doi.org/10.1016/j.resourpol.2018.07.011

Goldberg Y. 2017. *Neural Network Methods for Natural Language Processing.* Toronto: Morgan & Claypool. https://doi.org/10.2200/S00762ED1V01Y201703HLT037

Granger C. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3):424–438. https://doi.org/10.2307/1912791

Gujarati D, Porter D. 2009. B*asic Econometric*. New York: McGraw-Hill.

Gunawan, Manurung AH. 2008. Pengaruh komoditas terhadap indeks harga saham gabungan. http://www.finansialbisnis.com. [4 April 2021].

Junaid MT, Juliana A, Sabrina H. 2020. Studi perbandingan model arima dan garch untuk memprediksi harga saham pada perusahaan tambang di Indonesia. *Jurnal Ilmu Keuangan dan Perbankan* 10(1): 83–99. https://doi.org/10.34010/jika.v10i1.3331

Kang J, Hu J, Chen C. 2013. Linkage between international food commodity prices and the Chinese stock markets. *International Journal of Economics and Finance* 5(10):147–156. https://doi.org/10.5539/ijef.v5n10p147

Lasheras FS, Juez FJDC, Sánchez AS, Krzemień A, Fernández PR. 2015. Forecasting the COMEX copper spot price by means of neural networks and ARIMA models. *Resources Policy* 45:37–43. https://doi.org/10.1016/j.resourpol.2015.03.004

Macrotrends. 2020. Copper prices -45 year historical chart. https://www.macrotrends.net. [24 August 2020]

Maes J, Nuzman C. 2015. The past, present, and future of copper access. *Bell Labs Technical Journal* 20:1–10. https://doi.org/10.15325/BLTJ.2015.2397851

Mahmood T, Ali A. 2016. Forecasting of daily gold price by using box-jenkins methodology. *International Journal of Asian Social Science* 6(11):614–624. https://doi.org/10.18488/journal.1/2016.6.11/1.11.614.624

Mahto AK, Biswas R, Alam MA. 2019. Short term forecasting of agriculture commodity price by using ARIMA: based on Indian market. *Communications in Computer and Information Science* 1045:452–461. https://doi.org/10.1007/978-981-13-9939-8_40

Makridakis S, Hibon M. 1997. ARMA models and the box–jenkins methodology. *Journal of Forecasting* 16(3):147–163.

Mombeini H, Yazdani-Chamzini A. 2015. Modeling gold price via artificial neural network. *Journal of Economics, Business and Management* 3(7):699-

703. https://doi.org/10.7763/JOEBM.2015.V3.269

Momcilovic M, Begovic SV, Tomasevic S, Ercegovac D. 2015. Sustainable growth rate: evidence from agricultural and food enterprises. *Journal for Theory and Practice of Management* 20(76):63–75. https://doi.org/10.7595/management.fon.2015.0017

Olayiwola A. 2016. Forecasting copper spot prices: a knowledge-discovery approach [tesis]. Manchester: University of Manchester.

Paul JC, Hoque MS, Rahman MM. 2013. Selection of best ARIMA model for forecasting average daily share price index of pharmaceutical companies in Bangladesh: a case study on Square Pharmaceutical Ltd. Global Journal of Management and Business Research Finance 13(3):14-25.

Pearce M. 2019. The ‘Copper Age’- a history of the concept. *Journal of World Prehistory* 32:229–250. https://doi.org/10.1007/s10963-019-09134-z

Quandl. 2020. FCX stock price historical data. http://www.quandl.com. [24 August 2020].

Rötzer N, Schmidt M. 2020. Historical, current, and future energy demand from global copper production and its impact on climate change. *Resources* 9(4):44–74. https://doi.org/10.3390/resources9040044

Schipper BW, Lin H, Meloni MA, Wansleeben K, Heijungs R, Voet EVD. 2018. Estimating global copper demand until 2100 with regression and stock dynamics. *Resources, Conservation and Recycling* 132:28–36. https://doi.org/10.1016/j.resconrec.2018.01.004

Seguel F, Carrasco R, Adasme P, Alfaro M, Soto I. 2015. A meta-heuristic approach for copper price forecasting. *Information and Knowledge Management in Complex Systems* 449:156–165. https://doi.org/10.1007/978-3-319-16274-4_16

Statista. 2018. Leading copper miners worldwide in 2018 by production output. https://www.statista.com. [20 August 2020].

Stowell D. 2017. *Investment Banks, Hedge Funds, and Private Equity.* London: Academic Press.

Tylkowski J, Hojan M. 2019. Time decomposition and short-term forecasting of hydrometeorological conditions in the South Baltic coastal zone of Poland. *Geosciences* 9:68–85. https://doi.org/10.3390/geosciences9020068

Vivekananda A, Achsani NA, Maulana TNA. 2019. Pengaruh variabel kinerja keuangan perusahaan dan makroekonomi terhadap harga saham batubara: perbandingan antara emiten LQ45 dan nonLQ45. *Jurnal Aplikasi Bisnis dan Manjemen* (JABM) 5(3):347–360. https://doi.org/10.17358/jabm.5.3.347

Wang Y, Lin C, Li Y. 2013. The correlation and hedging effects between commodity and stock markets. *Journal of Applied Finance & Banking* 3(5):269–297.

Zevallos M, del Carpio C. 2015. Metal returns, stock returns and stock market volatility. *Economía* 38(75):101–122.