Cost Estimation Model for Open Pit Nickel Mining in Indonesia

by Barlian Dwinagara

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ABSTRACT

In the early stage of a mining project, cost estimation is one of the crucial aspects. Performing a poor cost estimation method may result in cost overruns leading to the project failure. In these days, O'Hara (1980) method is still commonly practiced and widely used. O'Hara heavily worked on statistical model, which the mining project data was observed from countries other than Indonesia. Nevertheless, performing O'Hara method assumes the cost is only affected by one variable (i.e., production rate), and the inflation rate should be adjusted since the formulation is done several years ago. Given that, O'Hara method is considered as obsolete and irrelevant to be applied in Indonesia. In this research, cost estimation model was intended to specifically estimate operating cost and fixed cost of open-pit nickel mining in Indonesia. The statistical model was still used, but enhanced by considering other significant variables (i.e., fuel consumption, number of trucks, or number of employees), as well as the data gathered within the country. The model validation was done by performing statistical test (i.e., t-test, F-test, and R2). In addition, the proposed method would be beneficial for Indonesian government and investors to see the company's performance.

Keywords: cost estimation, nickel mining, project evaluation, open pit mine cost monitoring.

INTRODUCTION

Nickel mining costs in Indonesia may vary depending on transportation distance, local employee salaries, fuel prices and several other parameters.

This research can be beneficial for the government to control costs, for investors to calculate investments and for other stakeholders with various objectives.

MATERIAL AND METHOD

Literature or research on unit cost predictions is still difficult to find. However, research on other cost analyzes is found, for example operating cost predictions, capital costs, maintenance costs, and labor costs (O'Hara, 1980, Shafiee and Topal, 2012). Outside the mining industry, cost estimation formulations have also been carried out for the railroad industry (Sonmez and Ontepeli, 2009), processing plants (Sayadi et al., 2014), and floatation machines (Arfania et al., 2017). These studies use both linear and non-linear regression statistical methods. Based on the library, statistical methods are still considered reliable for predicting mining costs.

The most well-known cost estimation formula and is still used today is from O'Hara's research (1980), which uses data from at least 9 countries and 17 years of experience. From these data, the prediction model is formed using a statistical approach. O'Hara got a formulation to predict capital costs, maintenance costs, labor costs, for open or underground mining.

A statistical approach is also still used by Shafiee and Topal (2012) to predict the cost of open-pit coal mining. In his research, Shafiee and Topal (2012) used data on production, capital costs, operating costs, reserves or reserves, and the final year of mining from 20 coal mining companies in Australia. In this research, it is important to note that capital costs and operating costs are influenced by reserve thickness, stripping ratio, and production level. Thus, the study produced a formula for predicting operating costs per ton based on reserve thickness, stripping ratio, capital costs, and production level. Based on the 2 studies above, in this study, a statistical approach is also used to predict the unit cost of nickel mining in Indonesia. But some things need to be considered in using the statistical approach. In the statistical approach, the amount of data is important. It is intended that the sample taken is expected to be able to describe the population.

There is a dependent variable which is usually denoted by the letter y and at least 1 independent variable which is usually represented by the letter x. In a statistical approach or so-called regression, there are at least 2 types, namely linear and non-linear regression. In general, linear regression can be illustrated by the equation below.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1)$$

Where y is the dependent variable, α is the intercept, β is the slope or gradient, x is the independent variable, n is the number of the independent variable. Slope values are obtained using formula (2), while intercepts use formula (3) below.

$$\beta = \frac{cov(x,y)}{var(x)} \quad (2)$$

$$\alpha = \bar{y} - \hat{\beta}(\bar{x}) \quad (3)$$

Where cov (x, y) is covariance x with y, it can be calculated by formula (4), var (x) is variance x can be calculated by formula (5), $\bar{y}$ and $\bar{x}$ are average variables x and y, sequentially.

$$cov(x,y) = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{n-1} \quad (4)$$

$$var\ (x) = \frac{\Sigma(x_1 - \bar{x})}{n-1} \quad (5)$$

As for non-linear regression, in general can follow equation (6) below.

$$y = \alpha x^{\beta} \quad (6)$$

For additional information, O'Hara (1980) obtained a non-linear model to predict costs, while Shafiee and Topal (2012) produced a significant model in a linear model with an R2 of 0.95.

Monte-Carlo Simulation

In statistics, the word simulation usually means a type of Monte-Carlo (MC) simulation. In MC simulations, random samples are taken based on the probability distribution (Torikian and Kumral, 2014). In this study, the MC simulation is used to simulate the unit-cost distribution based on the distribution and its correlation with the independent variables. In figure 1 illustrates how the MC simulation works.

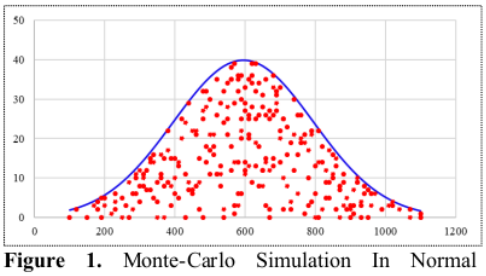

Figure 1. Monte-Carlo Simulation In Normal Distribution

The blue line is a Normal distribution, while the red dots represent random samples taken. The more random samples that are taken, the shape of the distribution of random samples is getting closer to the Normal distribution.

To use MC simulations do not always have to be obedient to the Normal distribution. Other distributions such as the Lognormal, Weibull, or PERT distributions can also be used if they match the character of the random variable. In general, the MC simulations application algorithm is as follows:

a. Estimation of the possible distribution parameters. For example, the mean and standard deviation for the Normal and Lognormal distribution. The lowest value, the highest value, and the value often appears for the distribution of the Triangle.
b. Take samples randomly in a predetermined probability distribution. For a Normal distribution, the inverse cumulative distribution function can be used with the most likely random, mean and standard deviation according to what was obtained in point a. Inverse cumulative distribution functions can generally be described below:

$$x = F^{-1}(p|\mu, \sigma) = \{x: F(x|\mu, \sigma) = p\} \quad (7)$$

Where x is the random sample value obtained from the inverse of the function F with the value of p 0, (0,1) and parameters μ and σ for the Normal distribution.

c. Do the steps in point b as many times as desired. The more the better. For a safe level of statistics, usually using a number of iterations of more than 1,000 times (Torikian and Kumral, 2014).

MC simulations are used for each variable. In the end there are several random samples that are independent of other independent variables.

Cholesky decomposition

Cholesky decomposition is a decomposition matrix used to correlate some random variables by binding them to a predetermined correlation coefficient (ρ). In this study, limited data aside from the estimated distribution parameters, the correlation coefficient was also estimated. The correlation coefficient used in this study is Pearson. Where X and Y are random variables and n is the number of samples, the Pearson correlation coefficient formula can be seen in the equation below.

$$\rho = \frac{n\sum(XY) - \sum(X)\sum(Y)}{\sqrt{(n\sum(X^2) - \sum(X)^2)(n\sum(Y^2) - \sum(Y)^2)}} \quad (8)$$

The correlation matrix values obtained in equation (8) above are used as the basis for *Cholesky* decomposition. Where A is the correlation coefficient matrix, L is the lower triangular matrix, in other words the *Cholesky* matrix, and L* is the transpose conjugation of the L matrix, then the *Cholesky* equation can be described as follows.

$$A = LL^{*} \quad (9)$$

Where:

$$L = \begin{bmatrix} \sqrt{A_{11}} & 0 & 0 \\ A_{21}/L_{11} & \sqrt{A_{11}} - L_{21}^2 & 0 \\ A_{31}/L_{11} & (A_{32} - L_{31}L_{21})/L_{22} & \sqrt{A_{33} - L_{31}^2 - L_{32}^2} \end{bmatrix} \quad (10)$$

Then the values of Lj, j and Li, j are obtained by the equation:

$$L_{j,j} = \sqrt{A_{j,j} - \sum_{k=1}^{j-1} L_{j,k}^2} \quad (11)$$

And

$$L_{i,j} = \frac{1}{L_{j,j}}\left(A_{j,j} - \sum_{k=1}^{j-1} L_{i,k}L_{j,k}\right) \quad (12)$$

By using the Cholesky L decomposition matrix, random samples obtained from MC simulations can be correlated according to predetermined correlation coefficients.

Ordinary least square (OLS)

Regression analysis is often used to predict the value of a variable based on other independent variables. Ordinary least square (OLS) is one of the most popular methods because at least 4 things (Greene, 2003):

a. Unbiased. This means that OLS produces parameters that describe the population well based on the sample.
b. Consistent, i.e. where the error is uncorrelated or allows no finite variance to occur, such a condition is commonly called homoscedasticity. ($Var[\varepsilon_i | x_i] = \sigma^2$)
c. Efficient. Statistically, an efficient estimator is the estimator that produces the smallest variance. OLS allows getting the smallest variance value because the OLS concept is to minimize the value of the variance itself.
d. Linear OLS is used to predict the dependent variable which is linearly correlated to the independent variable.

However, there are assumptions that must be met to use OLS as a basis for estimation. These assumptions are:

a. The dependent variable is correlated with the independent variable.
b. The average error value (error term) is 0.
c. All independent variables are not strongly correlated (exogeneity) where the value of the conditional mean is zero ($E[\varepsilon i | xi] = 0$).
d. Error (error term) does not correlate, or in other words does not appear autocorrelation.
e. The value of variance and error is constant.
f. Error distribution is Normal.

Not infrequently also some assumptions are not met. If the assumptions are not met, the following conclusions can be made:

a. Engineering variables with non-linear functions, such as rank or logarithm.
b. Calculates the value of the intercept in the model. The intercept value is a constant value where if all the values of the free variable are zero (0), then the value of the dependent variable is the same as the value of the intercept.
c. Adding the independent variable, then do the F test. There may be a free variable that is highly correlated, but not yet included in the calculation.
d. Look for suspicious independent variables, which in theory have no relationship to the dependent variable. For example, the price of a commodity is highly correlated to the interest rate and population of elephants in Indonesia. In that case, the variable number of elephant population is a variable that needs to be suspected because in theory it is not related to commodity prices.
e. Plot error value on the graph. If the error value is not constant, then step c can be performed.
f. If there are variables that produce a perfect correlation coefficient ($\rho = 1$ or $\rho = -1$), there is a possibility of autocorrelation. For example, car age predictions (dependent variable) use distance in meters as the first independent variable and mileage in kilometers as a second independent variable. It can be ascertained that the independent variable 1 and the independent variable 2 have the perfect correlation value because it is basically 1 entity, namely distance traveled. In this case, one of the independent variables can be removed.
g. Plot an error value to see the trend. The error should not have a trend or in other words be unpredictable. If the error value has a trend, it is necessary to look for other independent variables that explain the movement of the error value.

Of the advantages, assumptions, and anticipations that can be done as mentioned above, OLS is a good estimation tool by minimizing the value of variance.

$$min \sum_{i=1}^{k} [y_i + (\alpha + \beta_1 x_{1i} + \cdots + \beta_n x_{ni})]^2 \qquad (13)$$

Furthermore, it is possible to have outliers in the data. Outlier can be an error in data retrieval or indeed reflect the real situation (Sauvageau and Kumral, 2015). Eliminating data that is considered outlier is a common practice that is commonly done by researchers, but if the outreach does indeed reflect the real situation, then eliminating outlier is not a good practice, even important information will be lost.

In this research, if there are outliers, it will be analyzed whether the outliers are the result of data retrieval errors or indeed describe actual information. Outliers will be ignored if the data is invalid. Conversely, if outliers are valid data, outliers will be included in the calculation.

Model validation

Test statistic t-test

The t-test statistical test aims to test each independent variable whether it is significant to the model or not. If the value of t-test> t-table with 95% confidence level ($\alpha = 0.05$) means the null hypothesis (Ho) is rejected or in other words the independent variable is considered significant.

If t is the t-test value, $\bar{t}$ is the sample mean, μ is the population average, σ is the sample deviation standard, and n is the number of samples, then the t-test can be performed using the formula (14).

$$t = \frac{\bar{x} - \mu}{\sigma / \sqrt{n}} \qquad (14)$$

The p-value in the t-test can be seen in the graph below (Krzywinski and Altman, 2013). Where the higher the t-test value will produce the lower p-value, meaning that the more significant the model.

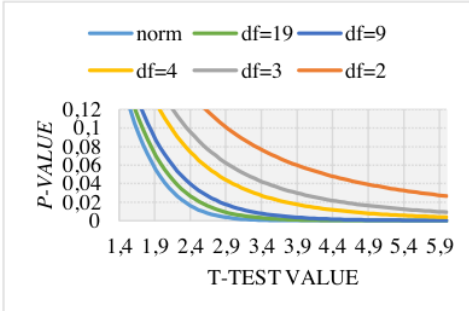

Figure 2. Graph p-value on t-test

The t-test statistical test is only to test the hypothesis whether the tested model is significant or not with a certain level of confidence. The model is considered significant if the p-value <α.

F-test statistical test

In contrast to the t-test that tests each independent variable, in the F-test statistical test, all independent variables contained in the model are tested simultaneously whether these variables are significant or not. If the value of F-test> F-table with a 95% confidence level (α = 0.05, p-value <α) means the null hypothesis (Ho) is rejected or in other words the combination of the independent variable is considered significant.

Where F is the F-test value, SSR_R is restricted accumulation of error squares (models assuming the coefficient of the independent variable = 0), SSR_{UR} is the unrestricted accumulation of error squares (the model using the coefficient of the independent variable as it is), q is the number of restricted parameters, n is the number of samples, k is the number of independent variables, and $n-k-1$ is the degree of freedom (Hristu-Varsakelis and Kyrtsou, 2010), then the calculation of the value of F (F-test) can be done using equation (15).

$$F = \frac{SSR_R - SSR_{UR}/q}{SSR_{UR}/(n-k-1)} \sim F_{q,\ n-k-1} \quad (15)$$

If F_q^{cdf} is the cumulative distribution of the $F_{a,b}$, then the p-value of the F-test is obtained from calculations in formula (16) (Hristu-Varsakelis and Kyrtsou, 2010).

$$p = 1 - F_{q,\ n-k-1}^{cdf}(F, q, n-k-1) \quad (16)$$

The F-test is only used for validation of multivariate regression models where the independent variable is more than one. The model is considered significant if the p-value <α (significance F <α).

Coefficient of determination (R^2)

Model validation is done by carrying out statistical tests, namely the coefficient of determination (R^2), F-test, t-test, and MAER (mean absolute error rate). The value R^2 looks at the accuracy of the model with respect to observational data with a range of values 0-1, where the value approaching 1 is the model with the highest level of accuracy. R^2 calculations can be seen in equation (17).

$$R^2 = 1 - \frac{SSR}{SST} \quad (17)$$

Where SSR is sum of square of residuals or the difference between the square of y-prediction and y-average $SSR = \sum(\hat{y} - \bar{y})^2$, SST is the total sum of squares or the total square of the difference between actual y-with y-average $SST = \sum(y - \bar{y})^2$. Because the more the number of independent variables will increase the value of R^2, the value of R^2 needs to be justified (Adjusted- R^2). Adjusted-R^2 will consider the number of independent variables, so it will be adjusted whether the increase in the value of R^2 is caused by the addition of the number of independent variables or because of observational data (Lacy, 2006). The Adjusted- R^2formula can be seen in equation (18).

$$R_{adj}^2 = 1 - \left[\frac{(1-R^2)\times(n-1)}{n-k-1}\right] \quad (18)$$

Therefore, to compare the univariate and multivariate models, the adjusted-R^2 value will be used.

MAER (mean absolute error rate)

The MAER value indicates the average absolute error rate of the model. Therefore, the smallest MAER value is the model with the fewest errors, so the model is chosen (Arfania et al., 2017). By using equation (19) the MAER value can be determined.

$$MAER = \frac{1}{n}\sum\left(\frac{C_e - C_a}{C_a}\right) \quad (19)$$

Where C_e is the predicted cost, C_a is the actual cost, and n is the number of samples. MAER calculation is the last indicator to determine the model to be chosen.

RESULTS

Data simulation

Monte-Carlo simulation is expected to be able to describe the state of the population based on the Normal distribution parameters, namely the mean (μ) and standard deviation (σ). Therefore, the unit-cost estimate using a statistical approach needs to use the MC simulation algorithm.

The characteristics of nickel mining in Indonesia in this study are divided into two, namely services and non-services or self-employed. So, the MC simulation also needs to be done twice, namely for data from Company A as a representation of mining using services, and data from Company B as a representation of mining carried out on its own.

Data to be tested includes unit-cost, production level, crude oil price, contribution-tax, amortization-

depreciation, and environmental costs. Where unit-cost is the dependent variable, and the remaining variable is the independent variable. It needs to be clarified, the level of production used is ore production and overburden (OB). The world oil price used comes from the US energy information administration (US Energy Information Administration, 2019). Environmental costs are reclamation costs per year. The parameters of each variable assumed to follow the Normal distribution can be seen in the table below.

Table 1. Normal distribution parameters of each variable

No	Var	Services		Non-services	
		Mean	Std. dev.	Mean	Std. dev
1	UC	20,70	1,83	10,62	0,57
2	PR	1.248.676	519.925	13.369.872	958.258
	OP	48,03	9,78	70,72	23,60
4	TX	202.599	22.544	2.862.990	1.277.161
5	AD	580.193	302.620	27.758	6.647
6	BL	481.511	40.857	7.401.670	3.608.573

For simplicity, the statistical variables are abbreviated as UC for unit costs in US $ / ton, PR for production (ore and OB) and tons, OP for world oil prices or oil prices in US $ / barrel, TX for tax-levies fees in US $, AD for amortization-depreciation in US $, and BL for environmental costs in US $.

Pearson correlation coefficients are also calculated at this stage using equation (8). Thus, the correlation matrix is obtained as in the table below.

Table 2. Correlation matrix actual unit-cost data with and without services

	Initial correlation (Jasa)					
	UC	PR	OP	TX	AD	BL
UC	1					
PR	-0.584	1				
OP	-0.231	0.919	1			
TX	-0.820	0.090	-0.310	1		
AD	-0.318	-0.581	-0.831	0.694	1	
BL	-0.649	-0.231	-0.590	0.929	0.910	

	Initial correlation (Non-Jasa)					
	UC	PR	OP	TX	AD	BL
UC	1					
PR	-0.583	1				
OP	0.517	-0.628	1			
TX	-0.344	0.848	-0.773	*1*		
AD	-0.250	0.679	-0.899	0.906	1	
BL	0.083	-0.045	-0.536	0.200	0.453	1

In the service correlation matrix, the correlation between unit-cost (UC) with oil prices (OP), fee-levy-tax (TX), amortization-depreciation (AD), and environmental costs (BL) is negative, or in other words, the higher the UC, the lower the TX, AD, and BL values. From data obtained from companies (UC), US energy information administration (OP) and London Metal Exchange (world nickel prices), UC has a downward trend, world oil prices have an upward trend, and nickel has a downward trend especially in 2015 to 2018 When the OP value rises, the UC value tends to go down, it could be due to a contract with the service that has occurred, then a negative correlation occurs. At UC-TX, the price of nickel has decreased, while costs are generally fixed or rising, the tax paid will be low or in other words the UC-TX correlation becomes negative. For UC-AD, further analysis is needed, but based on company data (primary), the value of amortization-depreciation and environmental costs is inversely proportional to unit-cost. One of the reasons that this might happen is because of company policy (age of tools and reclamation programs).

On the non-service correlation matrix, the UC-OP relationship is inversely proportional. Because mining is done alone, the increase in oil prices is followed by an increase in mining costs. At UC-TX as with the service matrix, low nickel prices can reduce the value of taxes. In UC-AD and UC-BL, company policy influences its value.

Furthermore, based on the parameters in table 1 above, the sample is randomly drawn 10,000 times (iteration) for each variable with the MC simulation algorithm, equation (7) is used to get the sample value. MC simulation results for each variable normally distributed can be seen in below Figures.

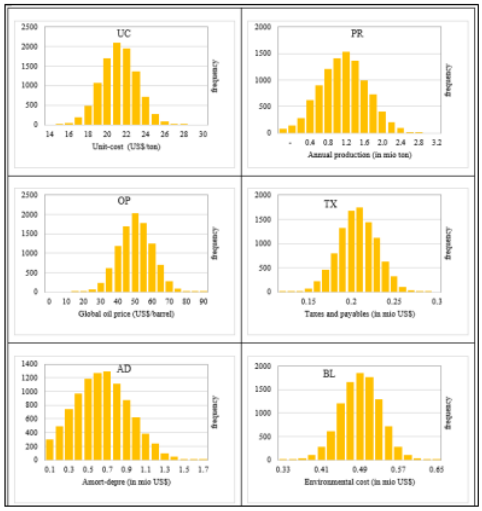

Figure 3. Normal distribution of each variable (Services)

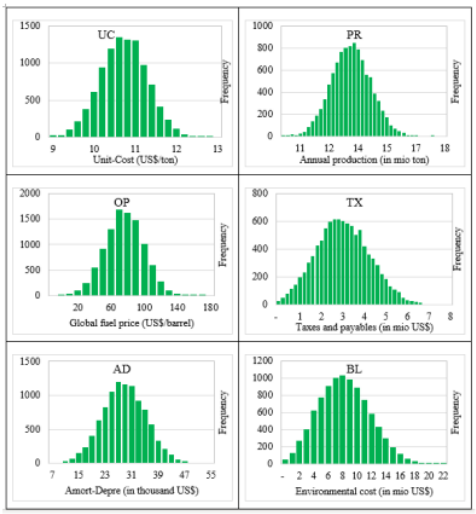

Figure 4. Normal distribution of each variable (Non-services)

Please note, the results of this simulation are still independent between variables, need to be correlated using the Cholesky decomposition to match or approach the initial matrix correlation value (table 2). So, correlating the simulation results is the next step. From the MC simulation results with 10,000 iterations and correlating the results based on the Cholesky decomposition, 10,000 canerations were correlated. The correlation between these random variables can be seen in the table below.

Table 3. Correlation of random variables on the results of MC simulations and Cholesky decomposition

	Initial correlation (Jasa)					
	UC	**PR**	**OP**	**TX**	**AD**	**BL**
UC	1					
PR	-0.577	1				
OP	-0.227	0.918	1			
TX	-0.878	0.217	-0.182	1		
AD	-0.325	-0.575	-0.825	0.603	1	
BL	-0.651	-0.228	-0.588	0.879	0.909	1

	Initial correlation (Non-Jasa)					
	UC	**PR**	**OP**	**TX**	**AD**	**BL**
UC	1					
PR	-0.577	1				
OP	0.532	-0.632	1			
TX	-0.340	0.847	-0.771	*1*		
AD	-0.260	0.681	-0.900	0.912	1	
BL	0.057	-0.034	-0.549	0.218	0.460	1

If observed, the correlation coefficient value in table 8 approaches the actual data correlation coefficient (table 3). This illustrates that the simulation results are sufficient to represent the characteristics of the data, especially in terms of correlation. Furthermore, the simulation results are used in the nickel unit-cost formulation in Indonesia with a statistical approach.

Unit-cost modeling

The unit-cost formulation is estimated using the OLS method. Intercept is calculated by formula (3), while the slope is determined by formula (2). Thus, the resulting unit-cost formula for mining using services is as follows.

$$y = 86{,}71 + 4{,}13 \times 10^{-6}(PR) - 0{,}41(OP) + 4{,}62 \times 10^{-5}(TX) + 5{,}75 \times 10^{-6}(AD) - 1{,}33 \times 10^{-4}(BL) \quad (20)$$

As for the prediction formula for unit-cost nickel mining in Indonesia that can be done alone can be as follows.

$$y = 6{,}14 - 2{,}12 \times 10^{-7}(PR) + 0{,}04(OP) - 1{,}35 \times 10^{-7}(TX) - 1{,}52 \times 10^{-4}(AD) + 4.82 \times 10^{-8}(BL) \quad (21)$$

It should be noted, the AD data of non-service companies needs to be studied more deeply. Because with Company B has greater production, so that the AD value of Company B should be bigger than Company A. Existing data could have occurred because of the mining amortization-depreciation of Company B is combined with amortization-depreciation of a matte nickel processing plant.

Statistical testing was performed on the 2 prediction models above. The results of the t-test and F-test stated that with a 95% confidence level the model was significant for mining with services as well as working alone (non-service). The results of the calculation of R2 adjustment for both types of models are 0.99 for mining with services, and 0.84 for mining which is done alone. The MAER value for each model is 4.05 × 10-5 for service mining and 5.39 × 10-4 for self-mining. Moreover, the two models do not show autocorrelation (error trend). Details of the statistical test can be seen in the appendix.

Using formulas (20) and (21) above the actual unit-cost value compared to the predicted results, where the value can be seen in the table below.

Table 4. Comparison of actual and predicted unit-cost (US $/ton) values

Year	UC actual (service)	UC Prediction (Service)	UC actual (Non-Service)	UC Prediction (Non-Service)
2011	n/a	n/a	10,05	10,40
2012	n/a	n/a	11,46	10,96
2013	n/a	n/a	11,02	11,18
2014	n/a	n/a	11,07	11,11
2015	21,17	21,21	9,71	9,48
2016	22,40	22,56	10,11	10,26
2017	18,11	18,25	11,00	10,99
2018	21,14	20,92	10,54	10,59

From the table above, the unit-cost formula is quite good in predicting the unit-cost value of nickel mining in Indonesia.

The statistical approach uses independent variables that correlate with the dependent variable (unit-cost) to

predict unit-cost values.

With the statistical approach multivariate linear regression models are obtained. Where unit-cost is the dependent variable, and the independent variable is annual production (PR), global oil prices (OP), taxes and payables (TX), amortization-depreciation (AD), and environmental costs (BL). Two models are produced, namely to predict unit-cost for mining using a third party and other models for mining activities that are done alone. Both models have passed the statistical tests with good results. Significant t-test and F-test with a confidence level of 95%, R^2 value of 0.99 for the service model and 0.84 for the model for self-mining, low MAER value for both models is 4.05 × 10-5 for mining uses services and 5.39 × 10-4 for mining which is done alone. independent variables in all models do not show autocorrelation. It should be noted, the statistical approach is very dependent on existing data, so outliers in the field need to be investigated more in its causes, especially if outliers occur in components contained in independent variables (PR, OP, TX, AD, and BL).

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