

HOW DOES BETTER QUALITY DATA AFFECT THE VALUE OF A MINING PROJECT?

Ishjantsan Gursuren^{1*}, Bryan Maybee², Ganbaatar Zagdsuren³

¹*Master of Science, Mineral and Energy Economics, MAusIMM, Australia*

²*Mineral and Energy Economics program, MAusIMM, Australia*

³*School of Arts and Sciences, National University of Mongolia, Ulaanbaatar, Mongolia*

ABSTRACT

With the advent of 3D software applications into geology and resource modeling world, data quality is going to become an issue. Electronic data can easily be corrupted due to weak data housing and ownership. Many people are aware of the issue, but they may not know how much it can affect the value of a mining project especially when making investment decisions. This research investigates the question *How does better quality data affect the value of a mining project?* Two geological primary data datasets were created. The first dataset was named “initial”; after manual entry errors were removed a second dataset was named “improved” (or verified). All the data errors raise from inadvertent human mistakes and coming out the source files. The methodology consisted of constructing two models for resource estimation based on both datasets, followed by developing two financial assessments and comparing their results. The approach was applied to evaluate the central orebody of the Erdenet-Ovoo copper-molybdenum group deposits in Mongolia. The actual operational and costing information of the existing operation was used for financial assessment. The most assumptions and parameters for the financial assessment were analysed and estimated to plug into the financial models.

The answer to the research question is not just a matter of finding a simple discrepancy in the resource amounts and Net Present Value (NPV) by discounted cash flow models. The study also examines project risks and compares the probabilistic distributions of NPVs for the two models based on the decision-making ability of them. It is found that the improved model is more accurate than the initial one and can provide a better decision making. Specifically, having better-quality data increases the probability of the project to make a profit by over 7% and 2.7% with a higher chance that the NPV will be greater than \$100M in this case study.

Keywords: Inadvertent data errors, Implicit – RBF based geology model, Fully integrate resource estimation workflow, Modern Asset Pricing – (MAP) model, Monte Carlo simulation, “Initial” & “Improved” model

*Corresponding author. Tel.: +976 9896 9798

E-mail address: ishee.ot@gmail.com

1. Introduction

Many studies for mining project valuations tend to consider external factors such as market risk, commodity price uncertainty and other macro-economic or socio-political influencing factors. Some studies focus on data representative issues including fundamental sampling errors, quality

assurance and quality control and so forth. This research, however, touches on inadvertent data errors, which are carried through during resource estimation and may result in the creation of misleading financial model a mining project.

This research study examines all errors that can be attributed to human mistakes, either

unintentional or intentional; it is not concerned with other data representing problems such as fundamental sampling errors. A key word here is *the value of geological primary data*, which should be treated like an asset, and how much it can impact on NPV of a mining project. Thanks to the development of combined implicit geological modeling with flexible workflows for resource estimation, software called Leapfrog was used, which ensured the models functioned in a consistent and comparable manner to reveal the results caused by data errors.

In practice, many of the geoscientific databases are likely have inadvertent data issues which can be attributed to a lack of post data entry checking or general lack of care. “Passion fingers, mistakes, cats on keyboards all happen. Add to this the well-meaning users with a little knowledge thinking they are doing good, and we have inadvertent changes. Changes that are not malicious, just accidental through use” (McManus, 2017).

THE SPECIFIC ISSUES TO BE ADDRESSED

It is agreed that “[a]ny resource and reserve estimation is guaranteed to be wrong; some, however, are less wrong than others” (Rozman, 1998). If we use poor-quality data, the estimations will become more wrong than the other estimations, and the geological uncertainty caused by data errors and risks compound at the project valuation stage. The priority is to use the most accurate outputs from resources estimations based on validated and verified databases for project valuation. Small errors made early in the recording of exploration data in a mining project may significantly affect the economics at the project valuation stage.

LITERATURE REVIEW

Many studies basically touch on garbage in, garbage out principle such as, fundamental

sampling error and the importance of quality assurance and quality control. These research studies mainly focus on data representative issues not inadvertent human errors. Consulting Engineer Dr. Pierre Gy once said “Sampling is one of the basic operations of the human mind. It does not receive the attention it deserves”. The evaluation of a new Mineral Resource and its economic viability is critically dependent on the quality of the assay data and it is this data that defines the grade of the resource (Roden and Smith 2014).

In Silva and Coimbra’s recent analytical paper “Selecting the maximum acceptable error in data minimising financial losses”, the authors create several scenarios by intentionally adding errors to sampled grades to show how “tolerance limits are based on the relation between data acquisition costs and block misclassification rate sensitivity to data uncertainty” (2016, 214).

THE CASE STUDY TO BE USED

To identify the effects of improved datasets for a mining project, the central orebody of Erdenet-Ovoo copper-molybdenum group deposits, was used as a case study. Erdenet is the second largest mining project in Mongolia. Erdenet has been operating as an open cut mine for the main orebody called “Northwest” since 1978. The annual throughput is 26Mt ore, 530,000-ton copper and 4,500-ton molybdenum concentration (Erdenet, 2018). The central orebody is adjacent to north-west orebody with over 300 exploration drillholes were drilled from 1972 to 2014 and has not been mined, yet. It is assumed that the main pit reserve has been exhausted and the new mine will continue to feed the existing mill at the same rate of throughput. Current operation & costing information were used for financial models

2. The research methodology

Two main staged methods Resource Estimation and Financial Assessment that have sub-sequent steps, were used to answer the

research question. The link between these two stages is the output of the resource estimation, which was used in the financial assessment (Fig. 1).

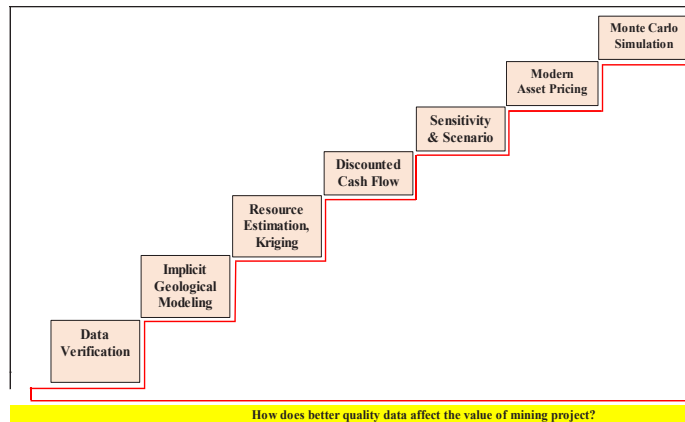


Fig. 1. Progression to answer the research question

In order to control the compounding errors from the initial datasets through these stages, the exact same estimation methods, geological interpretations, and financial models were carried out. The project NPV and its probabilistic distribution are the metrics to evaluate the output.

RESOURCE ESTIMATION

1.1.1 Data Verification

Two different datasets are going to be discussed in this section. The first one is called the “Initial dataset” which was created by Erdenet Mining Cooperation. The initial dataset was then verified by the consulting company Tsakiurt Khuder Ltd in 2015 and is called the “Improved dataset”. The improved dataset was updated with actual figures based on hard copies such as, original drilling logs, assay certificates, cross sections and so on (Gursuren, 2015). The difference between these two datasets is that there are many changes in the initial dataset such as, incorrect data entries, which have been corrected in the improved dataset based on data sources and some omitted drill logs that were found (**Error! Reference source not found.**).

The data verification team reconciled the paper copies back against what was entered and

found that some of the entries were wrong. As such, they were re-entered to create the improved database, which has some corrections.

The way to recognise any errors is that the data record in each cell has been compared with its hard copy source on a spreadsheet. Overall, three staged verification tasks have been carried out.

- The source data has been typed and compared to the initial data. If it exactly matches, it is indicated “TRUE”, otherwise “FALSE”.
- The all data recognized as FALSE, has been re-checked to validate any mistakes during the source data typing. The typing mistakes that resulted in mismatches, have been fixed via the double-checking process based on the hard copies. Finally, the mis-entered errors have been reported and fixed.

The error statistics by types of data, have been reported and the initial dataset has been updated based on the data verification protocol.

It is difficult to say that any electronic data is correct without first looking at a source file because of inadvertent data issues, data housing and ownership and so forth. The initial dataset, therefore, was transformed considerably when compared to its source file. The improved dataset now matches with the original source and is thus more accurate than the initial one.

The data verification project was conducted for a total of **319** drill-holes' collecting primary data such as, collar, down-hole survey, and assay. The lithology data was created from scratch as there was no lithology data in the initial dataset. A report was written for documenting all of these changes, and some statistics were made for showing the verification of results.

1.1.1.1 Collar data

The verification for collar data found that there were few errors in X, Y axis and hole length, more in elevation (**Table. 1.**)

Table. 1. Collar data errors

ORIGINAL DATABASE				SOURCE DATA				COMPARISON				
HOLEID	X_LOCAL	Y_LOCAL	Z_ELEVATION	HOLEID	X_LOCAL	Y_LOCAL	Z_ELEVATION	HOLEID	X	Y	Z	Y
550	219429.000	201822.000	1422.950	550	219429.000	201822.000	1422.950	TRUE	TRUE	TRUE	FALSE	FALSE
561	219619.000	201904.700	1469.700	561	219619.000	201904.700	1468.900	TRUE	TRUE	TRUE	FALSE	FALSE
577	219862.500	201682.000	1415.200	577	219862.500	201682.000	1416.100	TRUE	TRUE	TRUE	FALSE	FALSE
582	219895.600	201520.000	1418.600	582	219895.600	201520.000	1418.500	TRUE	TRUE	TRUE	FALSE	FALSE
583	219862.200	201465.300	1424.000	583	219862.200	201465.300	1423.800	TRUE	TRUE	TRUE	FALSE	FALSE
584	219830.100	201411.100	1430.300	584	219830.100	201411.100	1430.000	TRUE	TRUE	TRUE	FALSE	FALSE
5935	219627.501	201667.167	1436.404	5935	219627.501	201667.167	1436.350	TRUE	TRUE	TRUE	FALSE	FALSE
5936	219322.500	202141.343	1466.666	5936	219322.500	202141.343	1467.394	TRUE	TRUE	TRUE	FALSE	FALSE
5937	219290.180	202086.291	1457.220	5937	219290.180	202086.291	1457.851	TRUE	TRUE	TRUE	FALSE	FALSE
5938	219254.755	202038.660	1447.983	5938	219254.755	202038.660	1448.274	TRUE	TRUE	TRUE	FALSE	FALSE
5939	201874.065	219721.444	1447.302	5939	219721.444	201874.065	1447.900	TRUE	FALSE	FALSE	FALSE	FALSE
5940	201808.666	219686.464	1444.185	5940	219686.464	201808.666	1444.900	TRUE	FALSE	FALSE	FALSE	FALSE
5941	219641.478	201737.291	1443.220	5941	219641.478	201737.291	1443.800	TRUE	TRUE	TRUE	FALSE	FALSE
5942	219598.066	201601.462	1424.391	5942	219598.066	201601.462	1426.600	TRUE	TRUE	TRUE	FALSE	FALSE
5943	219226.066	201979.792	1440.424	5943	219226.066	201979.792	1440.418	TRUE	TRUE	TRUE	FALSE	FALSE
5944	201725.081	219785.393	1425.601	5944	219785.393	201725.081	1425.800	TRUE	FALSE	FALSE	FALSE	FALSE
5945	201651.314	219739.997	1425.729	5945	219739.997	201651.314	1426.000	TRUE	FALSE	FALSE	FALSE	FALSE
5946	219708.657	201592.514	1424.561	5946	219708.657	201592.514	1425.100	TRUE	TRUE	TRUE	FALSE	FALSE
5947	219669.830	201511.224	1419.352	5947	219669.830	201511.224	1419.400	TRUE	TRUE	TRUE	FALSE	FALSE
5948	219898.280	201637.600	1409.920	5948	219898.280	201637.600	1410.800	TRUE	TRUE	TRUE	FALSE	FALSE
5949	219778.100	201427.940	1429.520	5949	219778.100	201427.940	1430.800	TRUE	TRUE	TRUE	FALSE	FALSE
5950	220150.030	201570.005	1415.726	5950	220150.030	201570.005	1417.000	TRUE	TRUE	TRUE	FALSE	FALSE
5951	219974.130	201513.230	1422.470	5951	219974.130	201513.230	1423.500	TRUE	TRUE	TRUE	FALSE	FALSE
5952	219914.873	201413.267	1431.120	5952	219914.873	201413.267	1431.900	TRUE	TRUE	TRUE	FALSE	FALSE
5953	219862.639	201299.494	1439.336	5953	219862.639	201299.494	1439.300	TRUE	TRUE	TRUE	FALSE	FALSE

1.1.1.2 Down-hole survey

These are the most significant errors that may impact on the resource estimation result. Approximately, over 3-5% of total data has incorrect surveyed depth, dip, and azimuth. Detailed comparisons revealing the errors in surveyed depth, azimuth, and dip, are available in the unpublished data validation report by Tsakhiurt Khuder in 2015.

Many curved holes were entered as vertical in the initial datasets. For instance, it is

entered as 90⁰, whereas, the original paper document reveals it as being 88.2⁰ and such like. The paper sources were neglected when the initial dataset was established and consequently the data was assumed.

1.1.1.3 Assay data

Fig. 2. shows the number of errors out of the total number of assay data records. Sampling interval errors account for approximately 3.7%, while around 1.9% of Cu and Mo grade data has errors in turn. For

example, the copper assay data errors in 2m sampled exploration drill-holes, are shown (Table. 2.) Four different assay programs were

conducted for this project, each of their assay errors are shown in the data validation report by Tsakhiurt Khuder in 2015.

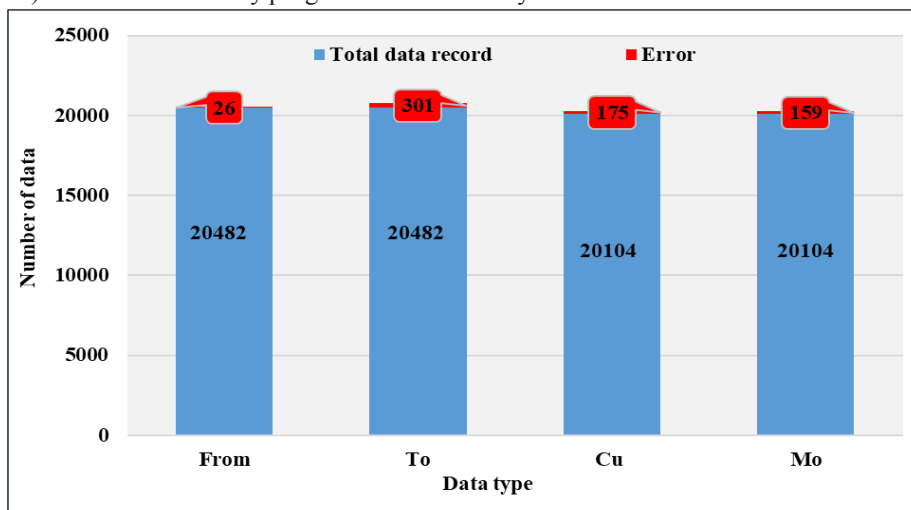


Fig. 2. Assay data verification result

Table. 2. Assay data errors in 2m samples of exploration drill holes

Initial Dataset				Source data				Comparison			
HOLEID	TO	FROM	Cu grade, %	HOLEID	TO	FROM	Cu grade, %	HOLEID	TO	FROM	Cu grade, %
27	152.7	153.8	0.03	27	152.7	155.8	0.08	TRUE	TRUE	TRUE	FALSE
45	100.7	104.5	0.01	45	100.7	104.5	0.11	TRUE	TRUE	TRUE	FALSE
505	162.6	165.2	0.01	505	162.6	167.7	0.05	TRUE	TRUE	TRUE	FALSE
507	24.7	27.1	0.26	507	24.7	27.9	0.25	TRUE	TRUE	TRUE	FALSE
511	46.8	48.5	n/s	511	46.8	48.5	-	TRUE	TRUE	TRUE	FALSE
511	127.9	129.8	0.01	511	127.9	130	0.05	TRUE	TRUE	TRUE	FALSE
515	183.8	187.8	n/s	515	183.8	187.8	0.00	TRUE	TRUE	TRUE	FALSE
515	187.8	191.5	n/s	515	187.8	191.5	0.00	TRUE	TRUE	TRUE	FALSE
515	196.5	199.4	n/s	515	196.5	199.4	0.00	TRUE	TRUE	TRUE	FALSE
516	84.7	87.9	n/s	516	84.7	87.9	-	TRUE	TRUE	TRUE	FALSE
530	62	64.5	n/s	530	62	64.5	0.20	TRUE	TRUE	TRUE	FALSE
544	302.4	303.2	0.03	544	302.4	303.2	0.02	TRUE	TRUE	TRUE	FALSE
561	109.5	113.4	0.01	561	109.5	113.4	0.09	TRUE	TRUE	TRUE	FALSE
600	114.7	119.2	0.01	600	114.7	119.2	0.05	TRUE	TRUE	TRUE	FALSE
111B	323.6	325.2	0.50	111BIS	323.6	325.2	0.58	FALSE	TRUE	TRUE	FALSE
111B	343.4	344.7	0.35	111BIS	343.4	344.7	0.55	FALSE	TRUE	TRUE	FALSE
113B	22.2	24.2	n/s	113BIS	22.2	24.2	-	TRUE	TRUE	TRUE	FALSE
115B	9	11.3	0.13	115BIS	9	11.3	0.12	TRUE	TRUE	TRUE	FALSE

1.1.1.4 Lithology data

As mentioned above, there is no verification for lithology data and as such it has been entered from the paper copies into electronic spreadsheet, instead. A total of 3090 row records have been typed and given specific category codes.

1.1.2 Implicit Geological Model

The traditional way of explicitly defining three-dimensional (3D) geological and ore-

waste boundaries heavily depends on a time-consuming process of manual digitisation (Cowan, 2003). “The implicit modeling, however, is the fast and automated formation of the boundaries directly from geological primary data” and it uses Fast Radial Base Function™ to interpolate or fill in the gaps where there is no data (Leapfrog3D, 2017).

The geological 3D model used for this project, was constructed via using the

application implicit modeling of Leapfrog Geo software owing to the following reasons for controlling the data errors:

- To eliminate manually digitised surfaces. It is hard to compare two geological models based on one dataset and created by two different geologists because of the differences in interpretation. Furthermore, it would not be comparable even if one geologist constructed the two models based on slightly different datasets using an explicit method.
- To produce geological models is a dramatically accelerated process, which allows two models based on initial and improved datasets to be updated dynamically and comparably provided that the initial setting-up used the same interpolant parameters.

1.1.2.1 Geology model

The strategy to build consistent geologic models is to firstly construct the first model based on the initial dataset and develop it completely. Once, the model of the initial dataset has been completed, it is then saved using a different name. The Leapfrog software then reloads the improved dataset and updates the second model dynamically.

The deposit geology is not complex due to the reasonable continuity and nature of mineralisation. The geology model is constructed from two main types of host rocks such as, granodiorite and biotite-granodiorite porphyry that has slightly higher mineralisation, and an andesite dykes' system (Fig.).

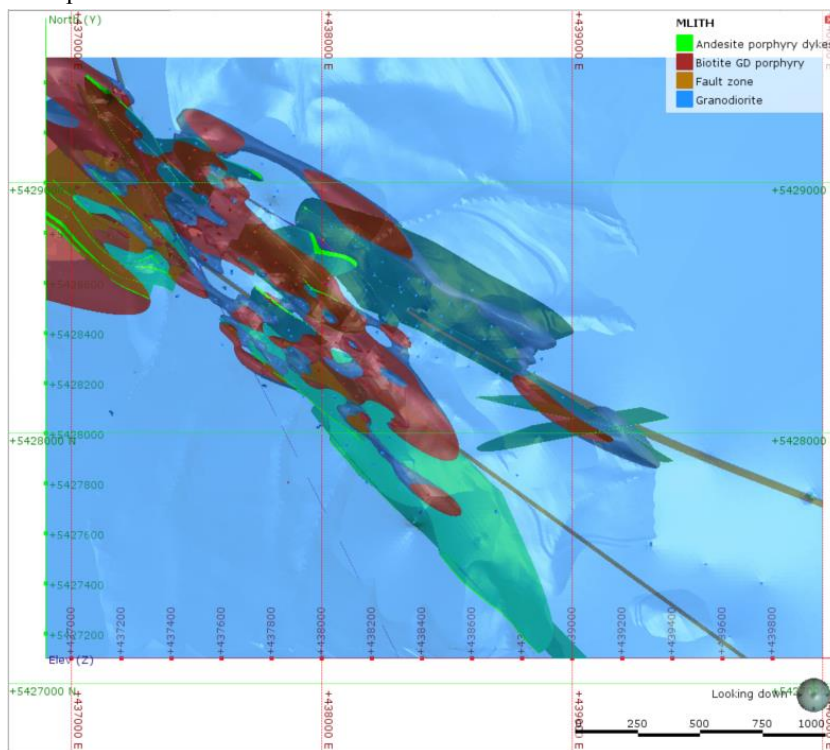


Fig. 3. Geological model based on the initial dataset

The volumes of Biotite-Granodiorite-Porphry and Clay decreased by approximately

6.5-7.5%, whereas, there was an increase of around 1% in the volume of Granodiorite that

accounts for the substantial change in the total amount (Table. 3.). As a result, the improved model's influence caused a decrease in the

resource tonnage because of the reduction in Biotite-Granodiorite-Porphry, which is a higher-grade lithology domain.

Table. 3. Volume discrepancy between the initial and improved geological models

Rock type	Initial	Improved	Change
Granodiorite	4,483,700,000	4,523,300,000	0.88%
Biotite GD porphyry	456,180,000	422,040,000	-7.48%
Andesite porphyry dykes	16,644,000	16,555,000	-0.53%
Clay	82,545,000	77,203,000	-6.47%

1.1.2.2 Orebody model

The ore-waste boundary was modelled based on the copper 0.25% cut-off grade that considered current mining costs, price, and recovery. The Indicator Radial Base Function (RBF) Interpolant numeric modeling tool of

Leapfrog Geo, has been used to model the ore bodies, and the interpolant modeling set-ups are the same for the ore bodies based on the two datasets, to keep them comparable (Fig. 2.) and Fig.

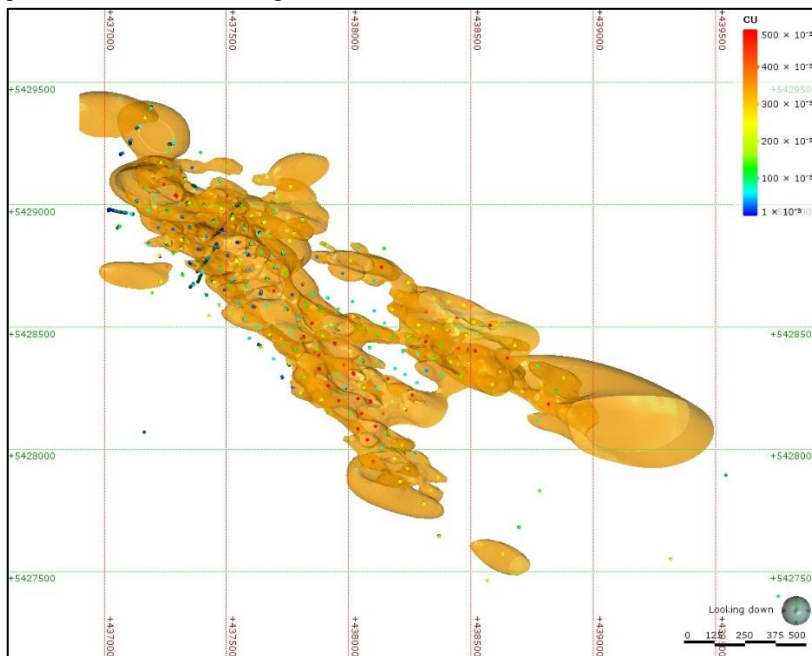


Fig. 2. Orebody model above 0.25% cut-off based on the initial dataset

In terms of volume, the initial orebody is larger than the improved one due to the different trends associated with the data errors. In other words, the errors have shifted the orebody position and reduced its total amount by approximately 7% (Table. 4.).

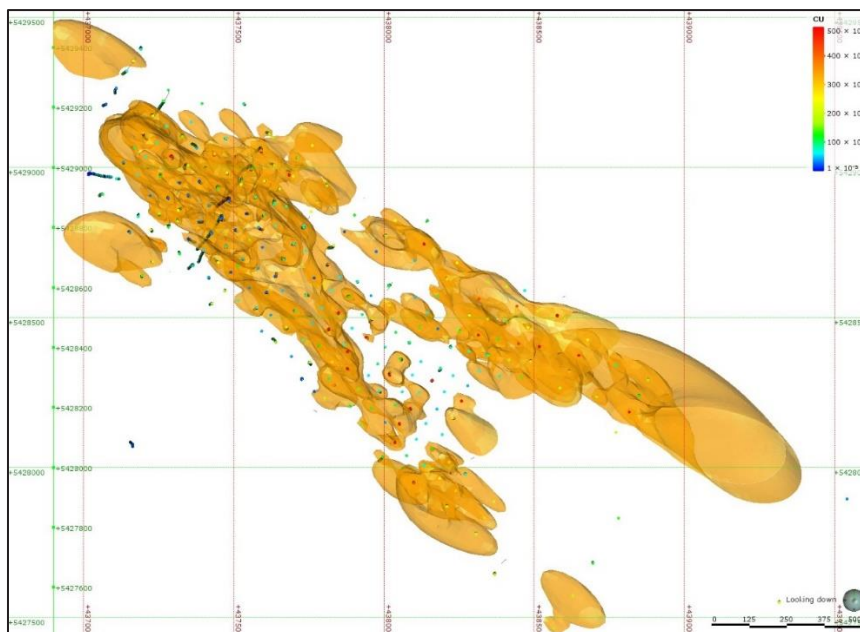


Fig. 5. Orebody model above 0.25% cut-off based on the improved dataset

Table. 4. Comparison for two ore bodies

CU_4mComp Indicator 0.25: Initial	
Volume	153,260,000
Area	6,295,700
Parts	8
CU_4mComp Indicator 0.25: Improved	
Volume	143,120,000
Area	6,024,800
Parts	13
Change	
Volume	-7%
Area	-4%
Parts	5

1.1.3 Resource Estimate

Resource estimation by geostatistics and the Kriging method was carried out using the application of Leapfrog EDGE (Estimation, Domaining, Geostatistical Evaluation), with Inverse Distance used for validation purposes. Leapfrog EDGE provides “fully integrated resource estimation workflow with geological model to ensure refining or adding data at any stage and changes flow downstream from your geological model to the resource model and everywhere in between” (Leapfrog3D, 2018).

It is essential to control the compounding error effects starting from the dataset for the research study. Hence, two separate resource models based on different datasets, are needed to conduct a consistent interpretation, analysis, and configurations. The capabilities of the software application can solve the issue by simply changing the datasets on the fully developed model and updating them dynamically. Despite this, there is still a need for minor changes in some set-ups such as, re-adjusting the variogram model fitting.

The estimation process by Leapfrog EDGE is repeatability and auditability and is in fact simplified. It can easily verify that the parameters for each domain used are correct within the estimate provided, and can quickly validate them (Levy, 2018). To estimate the resources (grade, tonnage) for both datasets, the following tasks, have been carried out:

- Domain
- Variogram
- Estimators
- Block Model

1.1.3.1 Domain and compositing

Two main types of estimation domains such as, lithology and grade-shell by Cu 0.25% cut-off, were defined to perform boundary analysis and composite data. It was decided to choose the composite length by 4m along the entire drill-hole considering both the mine bench height 8m and the sampling length statistics in the datasets.

There is a soft boundary contact between Biotite-Granodiorite-Porphry and Granodiorite. This means that the grade

continuity between these two types of rocks is not erratic, instead it continues gradually (Fig). Furthermore, regarding their visual characteristics these two rocks are quite similar except in texture. Also, a geologist who defined the rock boundaries is likely to mix them up when the rocks are altered intensively. It was, therefore, decided to either combine these rocks into one domain or go for the grade-shell domain.

In this research case study, it was necessary to reveal how the inadvertent errors impacted on the position of the orebody. If the combined rock domain has been used for estimation, it is unable to create an orebody boundary due to the limitation of the lithology domain-based estimation and software capability.

As such, the orebody models based on Cu 0.25% cut-off grade for both datasets were used for the final resource estimation. As well as this, the boundary plot of the grade-shell domain showed that there was a hard boundary between the ore and waste (Fig. 3).

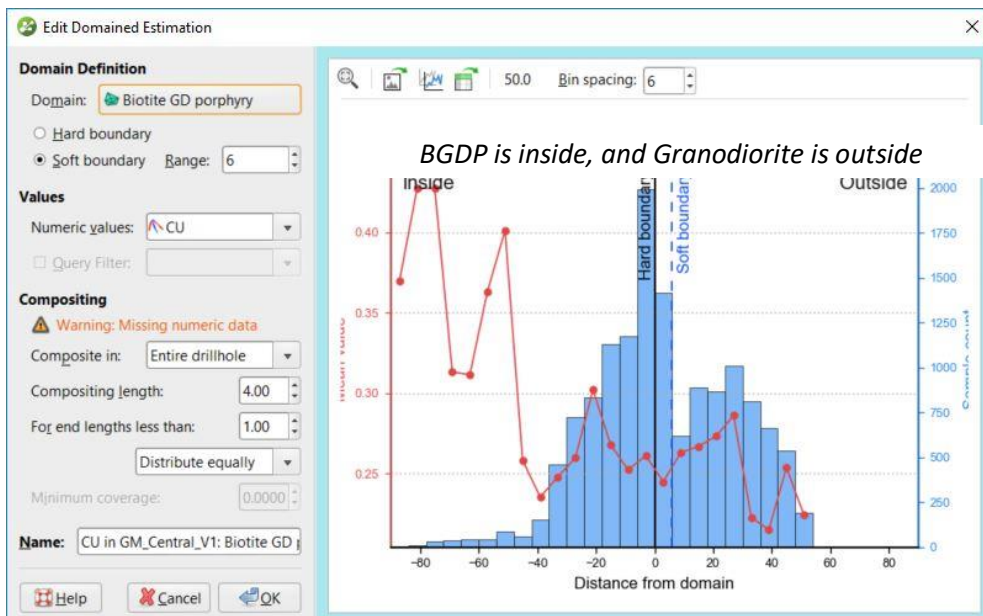


Fig. 6. Boundary plot for lithology domain (BGDP)



Fig. 3. Boundary plot for grade-shell domain

1.1.3.2 Variogram

Variogram is essential as Parker (2012) once said that “*No variogram ⇔ No geostat, No guts ⇔ No glory*”. Therefore, it is considered that the variogram model has far-reaching consequences on the resource discrepancy using different datasets and compounding the effect of errors in this research. Thus, it requires a significant effort to try to achieve the best fit.

Downhole and axis aligned experimental variograms based on two datasets of ore bodies, were built for the Cu, Mo values inside the grade-shell, and were fitted into the Spherical Variogram model, which is the

commonly used theoretic model in practice. Fig. 4 shows the variogram model for Cu values of the initial datasets. The other variogram models including down-hole variograms for the both datasets and Mo variograms were constructed as well.

A hundred variogram models were built for test purposes with the final one chosen based on its best fit derived from the value continuity trend (strike, dip, plunge) and spatial correlation between samples. By constructing the variograms models, the search radius and directions were available for estimators such as, Kriging and Inverse Distance etc.

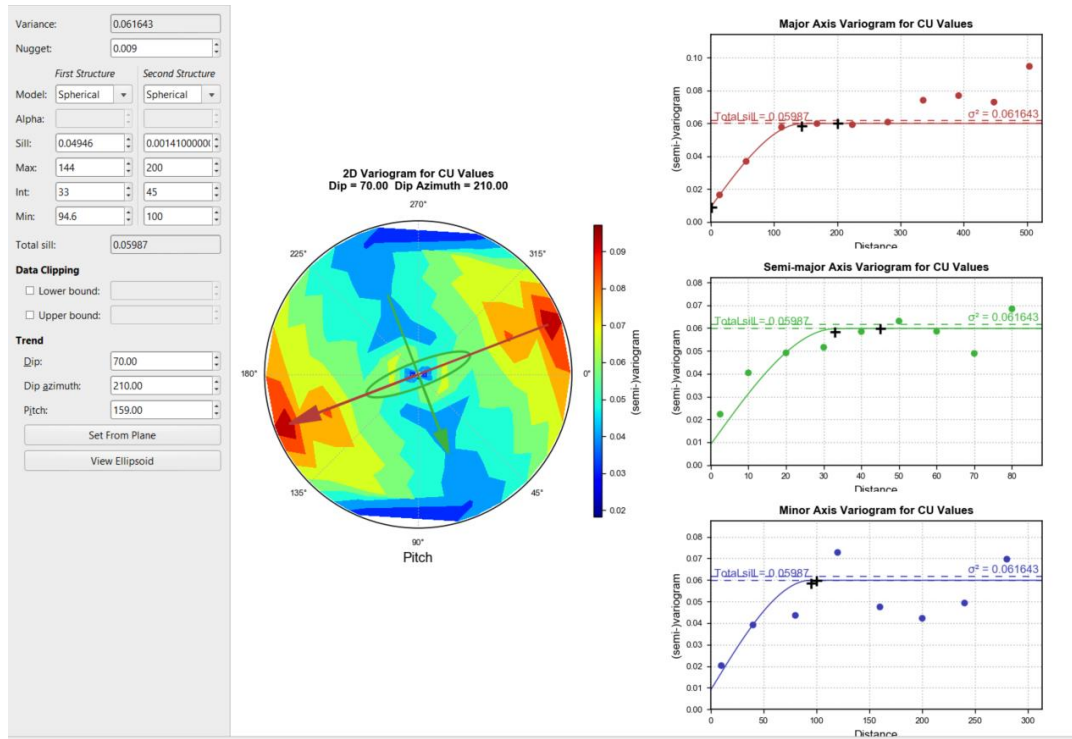


Fig. 4. Variogram model for Cu values in the orebody of the initial dataset

1.1.3.3 Estimators

Ordinary Kriging was used for estimating the tonnes and grade of the reported mineral resources, while Inverse Distance Weighted was used for validation purposes. These estimators connect with the composited values of samples in the domain and variogram model, and run for each domain.

Intentionally the top cut was not considered because of the research object seeking the effects of inadvertent data errors. If the outlier values are cut for both datasets, it would reduce the effects and comparability. Not too high and many extreme values were

observed for both datasets as well. For instance, 8 samples which are greater than Cu 1.5% and maximum 3.5%, were found in Cu 0.25% cut-off grade-shell domain of the initial dataset.

After the domain analysis and variogram models were completed, they were used for estimators and setting up the interpolant, search ellipsoid, and outputs to run the grade estimation (Fig. 9.) Three passes estimations were run for each domain to estimate the grade for the marginal blocks by increasing the search radius, which was also considered for resource classification.

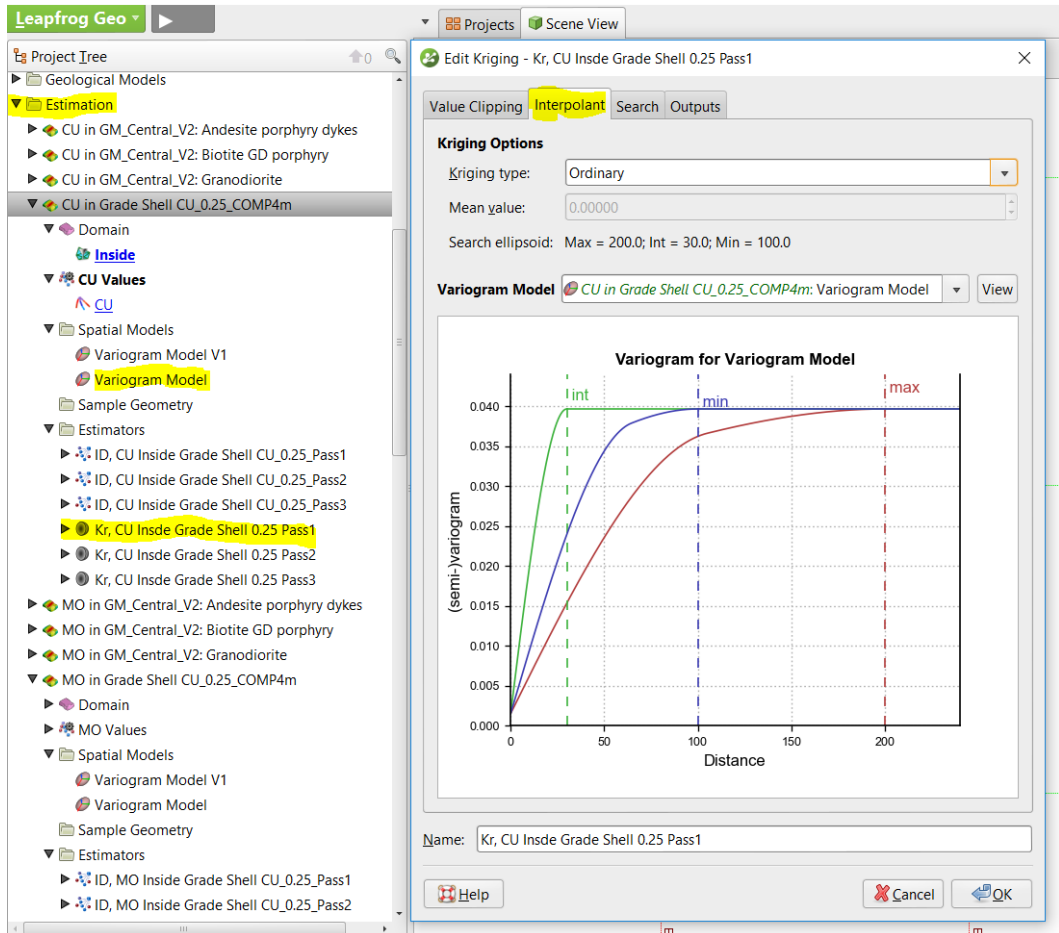


Fig. 5 Snapshot illustrating the estimation workflow

1.1.3.4 Block model

A block size of 20m (X) × 20m (Y) × 15m (Z) was used for the parent blocks. Parent blocks were divided into sub-blocks 5m (X) × 5m (Y) × 5m (Z). Due to the orebody azimuth, it was decided to rotate the block model by a 45° angle, and appropriate grid extents were applied.

The grade estimation process was completed by Leapfrog EDGE, and the block model was validated using a combination of visual, statistical, and swath plots comparing the actual grade and estimated grade (Fig. 6 and Fig. 7).

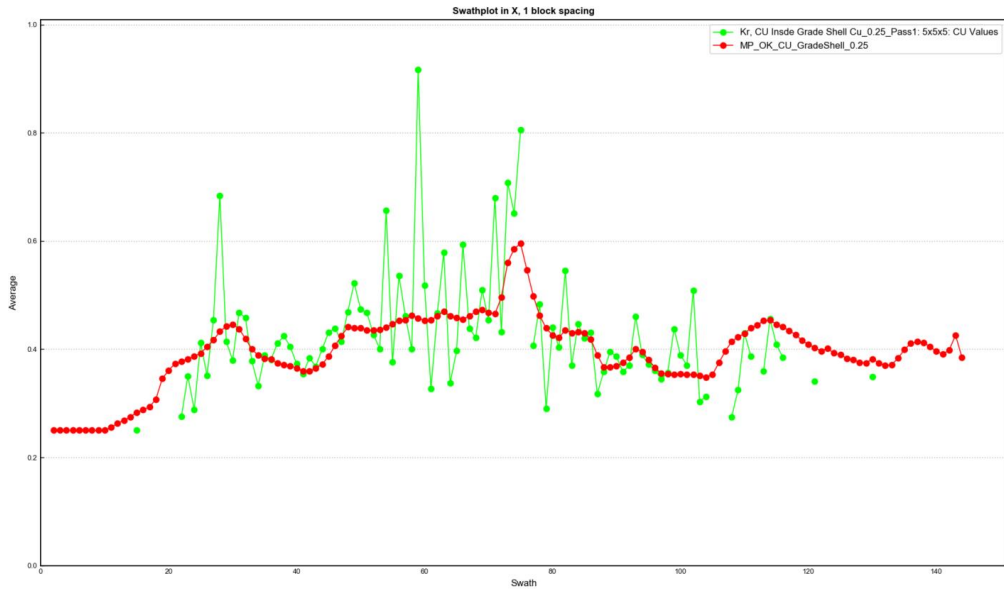


Fig. 6. Swath plot showing - Actual Cu grade in domain VS estimated Cu grade

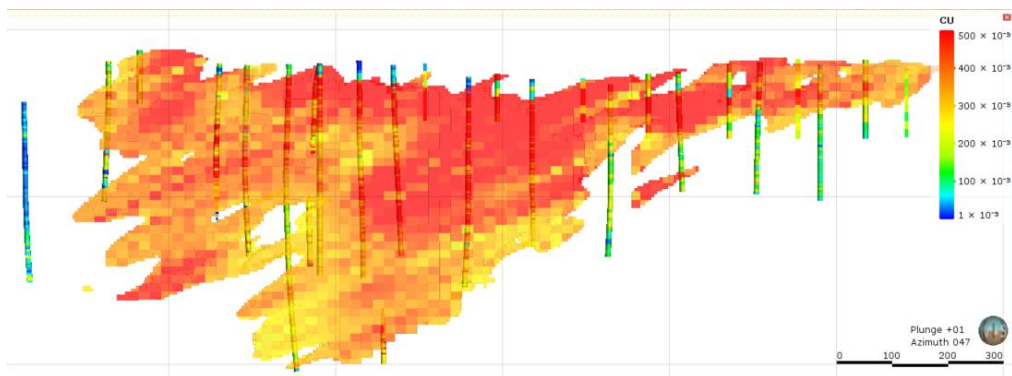


Fig. 7. Visual validaion for Cu grade distribution in estimated blocks

1.1.3.5 Resource classification and reporting

The resource model was classified into three categories such as, Measured, Indicated, and Inferred. Basically, the classification considered the average data density including the drill space and number of samples, the interpreted geological continuity and the estimation statistics such as the slope of regression. The criteria of categories are the exact same for both models.

The resource estimation reported that a total of **291Mt** geological resources with 0.42% copper and 0.016% Molybdenum grade based on the initial dataset above Cu 0.25% cut-off. The resource estimation using the improved dataset, however, reported a total of **256Mt** geological resources with 0.41% copper and 0.017% Molybdenum grade (Table. 5.)

Table. 5. Geological resources table comparing line items relating to datasets and category

Category	Dataset	Ore Tonnage	Cu grade, %	Mo grade, %	Cu Metal	Mo metal
Measured	Initial	235,570,275.00	0.43	0.017	1,015,465.72	39,357.78
	Improved	192,368,175.00	0.42	0.017	809,171.21	32,690.96
Indicated	Initial	40,953,000.00	0.38	0.016	155,400.01	6,388.02
	Improved	50,197,387.50	0.39	0.016	196,373.18	7,939.50
Inferred	Initial	14,508,225.00	0.37	0.015	53,039.77	2,204.29
	Improved	13,494,281.25	0.37	0.014	49,555.66	1,867.06
Total & Ave.grade	Initial	291,031,500.00	0.42	0.016	1,223,905.49	47,950.09
	Improved	256,059,843.75	0.41	0.017	1,055,100.06	42,497.52
Change		-12%			-14%	-11%

The research aim is not the 12% change rather it will be investigated to see how the error effect was expressed as the probabilistic distribution of NPV. The measured resource was taken into account for further analysis including the mine reserve estimation and financial assessment. Instead of using single global grade, tonnage for the financial assessment, it was decided to estimate the measured resources 100m level-by-level, and pick up each level's tonnage and average grade with its standard deviation for further assessment.

1.1.3.6 Mine reserve estimation

The current operation indicators of the adjacent open pit (the main pit called

Northwest) were used for the ore reserve estimation. The mining loss-3% and dilution-6% weights are based on the last 10 years average of the existing operation. Dilution came from barren dykes and low grade (less than Cu 0.25%) granodiorite, and its grade estimate as 0.1% for copper, 0% grade for molybdenum, in turn.

The mineralisation beyond the feasible limits of the pit was not converted to reserves at the design stage (design loss). It was assumed that the conversion factor resources to reserves was 90% based on the orebody geometry for mine design and low stripping ratio.

Table. 6. Mine ore reserve estimate by levels

Copper	Initial			Improved		
	Mine Ore Reserve(t)	Head Grade	Contained Metal	Mine Ore Reserve(t)	Head Grade	Contained Metal
Surface to 1400	25,962,460.03	0.432%	112,146.37	16,856,318.87	0.418%	70,432.80
1400 to 1300	85,349,168.10	0.429%	365,817.71	60,843,430.63	0.415%	252,559.58
1300 to 1200	51,359,073.47	0.404%	207,263.15	46,999,543.11	0.407%	191,070.15
1200 to 1100	39,328,849.86	0.370%	145,343.35	39,895,582.89	0.370%	147,433.11
1100 to 1000	13,897,074.15	0.349%	48,482.69	11,657,326.28	0.343%	39,988.45
Below 1000	2,477,019.32	0.322%	7,982.61	2,073,096.45	0.302%	6,259.98
Total	218,373,645	0.41%	887,036	178,325,298	0.40%	707,744

Financial assessment

In order to investigate the project value fluctuation due to the changes in ore reserve and head grade, the following consecutive analysis were conducted:

- Constructing “base case” discounted cash flow (DCF) models for two reserve outcomes under assumed certainty and 100% equity funding;
- Conducting sensitivity analysis based on the DCF models to identify the main factors influencing the project value;
- Applying modern asset pricing (MAP) model to estimate the mining project value as the price was one of the main significant factors to impact on it;

- Run Monte Carlo simulation for taking into account the grade variability.

1.1.4 Discounted Cash Flow

Model and value of this mine is in nominal US dollars, assumed certainty and 100% equity funding using simplistic pricing assumptions (spot price for Cu 15-May-2018). Copper prices will escalate in real terms (excluding inflation) over the life of the mine at a rate of 0.11% per annum based on the annual CPI rate and the average of price changes in copper during the last two decades. Cost and other estimates are in today (Year 0) US dollar.

Discounted Cash Flow (DCF) evaluation models in nominal dollars used the following inputs in

Table. 7. Input parameters used for DCF model

INPUTS	Initial Model		Improved Model	
	Cu	Mo	Cu	Mo
Diluted Mine Reserve (Mt)	218.4		178.3	
Head grade (%)	0.41%	0.016%	0.40%	0.016%
Conversion factor resources to reserves (%)	90.0%		90.0%	
Operational mining losses (%)	3.0%		3.0%	
Dilution by weight	6.0%		6.0%	
Grade of dilutant (%)	0.1%	0.0%	0.1%	0.0%
Waste:Ore Ratio	0.60		0.60	
Recovery (%)	86.5%	50.00%	86.5%	50.00%
Price US\$/t	\$6,822	\$24,000	\$6,822	\$24,000
Base Royalty rate (% of revenue for estimated at spot prices)	5.0%	5.0%	5.0%	5.0%
Surtax Royalty rate	2.0%	0.0%	2.0%	0.0%
Income Tax rate (%)	10.0%	25.0%	10.0%	25.0%
Nominal Cost of Equity funds (%) Pre-Tax	13.98%		13.98%	
Nominal risk-free rate of interest (%)	5.13%		5.13%	
Annual inflation rate (%)	2.17%		2.17%	
Real Price Escalation (%)	0.11%		0.11%	
Real Operating cost escalation (%)	0.76%		0.76%	

continued..

COSTS				
Total Capital in M\$(Year 0)	236.58		236.58	
Percentage spent in year 1	50%		50%	
Percentage spent in year 2	50%		50%	
Percentage of various capital categories				
Immediately expensed	10%		10%	
Normal depreciable assets	20%		20%	
Pooled project assets	70%		70%	
Weighted average useful life of normal depreciable assets (y)	10.00		10.00	
Initial working capital \$(Year 0)M spent in Y 2	20.00		20.00	
Sustaining capital \$(Year 0)M/p.a. excluding first and last year of production	5.00		5.00	
Percentage of capital expenditure borrowed	0%		0%	
Operating in \$(Year 0)				
Fixed costs \$M/p.a.	\$30.00		\$30.00	
Mining: Ore (\$/t)	\$2.40		\$2.40	
Mining: Waste (\$/t)	\$1.30		\$1.30	
Processing (\$/t ore)	\$7.00		\$7.00	
Grade control and other (\$/t ore)	\$1.00		\$1.00	
Service and Administration (\$/t ore)	\$1.00		\$1.00	
Grade of concentrate	23.0%	48.0%	23.0%	48.0%
Moisture (%)	8%	11%	8%	11%
Trucking & Shipping cost to smelters (\$/t concentrate)	\$28.00		\$28.00	
Net smelter value as percentage of gross value of Cu in concentrate	84%	64%	83%	64%
Salvage \$M written down nominal value after mine closure times	75%		75%	

Table 2. Outputs of DCF models

OUTPUTS	Initial	Improved	Difference
Net Present Value (NPV) \$M	\$234.27	\$140.16	(\$94.11)
Internal Rate of Return (IRR), %	35%	29%	-6%
Discounted Payback period (DPP), years	6.12	6.48	0.36
Capital efficiency Index (KE)	0.99	0.59	-0.40

1.1.4.1 Economic parameter

General inflation will average 2.17% based on the estimate that using Consumer Price Indexes (CPI) of the United States from 1999 to 2017. Capital and Operating costs will escalate in real terms at a rate of 0.42% and 0.76% per annum, respectively, based on the Mining Cost Service (MCS) Indexes of the United States between 1999 and 2017. To identify the real cost and price escalation or de-escalation factor, the average annual inflation has been subtracted from the calculated annual mining costs and price increases. Since the rise will be partially CPI, partially mining index it

will be necessary to break this down into escalation components.

1.1.4.2 Discount rate

Erdenet Mining Corporation is a state-owned company and not a stock exchange listed company in Mongolia and has no debt. A Capital Asset Pricing Model (CAPM) is, therefore, used to estimate the discount rate.

The company's cost of equity funds is 13.98%, the risk-free rate of interest is 5.125% (Mongolian Government bond yield) and the beta index of the company is 1.5. It is assumed that Erdenet Mining Corporation's beta should be slightly higher than the beta (1.25) of Turquoise Hill, which runs a similar project at

Oyu Tolgoi in Mongolia, which produces copper and gold.

Cost of equity $\Rightarrow r_e = r_f + \beta * (r_m - r_f) = 5.125\% + 1.5 * (11.03\% - 5.125\%) = 13.98\%$

Where:

r_f = risk-free rate of interest

r_m = return on market portfolio

β = Beta index of a specific asset

$(r_m - r_f)$ = market portfolio risk premium

$\beta * (r_m - r_f)$ = Asset risk premium

The market return (11.03%) was averaged using the historical return of S&P500 between May-2013 to May-2018 and the market risk premium was calculated as $11.03\% - 5.125\% \approx 6\%$.

1.1.4.3 Tax Regime

Mongolia mineral royalty is levied at different rates depending on type of mineral. According to Mineral Law of Mongolia 47.3, the exception for gold and coal is a 5% royalty, which is levied on all other minerals that are sold, shipped for sale or used (MTO, 2015).

In addition to the base rate royalty (5%), a surtax royalty that depending on the type of mineral, market price and the degree of processing, is imposed on the total sales value (MTO, 2015). If the copper price is \$6000-\$7000, the surtax royalty rate is 2%, and if the price is \$7000-\$8000, it is 3% and so on.

There is a progressive system in corporate tax, with an annual taxable income of up to MNT3 billion (equal to **\$1.25M**, \$1USD=2400MNT), which is subject to tax at a rate of 10%, with taxable profits in excess of this amount taxed at a rate of 25% (MTO, 2015).

1.1.4.4 Capital cost

Estimating the mining capital cost was derived using the estimation methodology detailed by O'Hara (1992). The figures provided in his paper are expressed in US\$ (Dec.1988).

The cost formulas for open pit mines were derived from the actual costs of certain mine

projects completed in the 1980s (O'Hara, 1992). The weighted average cost for each item of capital cost was escalated by statistical indices as appropriate for May-2018.

The Mining Cost Services (MCS) indices of the United States, are used to convert O'Hara's figures from December 1988 to May 2018 US\$, which is 29.42 years period.

The Open Pit Mining Capital Cost Index from 1999 to 2017 is 58.32% showing an average of 2.59% per annum, which is higher than the change in CPI over the same period, which is 47.12% (av. 2.17% p.a.). No information about MCS indices between 1988 and 1999 was found. Based on the above available source the average capital cost index is 2.59%, which was used to escalate the capital cost over the 29.42 years.

Capital cost estimates using the O'Hara method, which is an econometric method using relevant empirical power cost-capacity regression equations requires a number of inputs such as (Lilford, 2017):

- Ore mined and milled (t/d) –the O'Hara algorithms use tons per day, hence tonnes/d;
- must be converted to tons/d by multiplying by 1.1023;
- Waste to Ore ratio;
- Area to clear and related scenario, e.g. flat shrubby;
- Tonnes of soil and waste to be stripped;
- Drill, shovel, truck size, and so forth.

The mine requires **\$236.6M** in initial capital investment, with approximately \$5M sustaining capital required throughout the productive life of the project excluding the first and last year of production. The following assumptions for the percentage of various capital categories and taxation rules were considered for calculating depreciation

- Initial investment: \$236.6 million to be spent over a 2-year pre-production period with 50% of the total spent in Year 1 and

50% in Year 2. In addition, it is expected that capital expenditure in each year will include:

- Items, which can be expensed immediately (10%);
- Initial working capital: \$20 million spend in Year 2;

1.1.4.5 Depreciation

Even though the total capital expenditure for both models are identical due to the same throughput, the depreciation estimates are dissimilar because of the different mine reserves. This is because the initial model has a 2-years longer mine life than the improved model.

In contrast, there is more salvage value for the improved model compared to the initial one. According to a conservative estimate, the salvage values were taken as the outstanding value of the assets at the end of the mine's life and assumed they could be sold for 75% of that value according to the taxation rules:

- Capital gains and losses are treated in the same manner as other taxable income and losses. Gains are subject to the progressive Mongolian corporate tax rates of 25% (MTO, 2015);
- Both pooled project assets and normal depreciable items with a weighted average useful life of 10 years for machinery equipment are to be depreciated on a straight-line basis. Machinery and equipment typically includes equipment fixed or attached to a building, machinery and equipment fixed or attached to a construction (MTO, 2015).

1.1.4.6 Operating cost

The following recurrent operating expenditures of Erdenet MC, were taken into account.

Recurrent expenditure:

- Fixed cost: \$30 million per annum
- Variable operating costs:
- Mining: \$2.4/t ore
- Mining waste \$1.3/t
- Grade control and others: \$1.0/t ore
- Processing: \$7.0/t ore
- Service and Administration: \$1.0/t ore
- Trucking & Shipping cost to smelters (\$/t concentrate): \$28

1.1.4.7 Revenue estimation

The main determinants of revenue such as, tonnages after conversion of resources to reserves, dilution, mining losses and head grades have been estimated and discussed in section 3.1.3.6. The current recovery of the mill for Cu 86.5%, 50% for Mo and LME spot prices on 15-May-2018 such as copper \$6822/t and Molybdenum \$2400/t, was used for estimating mine revenue. The Cu price will escalate in real terms over the life of the mine at a rate of 0.5% per annum apart from the general inflation rate.

Copper and molybdenum concentrates are sold to smelters. The revenue net of transport, smelting and refining charges is known as Net Smelter Return or NSR. To estimate NSR, Recovery Formula – Base metal Ores by Flotation, has been used. This is an order of the magnitude estimate of metallurgical recovery and NSR, which was adapted from O'Hara in the 1980's, based on types of metal, ore and head grade.

In this case, the net smelter value as a percentage of gross values of Cu and Mo in concentrated form, were calculated using the following formulas:

$$NSR (\%)_{Cu, \text{ sulfide ore}} = 100\% * (1 - 0.08 * (Cu\%_{\text{Head}} * 100)^{-0.8})$$

$$NSR (\%)_{Mo} = 100\% * (1 - 0.06 * (Mo\%_{\text{Head}})^{-0.8})$$

1.1.5 Sensitivity Analysis

It is a basic sensitivity analyses to identify the bands that affect to the overall value, if 10% change in the input variables. This will direct the focus of future investigations on attaining better estimates of those inputs to which the project is most sensitive, thus achieving maximum information value.

An excel add-in so-called “SensIt 1.51 Student version” was used to conduct this analysis. Many inputs (Price Cu \$/t, Head grade, Recovery %, CAPEX, Processing cost \$/t, Mining Ore cost (\$/t), and Waste: Ore Ratio) and one output (NPV \$M) were used to run a single-factor sensitivity analysis for both the initial and improved DCF models (Fig. 8).

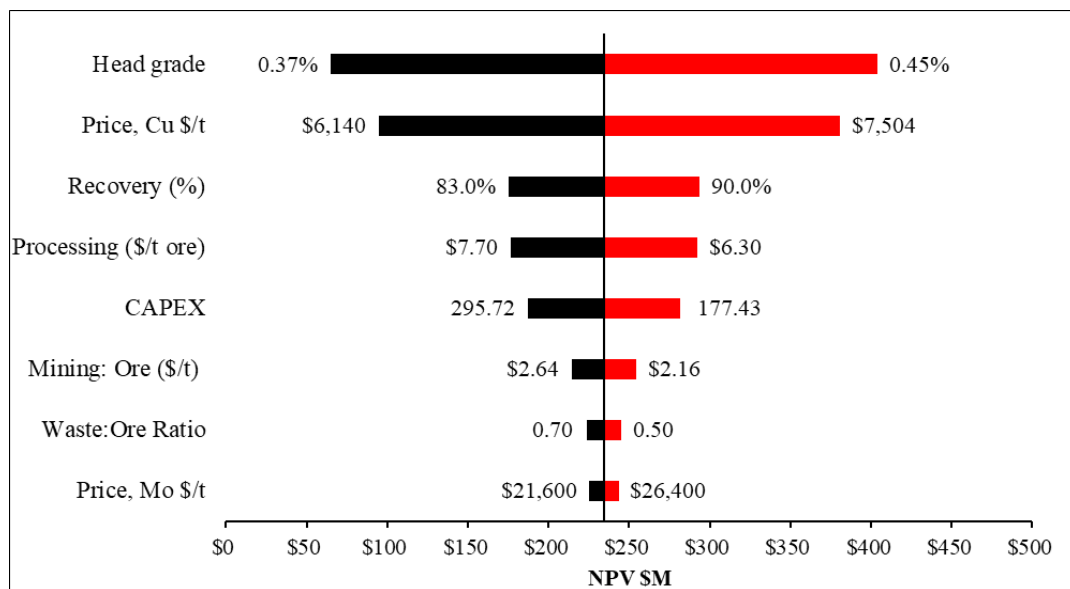


Fig. 8. Single-Factor Tornado chart for the initial model

As a result, the head grade and copper price have been identified as the most influencing input values to the output (NPV). The percentage of swing for head grade takes almost half of the total swing, which corresponds to the value of the project. The copper price has the second most force of impact on NPV. Its swing percentage accounts for over one third of the total corresponding swing. Unlike head grade and price, the other inputs have marginal impacts on NPV as their influencing percentages were from 0.2% to 6%.

DCF applies the same risk and time adjusted discount rate to both revenue and costs irrespective of their very different risks.

Revenue is very risky mainly because of price volatility which cannot be reduced or controlled, while capital and operating costs are less risky because they can be estimated with greater confidence, can be controlled and are not subject to price risk (Maybe, 2017).

1.1.6 Modern Asset Pricing Model (MAP)

While, it is still comparable for both initial and improved DCF models due to the same risk characteristics, discount rate, capital-intensity and operating leverage and so forth; the research aim is to estimate the project value as accurately as possible to reveal the effect of primary data errors at the end. Therefore, the MAP model, was used for evaluation in

nominal dollars using stochastic forwards price forecasts and a simple mine plan that estimates grade variability in levels (*Appendix 1* and). This evaluation estimated that the NPV of the initial model is greater by \$77M than the improved one.

DCF valuation can be biased because a high rate of discount (13.98%) is applied to the project with high cash flow volatility to compensate for this. If costs are less risky than revenue, then using a high risk-adjusted discount rate over-discounts future operating costs discourages capital investment in the present to reduce them (Maybee, 2017).

The sensitivity analysis found that the main drivers for the project value are the head grade and copper price. To bear the price risk, MAP was used for evaluating the project values. MAP is a technique whereby (Maybee, 2017):

- The revenue and cost functions are separated;
- The commodity price volatility, i.e. the most significant source of risk, is neutralized;
- The revenue and cost functions are recombined and discounted at the risk-free rate of interest (government bond) to compensate only for the time-value-of money.

1.1.6.1 Stochastic price model - GBM

The price forecast model was constructed based on the following equations of the theoretical approach. Due to the uncertainty in future price, simulation techniques, stochastic models (such as Geometric Brownian Motion - GBM) combined with sophisticated cyclical econometric forecasts were used. Proportional changes in prices over time intervals (Δt) follow a log-normal diffusion process known as the GBM of the discrete type (Maybee, 2017):

$$S_{t+\Delta t}/S_t = \exp(\mu\Delta t + \sigma z\Delta t^{0.5})$$

Or

$$\ln(S_{t+\Delta t}/S_t) = \ln(S_{t+\Delta t}) - \ln(S_t) = \mu\Delta t + \sigma z\Delta t^{0.5}$$

Where: S_t = price at time t , μ = mean of x , σ = standard deviation of x and z = standard normal distribution variable.

Commodity prices tend to revert over time to the long-run mean and variances increase initially following a price shock and then stabilise (Dias, 2002, as cited in Maybee, 2017). If the spot price (S) is higher than the long-term median (S^*) it will tend to progressively fall and vice versa.

1.1.6.2 Estimating the GBM formula parameters

The below analysis was conducted in order to plug the parameters into the GBM model for a forecast (Table. 9.)

- $\alpha^* = \mu - \delta$ the growth inherent in LME the futures quotes. Set to 0 as the rate of growth was achieved by calibrating the forwards forecast against the future market quotes.
- S = Current spot price (\$6822) as quoted on the LME 15-May-2018
- Price of mineral price risk (1.83%). This represents the risk discount per unit of price volatility. To estimate this the previous CAPM estimate in section 4.1.3 and five staged formulas estimating cost of equity, price of market risk, return on mineral and mineral risk premium, are used.
- S^* = Current long-term price median annualised (\$6725) around 8 years.
- σ = Short-term price volatility (17.83%) as the standard deviation of the logarithmic returns on holding the commodity over the last 6 months annualised
- Reversion half-life will be used as a calibrating input (7 years).

Table 3. Price forecast model inputs

Current Spot price (\$US/t)	\$6,822
Current Long-term Price Median (\$US/t)	\$6,725
Price of Mineral Price Risk (%)	1.83%
Short-term Growth Rate of Price Median (%) Set at	0.0%
Short-term Price Volatility (%)	17.83%
Reversion Half-life (years)	7.0
Reversion Factor = Ln(2)/Half-life	0.10
Confidence Interval Percentile Plus and minus	10.0%



Fig. 9. Copper spot price from 15-May-2004 to 15-May-2018

From the historical price (*Fig. 9*) distribution from LME daily prices one can generate the historical daily changes in price, specifically, $(St+\Delta t - St)/St$ over an interval of time t , which in the case of commodities and financial stocks is of the order of $1/252$ to 254 trading days = 0.00394 years $(St+1 - St)/ St$ is annual if $\Delta t = 1$ (Maybee, 2017).

It is necessary to extend the MAP model beyond the longest LME forward quote. LME forward quotes are limited to 3.25 years which is shorter than the 10-year life of the project. Thus, forward prices beyond this time were forecasted using the reverting stochastic model. A high level of realism can be achieved by calibrating the GBM model forwards against the LME quotes (*Fig. 10*).

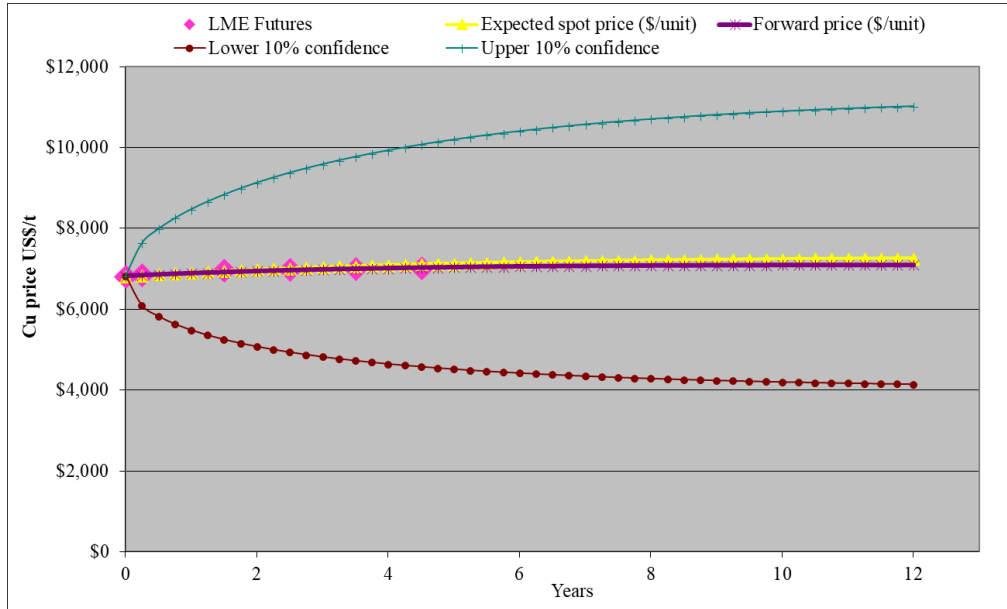


Fig. 10. Copper price stochastic model as at 15 May 2018

1.1.7 Monte Carlo Simulation

The sensitivity analysis highlighted that the head grade has far-reaching consequence on the outputs (NPV) of the models. As mentioned previously, the resources and reserve estimations were carried out at 100m

level steps. Consequently, each level’s average head grade with its own standard deviation were utilised for simulating the grade uncertainty via the Monte Carlo risk simulation technique, instead of using single global grade and its standard deviation (Table. 10.)

Table. 10. Probabilistic grade input of the simulations for both models

Level	Diluted mining reserves (Mt)	Random Cu Head grade, %	Random Mo Head grade, %	Function	Estimated Cu Head grade, %	Estimated Mo Head grade, %	Cu, Std.Dev	Mo, Std.Dev
Surface to 1400	26.0	0.30%	0.006%	logn	0.43%	0.010%	0.185%	0.005%
1400 to 1300	85.3	0.29%	0.008%	logn	0.43%	0.015%	0.178%	0.009%
1300 to 1200	51.4	0.46%	0.020%	logn	0.40%	0.019%	0.115%	0.008%
1200 to 1100	39.3	0.40%	0.017%	logn	0.37%	0.018%	0.084%	0.008%
1100 to 1000	13.9	0.39%	0.012%	logn	0.35%	0.013%	0.064%	0.006%
Below 1000	2.5	0.30%	0.008%	logn	0.32%	0.010%	0.063%	0.005%
Total	218.37				0.41%	0.016%	0.149%	0.009%
Level	Diluted mining reserves (Mt)	Random Cu Head grade, %	Random Mo Head grade, %	Function	Estimated Cu Head grade, %	Estimated Mo Head grade, %	Cu, Std.Dev	Mo, Std.Dev
Surface to 1400	16.9	0.54%	0.005%	logn	0.42%	0.010%	0.139%	0.005%
1400 to 1300	60.8	0.41%	0.016%	logn	0.42%	0.015%	0.153%	0.007%
1300 to 1200	47.0	0.47%	0.019%	logn	0.41%	0.019%	0.104%	0.007%
1200 to 1100	39.9	0.32%	0.010%	logn	0.37%	0.018%	0.075%	0.008%
1100 to 1000	11.7	0.42%	0.012%	logn	0.34%	0.013%	0.055%	0.005%
Below 1000	2.1	0.33%	0.011%	logn	0.30%	0.010%	0.054%	0.004%
Total	178.33				0.40%	0.016%	0.122%	0.008%

Monte Carlo simulation uses random sampling from probability distributions of inputs (each level’s grade) over a large number

of iterations and generates a probability distribution of all possible values surrounding

the expected value of the simulated output, for instance NPV (Hall, 2017).

It is assumed that the probability distribution of grade is log-normal depending on the nature of the input. The base case MAP models haven been used for the simulation by:

- Inputting the probability distributions (not the single point, expected estimates) of possible grades for each level.
- Sampling input variables simultaneously and randomly, but according to their respective probability of occurrence (standard deviation), during thousands of iterations of the model, thus generating thousands of possible scenarios
- Resulting in the model outputs being not just expected values but also probability distributions of all possible outcomes surrounding expected values (NPV).

The simulation process was carried out via an excel add-in called “SimVoi 3.303” Student version and ran 10,000 and 30,000

number of trials for only one probabilistic input (grade) and multi inputs to report the results for both models.

1.1.7.1 Simulation for one probabilistic input (grade)

Monte Carlo Simulation provides not only expected values (e.g. NPV = -\$17.93M for Initial, \$70M for Improved), but a full distribution of all possible NPV outcomes and their related probability of occurrence.

The results of the models NPV histograms says that keeping everything is constant as it has simulated only grade. The initial model says that there is an approximately 48.2% probability to earn below \$100M (or 51.8% chance to get at least \$100M). The improved model, in contrast, shows that it has an approximately 45.5% probability to gain below \$100M (or 54.5% chance to gain above \$100M) (Fig. 11 and Fig. 12).

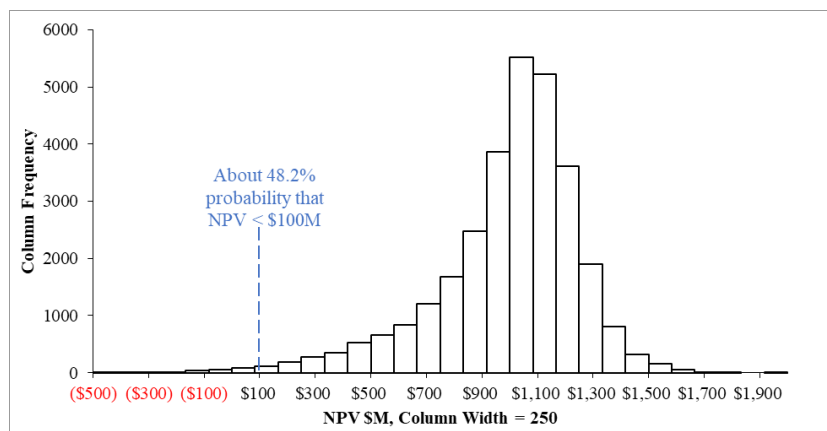


Fig. 11. NPV Histogram of only grade simulation with 30000 trials for the initial model

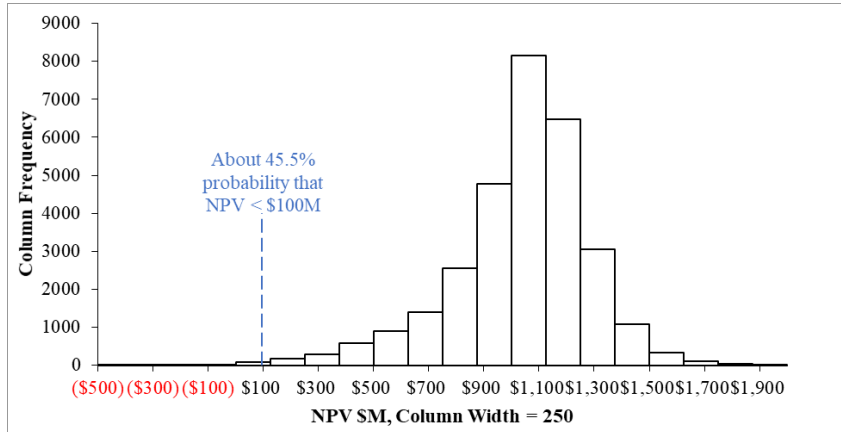


Fig. 12. NPV Histogram of only grade simulation with 30000 trials for the improved model

If it is a go or no-go decision making and looking at NPV is less than “0”. The initial model says there is a 42% chance that it is going to lose money, whereas, the improved model says there is a 34.3% chance that the

NPV will be negative (Fig. 13 and Fig). This means that the improved model has over a 7% higher probability to make a profit than the initial one.

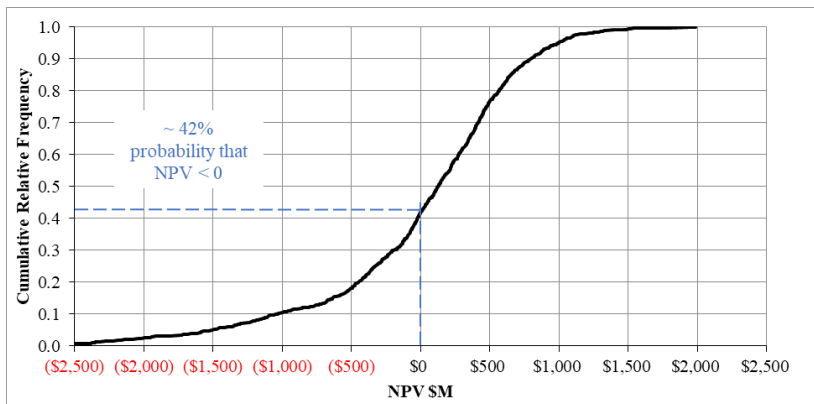


Fig. 13. Cumulative chart of only grade simulation with 30000 trials for the initial model

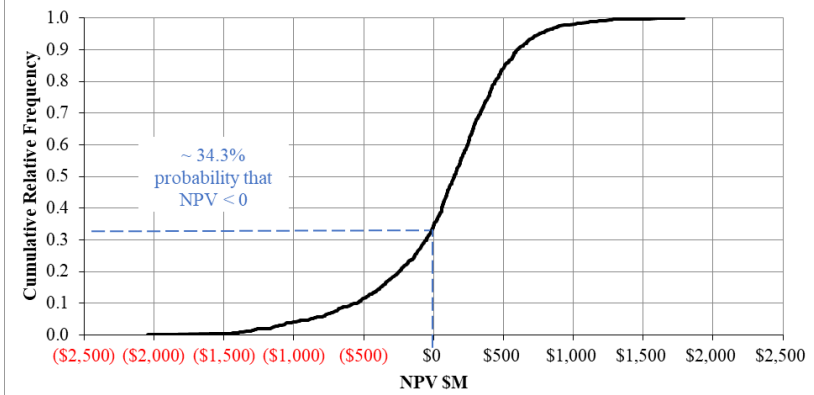


Fig. 18. Cumulative chart of only grade simulation with 30000 trials for the improved model

3. Limitations and results

The resource estimation is not robust because it has not been conducted by a competent person who has sufficient experience in the resource modeling field. Notwithstanding this, the research tried to achieve as accurate as possible results and maintain methodology consistency for both models concerning the same interpretation preference and dynamic update via probabilistic modeling.

The orebody is based on grade data, which excludes lithology and structure data. If there were any other recorded geology data including lithology, alteration, mineralisation and structure in the initial dataset, more data errors would have been found and the resource model might have been based on lithology domains. Single density value (Ore - 2.55t/m^3) was used, which means there is no consideration for tonnage uncertainty. As such, the result would have been different.

No proper mine plans were carried out due to the short timeframe and lack of experience. In mineral development stages, mine plan is one stage that supposed to be between resource estimation and financial model. If proper mine designs were executed based on both resource models, they could have been changed the project profile.

4. Result and discussion

Poor-quality data causes geological uncertainty and compounds the possibility of risk at the project valuation stage. The priority is to use the most accurate outputs from resources estimations based on validated and verified databases for project valuation. Small errors made early in the recording of exploration data in a mining project affect to some degree the economics at the end. In this case study, approximately 3-6% of inadvertent data errors were found in the initial datasets and were then corrected based on their original hard copies. The research investigated the

effect of those errors through the resource development stages from geological modeling to financial assessment.

The methodology had two main stages Resource Estimation and Financial Assessment. The link between these two stages is the output of the resource estimation, which was used for the financial assessment. To control the compounding errors effect from the initial datasets through these stages that have subsequent steps, the exact same estimation methods, geological interpretations, and financial models were carried out. The NPV of the project and its probabilistic distribution are the metrics to evaluate the output.

It was found that the improved model had a lower value, but it also had a shorter mine life (mine reserve 178Mt vs. 218Mt), and the initial model actually over-valued the project. The DCF models indicated that the initial model (\$234M) overestimated by \$94M compared to the improved one (\$140M). Moreover, the MAP evaluation using a simple mine plan model estimated that a \$77M difference had been derived from inadvertent human errors in the geological datasets.

The main answer is not to be found in the above simple discrepancies of the resource amounts and NPVs. The research also examines the project risks and compares the probabilistic distributions of NPVs for the two models based on their decision-making ability. Even if it has a lower value, the improved model is more accurate than the initial one and can provide for better decision making. Having better-quality data increases the probability of the project to make a profit by over 7% and 2.7% with a higher chance that the NPV will be greater than \$100M in this case study. The approximate 2.7% probability difference between the two models under the same comparing point (NPV will be less than \$100M), is not a large, but it is a difference.

Table 1. A summary of the research result

Research Steps	Criteria	Initial	Improved	Difference
Data verification	Inadvertent Error, %	3-6%	-	3-6%
Geological Modeling, Implicit RBF	Orebody volume, cubic metre	153,260,000	143,120,000	-7%
Resource Estimation, Kriging	Geological Resources, (Mt)	291	256	-12%
Discounted Cash Flow	NPV, (Million, \$)	\$234.27	\$140.16	(\$94.11)
Sensitivity analysis	Influencing inputs	Grage, price	Grage, price	-
Modern Asset Pricing Model	NPV	\$281.59	\$203.80	(\$77.78)
Monte Carlo Simulation	The probability of NPV>0	58.1%	65.8%	7.7%
	The probability of NPV>\$100M	52%	55%	2.7%

Reference

- Cowan, E J. 2003. "Practical Implicit Geological Modelling." In Fifth International Mining Geology Conference, Bendigo, Vic, 17 - 19 -May-2018, <https://www.erdenetmc.mn>.
- Hall, Brian. 2017. Unpublished "Mineral Finance and Project Evaluation." Resource Sector Finance / Intensive: Trimester 1, 2017 Lecture Note. DMEE. Curtin Graduate School of Business.
- Guj, P. 2007. "Modern Asset Pricing — a Valuable Real Option Complement to Discounted Cash Flow Modelling of Mining Projects." In *Project Evaluation, Melbourne*, 19 - 20 June 2007. 113-119. Melbourne, Vic,
- Guj, P, 2006b. Mineral project evaluation – Dealing with uncertainty and risk, in *Australian Mineral Economics* (eds: P Maxwell and P Guj), Chapter 12 (The Australasian Institute of Mining and Metallurgy:Melbourne).
- Gursuren, I. 2015. Unpublished internal report "Report on Datasets Verification of Erdenet-Ovoo Cu-Mo Group Deposit (Baruunkhoid, Tuv, Oyut and Shand)." Erdenet MC. November 2003. AusIMM. <https://www.ausimm.com.au/publications/epublication.aspx?ID=1308>.
- Erdenet, Mining Corporation. 2018. Accessed 01
- Gy, Pierre. 1993. *Pierre Gy's Sampling Theory and Sampling Practice : Heterogenety, Sampling Correctness, and Statistical Process Control*. Edited by Francis F. Pitard. 2 ed. Boca Raton, London, New York, Washington. D.C: CRC Press.
- Leapfrog3D. 2017. What Is Implicit Modelling? Accessed 22-May-2018, <http://www.leapfrog3d.com/about/implicit-modelling-technology>.
- Leapfrog3D. 2018. Capabilities Leapfrog EDGE. Accessed 22-May-2018 <http://www.leapfrog3d.com/products/leapfrog-edge/capabilities>
- Levy, Iain. 2018. Where Have the Macros Gone? An Immersive Approach to Estimation. 20th March 2018 Accessed 24-May-2018, <http://blog.leapfrog3d.com/2018/03/20/leapfrog-edge-blog-validating-throughout-domaining-where-have-the-macros-gone/>.

- Lilford, Eric. 2017. Unpublished "Order of Magnitude and Top-Down Cost Estimation." Resource Cost and Capital / Intensive: Trimester 3, 2017 Lecture Note. DMEE. Curtin Graduate School of Business.
- Maybee, Bryan. 2017. Unpublished "Def Bias and Weaknesses and Modern Asset Pricing (Map)." Resource Sector Finance / Intensive: Trimester 2, 2017 Lecture Note. DMEE. Curtin Graduate School of Business.
- McManus, Scott. 2017. "Data Quality." LinkedIn. https://www.linkedin.com/pulse/data-quality-scott-mcmanus?trk=portfolio_article-card_title.
- Minnitt, R.C.A. 2007. "Sampling: The Impact on Costs and Decision Making." *Journal of the Southern African Institute of Mining and Metallurgy* 107 (7): 451 - 462. https://journals.co.za/content/saimm/107/7/AJA0038223X_3284.
- MTO, Mongolia Tax Office. 2015. Mining and Metals Tax Guide. <https://www.resourcedata.org/dataset/rgi-mining-and-metals-tax-guide-mongolia/resource/8f9f10ec-70f2-485f-98d3-5c00003c3451>.
- O'Hara, Suboleski S.C. and T.A. 1992. "Costs and Cost Estimation". In "Sme Mining Engineering Handbook", ed. H.L. Hartman, 405-424.
- Roden, S., and Smith, T., 2001, Sampling and analysis protocols and their role in mineral exploration and new resource development, in Edwards, A., ed., Mineral resources and ore reserve estimation—The AusIMM guide to good practise: Australasian Institute of Mining and Metallurgy, p. 73–78.
- Rozman, L.I. 1998. "Measuring and Managing the Risk in Resource and Reserves." In *Ore Reserves and Finance Seminar, Sydney*. AusIMM.
- Salahor, G, 1998. Implications of output price risk and operating leverage for the evaluation of petroleum development projects, *The Energy Journal*, 19(1):13-46.
- Samis, M, Poulin, R and Blais, V, 2005. Using real options to incorporate price risk into the valuation of a multi-mineral mine, in *Orebody Modelling and Strategic Mine Planning*, pp 9-15 (The Australasian Institute of Mining and Metallurgy: Melbourne).
- Silva, V. M. 2016. "Selecting the Maximum Acceptable Error in Data Minimising Financial Losses." *Applied Earth Science* 125 (4): 214-220. <https://doi.org/10.1080/03717453.2016.1230972>.

Appendix 1: MAP evaluation in nominal dollars using stochastic forwards price forecasts and grade ranges in levels for the initial model

PRODUCTION Mt	TIME / YEAR			PRE-PRODUCTION			PRODUCTION			CLOSURE			
	0	1	2	3	4	5	6	7	8	9	10	11	12
Mo. produced (M tn)				15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6
One produced M tn				26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0
Orct. transfers between levels													
Diluted Head Grade, Cu%				0.04	33.4	7.4	32.7	6.7	20.1	5.9	20.1	5.9	2.48
Diluted Head Grade, Mo%				0.432%	0.429%	0.411%	0.404%	0.378%	0.365%	0.365%	0.365%	0.365%	0.365%
Cu Produced, Million tn				0.010%	0.015%	0.018%	0.019%	0.019%	0.019%	0.019%	0.019%	0.019%	0.017%
Mo Produced, Million tn				0.097	0.096	0.096	0.091	0.091	0.085	0.082	0.082	0.082	0.082
Cu, Concentrate Produced (tonnes) coal moisture (M tn)				0.0013	0.0020	0.0023	0.0025	0.0025	0.0024	0.0022	0.0022	0.0022	0.0022
Cu, Concentrate Produced (tonnes) incl moisture (M tn)				0.02234	0.02217	0.02214	0.02287	0.02287	0.02287	0.02287	0.02287	0.02287	0.02287
Mo, Concentrate Produced (tonnes) coal moisture (M tn)				0.00062	0.00094	0.00114	0.00118	0.00118	0.00116	0.00116	0.00116	0.00116	0.00107
Mo, Concentrate Produced (tonnes) incl moisture (M tn)				0.00069	0.00104	0.00123	0.00131	0.00131	0.00128	0.00119	0.00119	0.00119	0.00119
REVENUE \$M													
Estimated Cu Forward Prices US\$/t				\$6,986.54	\$7,019.15	\$7,044.02	\$7,062.69	\$7,076.40	\$7,086.18	\$7,092.86	\$7,097.13		
Mo Spot Prices US\$/t				\$25,595.05	\$26,149.95	\$26,716.88	\$27,296.10	\$27,887.89	\$28,492.50	\$29,110.21	\$29,741.32		
Sales SM Forward, Cu				\$567.08	\$665.33	\$667.33	\$645.03	\$536.62	\$537.36	\$504.31	\$486.56		
Sales SM Spot, Mo				\$21.25	\$32.64	\$33.35	\$40.38	\$43.82	\$44.77	\$44.91	\$42.61		
EXPENDITURE \$M													
Royalty for Cu													
Royalty for Mo													
Total Operating costs + Tracking SM													
Depreciation													
OPERATING INCOME BEFORE INTEREST AND TAXES													
Less: Interest													
OPERATING INCOME BEFORE TAXES													
Less: Income tax													
TAXABLE INCOME													
Less: taxable income of up to NINT3 billion													
Less: Income Tax													
NET AFTER-TAX PROFIT													
Add back													
Losses carried forward													
Depreciation													
Losses carried forward													
Working capital													
CAPEX													
Sustaining capital													
Loan principal drawdowns and repayment \$M nominal													
NET CASH FLOW													
Risk-free discount factor for CF timing only													
Discounted CFs													
NPV \$M													
IRR													
K/E													
Inflation factor													
Real cost escalation factor													

Appendix 2: MAP evaluation in nominal dollars using stochastic forwards price forecasts and grade ranges in levels for the improved model

PRODUCTION Mt	TIME / YEAR	PRE-PRODUCTION			PRODUCTION			CLOSURE					
		0	1	2	3	4	5	6	7	8	9	10	
Waste produced M tn					15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6	15.6
Ore produced M tn					26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0
	Ore transfers between levels				9.14	25.7	-0.3	20.7	34.6	8.6	8.6	8.6	8.6
Diluted Head Grade, Cu%					0.415%	0.415%	0.415%	0.406%	0.399%	0.370%	0.370%	0.370%	0.370%
Diluted Head Grade, Mo%					0.012%	0.015%	0.015%	0.019%	0.018%	0.018%	0.018%	0.018%	0.018%
Cu Produced, Million tn					0.094	0.093	0.093	0.091	0.090	0.090	0.090	0.090	0.090
Mo Produced, Million tn					0.0015	0.0020	0.0020	0.0024	0.0024	0.0024	0.0024	0.0024	0.0024
Cu, Concentrate Produced (tonnes) excl moisture (M Tn)					0.02156	0.02147	0.02147	0.02102	0.02064	0.02064	0.02064	0.02064	0.02064
Cu, Concentrate Produced (tonnes) incl moisture (M Tn)					0.02329	0.02319	0.02319	0.02271	0.02229	0.02229	0.02229	0.02229	0.02229
Mo, Concentrate Produced (tonnes) excl moisture (M Tn)					0.00073	0.00096	0.00096	0.00116	0.00115	0.00115	0.00115	0.00115	0.00115
Mo, Concentrate Produced (tonnes) incl moisture (M Tn)					0.00081	0.00106	0.00106	0.00129	0.00128	0.00128	0.00128	0.00128	0.00128
REVENUE \$M													
Estimated Cu Forward Prices US\$/t	US\$				\$ 6,986.54	\$ 7,019.15	\$ 7,044.02	\$ 7,062.69	\$ 7,076.40	\$ 7,086.18	\$ 7,086.18	\$ 7,086.18	\$ 7,086.18
Mo Spot Prices US\$/t	US\$				\$ 25,595.05	\$ 26,149.95	\$ 26,716.88	\$ 27,296.10	\$ 27,887.89	\$ 28,492.50	\$ 28,492.50	\$ 28,492.50	\$ 28,492.50
Sales SM Forward, Cu	US\$				\$ 545.27	\$ 545.48	\$ 547.41	\$ 537.41	\$ 537.41	\$ 528.60	\$ 490.26	\$ 490.26	\$ 490.26
Sales SM Spot, Mo	US\$				\$ 24.96	\$ 33.33	\$ 34.05	\$ 42.15	\$ 42.15	\$ 42.77	\$ 42.89	\$ 42.89	\$ 42.89
Other (Salvage)													\$71.66
Less: EXPENDITURE \$M													
Royalty for Cu	5.00%												
Royalty for Mo	5.00%												
Total Operating costs + Trucking \$M													
Depreciation					(\$11.83)	(\$12.18)	(\$23.89)	(\$23.89)	(\$23.89)	(\$23.89)	(\$23.89)	(\$23.89)	(\$23.89)
OPERATING INCOME BEFORE INTEREST AND TAXES													
Less: Interest													
OPERATING INCOME BEFORE TAXES													
Less losses carried forward					(\$11.83)	(\$12.18)	(\$12.18)	(\$12.18)	(\$12.18)	(\$12.18)	(\$12.18)	(\$12.18)	(\$12.18)
TAXABLE INCOME													
Less taxable income of up to MNT 3 billion ~\$1.25M	\$1.25				\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00
Less Income Tax					\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00
NET AFTER-TAX PROFIT					\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00
Add back													
Losses carried forward					(\$11.83)	(\$24.01)	(\$24.01)	(\$24.01)	(\$24.01)	(\$24.01)	(\$24.01)	(\$24.01)	(\$24.01)
Depreciation					\$11.83	\$12.18	\$12.18	\$12.18	\$12.18	\$12.18	\$12.18	\$12.18	\$12.18
Initial working capital													
CAPEX													
Sustaining capital													
Other (Salvage)													\$71.66
NET CASH FLOW					\$329.50	(\$20.00)	(\$130.12)	\$101.75	\$108.38	\$101.60	\$91.60	\$76.83	\$46.09
Risk-free discount factor for CF timing only													
Discounted CFs	5.13%				0.95	0.90	0.86	0.82	0.78	0.74	0.70	0.67	0.64
NPV \$M					(\$20.00)	(\$117.74)	\$87.58	\$88.74	\$79.13	\$67.87	\$54.15	\$30.90	\$45.70
IRR													
k/F													
Inflation factor					1.00	1.02	1.04	1.07	1.09	1.11	1.14	1.16	1.19
Real cost escalation factor					1.00	1.01	1.02	1.02	1.03	1.04	1.05	1.05	1.06