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Preprint 17-054

EMBRACE THE UNKNOWN: STOP SAYING "IT'S TOO HARD" AND START EMBRACING UNCERTAINTY IN YOUR MINE PLANS

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ABSTRACT

Nearly every input to a mine plan is based on an estimate. The estimates may be from sample data, historical information, models, or personal opinion, but in all cases, these values are simply expected values (means). In real life, we do not get to iterate the exact conditions at our mining operation many times to ensure that that average value is attained. The expected value also tells us nothing about the spread of values that that input might take on. The result is a significant amount of unquantified uncertainty in our mine plans. Unfortunately, it is often too expensive or time consuming to update planning processes and software. This paper presents a proof of concept spreadsheet scheduling tool that can be utilized to incorporate many geologic realizations (simulated models) into the mine scheduling process. While this POC is not intended to be a detailed model of uncertainty, it is to show that there are stepping stones available for mine planners to begin to embrace uncertainty and produce more achievable plans without requiring a significant change in their planning process.

INTRODUCTION

Mining companies have included quantifying uncertainty, or at least risk, as a requirement of project justification for many years, however many times this process lags behind the traditional mine planning process and the results are rarely used to improve the plan. Nearly every parameter used in a mine plan is an estimate and the mine planning engineer should recognize and even embrace the inherent uncertainty in those parameters and its effect on their forecast results. While many of the uncertainties are beyond the scope of the traditional mine plan (e.g. global market uncertainty, socio-political uncertainty, environmental uncertainty), some uncertainties can, and should, be included in the mine planning process.

Many mining engineers have incorporated techniques such as Monte Carlo Simulation or Discrete Element Simulation to understand the range of productivity that can be expected for an operation but most still rely upon one estimated model for what is likely the critical component of technical uncertainty, the geologic resource. Modern geostatistical methods can provide multiple ore body realizations to provide a thorough unbiased "picture" of the geologic uncertainty but most traditional mine planning techniques are not formulated to allow for multiple (100-200) realizations of each material quality/grade parameter.

Commercial software companies and research groups are progressing with development of tools that can incorporate geologic uncertainty, and even optimize extraction plans in the uncertain environment. Unfortunately, this author believes that a significant number of mining operations will not be able to adopt these techniques due to the computational requirements of the advanced techniques and the costs associated with implementing proprietary software. In an attempt to encourage mining engineers to embrace the inherent uncertainty in their mine plans, this paper presents a cost-effective alternative that can be developed in-house, at any mine, to schedule mid to long-term mine plans while continuously monitoring the uncertainty in the results. The author hopes that by demonstrating the usefulness of such a system that mining companies will encourage engineers, geologists, and geostatisticians to find ways to incorporate this powerful data into their processes and procedures.

LITERATURE REVIEW

Historically, mine planning techniques and software have been developed based upon the assumption that there is one (1) estimated model of the ore body developed using the estimation-based techniques of inverse distance or the many variants of kriging. Unfortunately, these estimated models cannot be used to understand the uncertainty in the estimate and can tend to be systematically biased. To develop an understanding of geologic uncertainty and produce models that are unbiased, modern geostatisticians have developed stochastic methods based upon Monte Carlo simulation, such as sequential Gaussian simulation (SGS) (Isaaks, 1990) and sequential indicator simulation (SIS) (Alabert, 1987). Further information on these modern techniques is beyond the scope of this paper, however additional information can be found in many sources, such as Rossi and Deutsch (2014).

These modern geostatistical methods produce many (50-200+) realizations of the geologic resource, however, as all the realization are equally probably, no one realization can be used independently of the others and all realizations should be considered at all times in the mine planning process and the results should be viewed as a distribution of possible outcomes. Academic researchers and software vendors are developing processes and software to incorporate multiple geologic realizations, however these techniques will be computationally expensive and limited to long-range strategic planning. The COSMO Stochastic Mine Planning Laboratory is likely the most notable example of an organization that has embraced the development of tools to utilize simulated resource models as well as other stochastic parameters (e.g. market uncertainty) (Dimitrakopoulos, 2011; Godoy & Dimitrakopoulos, 2011; Boland, Dumitrescu, & Froyland, 2008).

The practical issue that arises from trying to optimize a stochastic framework is that each additional source of uncertainty multiplies the number of calculations that must be performed by the number of potential values for that attribute (Vann, J, et al., 2012). The result is that the optimization algorithms used in a stochastic environment will likely need to simplify the problem through in order to produce results in a reasonable time duration.

Finally, another difficulty of implementing an advanced multivariate stochastic approach will be communicating the result so the appropriate decision makers (Project Managers, Vice Presidents, COO's & CEO's). With each additional level of uncertainty, the ability to communicate the effects of that uncertainty becomes increasingly difficult (Vann, J, et al., 2012). While many of these decision makers expect to see some form of confidence interval around the estimate, they still expect to base their decisions on an estimate and not on a distribution of values.

Eventually, the mining industry will be ready to adopt a multivariate stochastic approach to mine planning, however until then, stepwise changes in our processes are necessary to allow for a seamless adoption of new techniques. One such example is the pit limit definition workflow presented by Deutsch, Gonzalez, and Williams (2015). This paper presents a scripted workflow to perform pit optimization on multiple geologic realizations mapped with samples from distributions of other input parameters (e.g. metal price and geotechnical slope angles). Again, this approach is computationally time consuming, however advancements in pit optimization algorithms

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reduces it significantly and the scripted workflow allows the computations to progress without user input.

SPREADSHEET MODEL

The mining research community has been continuously improving the scheduling and optimization techniques available to the industry for three or four decades. The result is that there are many commercial scheduling software packages in the marketplace and each one has a niche where it is likely the "best" tool for the job. In a perfect world, every situation would allow for the appropriate tool and technique to be implemented for each specific scheduling challenge. In reality, many mining operations, technical services groups, and consulting houses rely upon manual or semi-automated scheduling tools based in a computer aided design (CAD) environment and/or Microsoft Excel for at least some of their planning horizons. This reliance is due to a variety of reasons but may include: cost prohibitive software license and implementation, required flexibility to changing priorities and parameters, and reluctance to change.

The model described in this section has been developed to demonstrate that multiple geologic realizations can be incorporated into a spreadsheet based scheduling tool and that an engineer can monitor the results geologic uncertainty while manipulating the mine plan drivers. Every mine has specific requirements and every mine planner has a preferred layout and style to their custom spreadsheet models but generally speaking the components are consistent. A quality mid to long-range mine schedule spreadsheet must include the following modules: geologic resource/reserve input and summary, mine productivity input drivers, automatic or semi-automatic production cascade logic, mine schedule summary, processing capacity and throughput estimates, automatic stockpile movement logic, and finally a financial analysis. The proposed model includes an additional dashboard module that summarizes graphical results that can be displayed on a multi-display computer to allow the engineer to modify the schedule as needed in response to the uncertainty in the results.

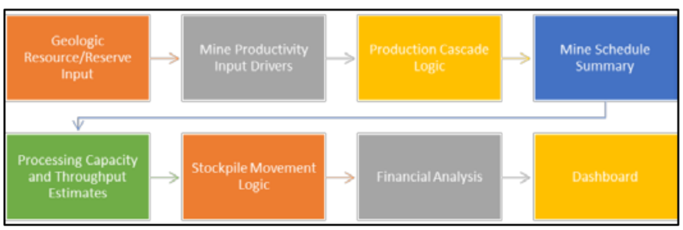

Figure 1. Mine Schedule Spreadsheet Configuration.

Geologic Resource/Reserve Input

As the traditional spreadsheet environment is not configured for three-dimensional design and block model data, the geologic resources must be summarized using a generalized mine planning package (GMP) based upon a predefined volume (shell or design). These volumes would typically consist of an open pit bench or blast size block or an underground level or stop size shape, depending on the resolution required for the mine planning horizon. The resource estimates need to include the tonnage of ore and waste, the grade of the ore, and a unique volume name that can be sorted to ensure mining precendences are met. To include geologic uncertainty, the resource summary must be completed for each of the realizations to be included in the analysis.

For this paper, the small copper deposit presented by Deutsch, Gonzalez, and Williams (2015) was utilized and 200 of the realizations were randomly selected to ensure the distribution of uncertainty was maintained. Pit shells were developed for four distinct mining phases and the resources were summarized on a bench/partial bench basis. Table 1 shows a subset of the data for this project and includes three of the copper realizations (001, 007, 012) and Figure 2 shows long-sections through three of the realizations. Note that while the format of this input file is not critical, it is the author's experience that a "database style" layout makes spreadsheet development simpler by utilizing PivotTables and their affiliated lookup function (getpivotdata).

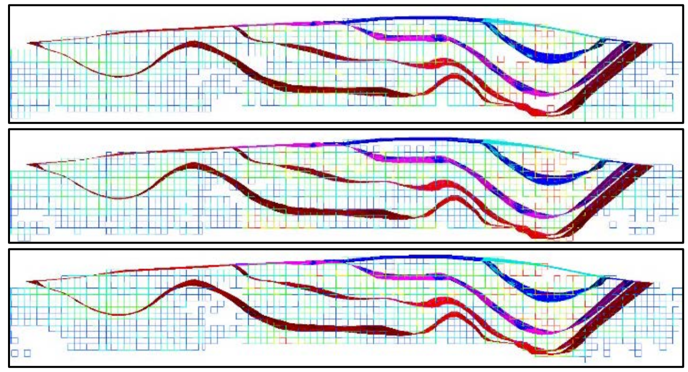

Figure 2. Example of Randomly Selected Realizations

Table 1. Resource Input Example.

VAR	PHASE	BENCH	BLOCK	O/W	CUPCT	VOLUME	TONNES	CU T	CUTCODE
CU_001	1	584	B	ore	1.23	21.91	63.43	0.78	1_584_B
CU_001	1	580.5	B	ore	1.32	1,514.32	4,210.00	55.39	1_580.5_B
CU_001	1	577	B	ore	1.69	4,477.48	12,159.93	205.96	1_577_B
CU_001	1	577	B	waste	0.00	0.29	0.76	0.00	1_577_B
CU_007	3	587.5	C	ore	0.96	10,643.87	29,176.20	280.96	3_587.5_C
CU_007	3	587.5	C	waste	0.17	395.26	1,067.19	1.79	3_587.5_C
CU_007	3	584	A	ore	0.99	28,412.58	77,194.05	762.35	3_584_A
CU_007	3	584	A	waste	0.14	1,086.63	2,870.40	3.95	3_584_A
CU_007	3	584	B	ore	0.54	3,177.42	8,586.65	46.60	3_584_B
CU_012	4	549	B	waste	0.14	2,462.94	6,574.08	9.37	4_549_B
CU_012	4	549	C	ore	1.41	13,400.79	36,426.38	512.01	4_549_C
CU_012	4	549	C	waste	0.15	178.62	481.63	0.72	4_549_C
CU_012	4	545.5	A	ore	1.19	1,348.39	3,647.34	43.53	4_545.5_A
CU_012	4	545.5	A	waste	0.13	278.82	752.82	0.98	4_545.5_A
CU_012	4	545.5	B	ore	0.94	21,696.56	58,899.73	552.61	4_545.5_B

Mine Productivity Input Drivers

One the resource estimate is imported into a spreadsheet; the modeler must select the productivity driver(s) that will constrain the schedule and divide the resources into periods. For this proof-of-concept, the author chose to reduce the complexity by not incorporating a first-principle equipment productivity buildup and rather, chose to input the daily production (tonnes) for each period by phase. Future work is planned to not only incorporate a first-principle productivity estimate but to also include a Monte Carlo simulation of productivity based on the uncertainty in the load and haul cycles.

Production Cascade Logic

While some spreadsheet scheduling tools are driven by manual scheduling of volume/block percentage input by period, this model makes use of automatic cascading logic. In other words, the user inputs the tonnes per day for each period and the spreadsheet calculates the total tonnes for that period and phase. It then cascades down the reserve list until it satisfies that tonnage requirement. Table 2 shows the results of the cascade logic for the case study Phase 1, periods 1-6 while Table 3 shows the percentage of each block mined in each period. This specific model makes use of logical "if" statements and lookup functions to automate the scheduling and to ensure that no precendences are violated and all material is scheduled.

Table 2. Automatic Tonnage Cascade

				Period	1	2	3	4	5	6
				Label	Jan 2017	Feb 2017	Mar 2017	Apr 2017	May 2017	Jun 2017
				Sched Days	31	28	31	30	31	30
				Sched tpd	200.0	300.0	300.0	300.0	250.0	250.0
Phase 1				Sched Tons	6,200	8,400	9,300	9,000	7,750	7,500
	Bench	**Block**	**Total Tons**	**Total Tons**						
Total	**15**	**-**	**103,361**	**103,361**	**6,200**	**8,400**	**9,300**	**9,000**	**7,750**	**7,500**
1_584_B	584	B	63		63	-	-	-	-	-
1_580.5_B	580.5	B	4,210		4,210	-	-	-	-	-
1_577_B	577	B	12,161		1,927	8,400	1,834	-	-	-
1_573.5_A	573.5	A	6,808		-	-	6,808	-	-	-
1_573.5_B	573.5	B	15,523		-	-	658	9,000	5,866	-
1_570_A	570	A	16,781		-	-	-	-	1,884	7,500

Two major assumptions have been made to ensure the cascade logic can utilize multiple realizations. The first assumption is that the density is consistent between all realizations. As the productivity is tonnage based, the cascade logic is set to cascade through the total tonnes in each block, if the density is not consistent between realizations, the cascade logic and productivities would need to be volume based. The second assumption is that the productivity is

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independent of the ore/waste classification. As each realization has a different distribution of ore and waste for each individual scheduling volume, a change in productivity between ore and waste would require a different approach.

Table 3. Resulting Block Percentage.

			Period	1	2	3	4	5	6
			Label	Jan 2017	Feb 2017	Mar 2017	Apr 2017	May 2017	Jun 2017
			Sched Days	31	28	31	30	31	30
			Lowest Bench	577.0	577.0	573.5	573.5	570.0	570.0
Phase 1	Bench	Block	Total Tons	Block Percentage					
Total	15	-	103,361						
1_584_B	584	B	63	100%	-	-	-	-	-
1_580.5_B	580.5	B	4,210	100%	-	-	-	-	-
1_577_B	577	B	12,161	16%	69%	15%	-	-	-
1_573.5_A	573.5	A	6,808	-	-	100%	-	-	-
1_573.5_B	573.5	B	15,523	-	-	4%	58%	38%	-
1_570_A	570	A	16,781	-	-	-	-	11%	45%

Mine Schedule Summary

Once the volumes have been scheduled on a total tonnage basis, the model calculates the quantities of material from each realization for each period using a summation of the product of Block Percentage (Table 3) and each realization attribute (Table 4). Tables 5 and 6 show the resulting schedule of material from each realization for each period, along with an average, expected value from all realizations. If available, an estimated (Kriged or Inverse Distance) model could also be included at this step for comparison.

Table 4. Realization Summary By Block.

				Average	cu_001	cu_002	Average	cu_001	cu_002	Average	cu_001	cu_002
Phase 1				Tonnes			Tonnes			Tonnes		
	Bench	Block	Total Tons	Ore			Cu			Waste		
Total	15	-	103,361	102,296	102,392	101,831	2,404	1,953	2,808	1,065	970	1,531
1_584_B	584	B	63	63	63	63	1	1	1	0	-	-
1_580.5_B	580.5	B	4,210	4,199	4,210	4,210	67	55	65	11	-	-
1_577_B	577	B	12,161	12,066	12,160	12,160	247	206	301	95	1	1
1_573.5_A	573.5	A	6,808	6,730	6,808	6,719	150	103	194	78	-	89
1_573.5_B	573.5	B	15,523	15,383	15,390	15,222	346	290	416	140	133	301
1_570_A	570	A	16,781	16,182	16,186	15,887	363	270	456	599	596	894

Table 5. Realization Schedule By Period (Ore Tonnes and Contained Cu Tonnes).

	Period	1	2	3	1	2	3
	Label	Jan 2017	Feb 2017	Mar 2017	Jan 2017	Feb 2017	Mar 2017
	Sched Days	31	28	31	31	28	31
Phase 1							
Total	Variable	Ore Tonnes			Cu Tonnes		
	Average	6,174	8,334	9,201	107	171	202
	cu_001	6,200	8,399	9,294	89	142	146
	cu_002	6,200	8,399	9,198	113	208	257
	cu_005	6,200	8,400	9,231	100	159	157
	cu_006	6,200	8,399	9,300	134	226	222

Table 6. Realization Schedule By Period (Waste and Total Tonnes).

		1	2	3	1	2	3
		Jan 2017	Feb 2017	Mar 2017	Jan 2017	Feb 2017	Mar 2017
		31	28	31	31	28	31
Phase 1							
Total	Variable	Waste Tonnes			Total Tonnes		
	Average	26	66	99	6,200	8,400	9,300
	cu_001	0	1	6	6,200	8,400	9,300
	cu_002	0	1	102	6,200	8,400	9,300
	cu_005	0	0	69	6,200	8,400	9,300
	cu_006	0	1	0	6,200	8,400	9,300

Processing Capacity, Throughput Estimates, and Stockpile Movement Logic

Modeling process capacity and throughput can involve complicated techniques but for this study an input throughput per period was used along with a fixed metallurgical recovery. All processing calculations, including stockpile tracking, are done for each realization independently. This allows for a true understanding of the production variability and stockpile requirements. The model assumes that avoiding rehandle is preferred and routes material to the process first. If the process capacity is exceeded, the excess is routed to stockpile and if the process capacity is not met, material from stockpile is routed to process as shown in Table 7.

The stockpile logic (Table 8) assumes material is added to stockpile at the average mined grade for the period and material is removed from stockpile at the average grade that stockpile opened the period with. Note that due to the fact that each section on this worksheet includes 200 realizations, the worksheet itself uses approximately 5,000 rows. To ensure usability, the author has included outline groups in most of the worksheets to automatically hide or unhide the realizations in each section.

Table 7. Process Summary.

	Period LOM	7 Jul 2017	8 Aug 2017	9 Sep 2017	10 Oct 2017	11 Nov 2017	12 Dec 2017	13 Jan 2018
PROCESS								
Mill Capacity	*1,128,000*	*31,000*	*31,000*	*30,000*	*31,000*	*30,000*	*31,000*	*93,000*
Mill								
Direct Feed (tonnes)		22,588	31,000	30,000	31,000	30,000	31,000	87,011
cu_001		23,360	30,312	30,000	31,000	30,000	31,000	85,234
cu_002		20,864	30,104	30,000	31,000	30,000	31,000	87,753
Grade		1.45%	1.51%	1.50%	1.45%	1.41%	1.44%	1.25%
cu_001		1.39%	1.53%	1.52%	1.53%	1.48%	1.33%	1.14%
cu_002		1.64%	1.47%	1.53%	1.36%	1.30%	1.32%	1.08%
Cont. Cu (tonnes)		327	469	451	450	422	445	1,090
cu_001		324	464	456	476	445	414	974
cu_002		343	444	458	423	391	411	951
From Stockpile (tonnes)		8,412	-	-	-	-	-	5,989
cu_001		7,640	688	-	-	-	-	7,766
cu_002		10,136	896	-	-	-	-	5,247
Grade		2.14%	-	-	-	-	-	1.75%
cu_001		1.69%	1.69%	-	-	-	-	1.57%
cu_002		2.61%	2.61%	-	-	-	-	1.88%
Cont. Cu (tonnes)		180	-	-	-	-	-	105
cu_001		129	12	-	-	-	-	122
cu_002		264	23	-	-	-	-	98
Total Feed (tonnes)	4,417,403	31,000	31,000	30,000	31,000	30,000	31,000	93,000
cu_001	4,440,327	31,000	31,000	30,000	31,000	30,000	31,000	93,000
cu_002	4,313,767	31,000	31,000	30,000	31,000	30,000	31,000	93,000
Grade	1.13%	1.63%	1.51%	1.50%	1.45%	1.41%	1.44%	1.28%
cu_001	1.09%	1.46%	1.53%	1.52%	1.53%	1.48%	1.33%	1.18%
cu_002	1.06%	1.96%	1.51%	1.53%	1.36%	1.30%	1.32%	1.13%
Cont. Cu (tonnes)	49,971	507	469	451	450	422	445	1,195
cu_001	48,351	454	475	456	476	445	414	1,095
cu_002	45,692	607	467	458	423	391	411	1,050
Rec. Cu (tonnes)	37,478	380	352	338	337	316	334	896
cu_001	36,264	340	357	342	357	334	310	821
cu_002	34,269	455	350	343	317	293	308	787

Table 8. Stockpile Logic.

	Period LOM	2 Feb 2017	3 Mar 2017	4 Apr 2017	5 May 2017	6 Jun 2017	7 Jul 2017	8 Aug 2017
PROCESS								
Mill Capacity	*1,128,000*	-	-	-	-	-	*31,000*	*31,000*
Expit Ore	4,417,403	8,334	9,201	8,919	7,630	7,232	22,588	31,138
cu_001	4,440,327	8,399	9,294	8,923	7,633	7,234	23,360	30,312
cu_002	4,313,767	8,399	9,198	8,825	7,536	7,100	20,864	30,104
Grade	1.13%	2.05%	2.19%	2.25%	2.25%	2.24%	1.45%	1.51%
cu_001	1.09%	1.69%	1.57%	1.88%	1.83%	1.67%	1.39%	1.53%
cu_002	1.06%	2.47%	2.80%	2.74%	2.77%	2.87%	1.64%	1.47%
Cont. Cu (tonnes)	49,971	171	202	201	172	162	327	471
cu_001	48,351	142	146	168	140	121	324	464
cu_002	45,692	208	257	241	208	204	343	444
Stockpile Balance								
Opening Inventory (tonnes)		6,174	14,508	23,710	32,628	40,258	47,490	39,079
cu_001		6,200	14,599	23,894	32,817	40,450	47,683	40,043
cu_002		6,200	14,599	23,798	32,623	40,159	47,259	37,123
Grade		1.74%	1.92%	2.02%	2.09%	2.12%	2.14%	2.14%
cu_001		1.43%	1.58%	1.58%	1.66%	1.69%	1.69%	1.69%
cu_002		1.82%	2.20%	2.43%	2.51%	2.56%	2.61%	2.61%
Cont. Cu (tonnes)		107	278	480	681	852	1,014	835
cu_001		89	231	377	545	685	806	677
cu_002		113	321	578	819	1,028	1,232	967
Added (tonnes)		8,334	9,201	8,919	7,630	7,232	-	138
cu_001		8,399	9,294	8,923	7,633	7,234	-	-
cu_002		8,399	9,198	8,825	7,536	7,100	-	-
Grade		2.05%	2.19%	2.25%	2.25%	2.24%	-	1.51%
cu_001		1.69%	1.57%	1.88%	1.83%	1.67%	-	-
cu_002		2.47%	2.80%	2.74%	2.77%	2.87%	-	-
Cont. Cu (tonnes)		171	202	201	172	162	-	2
cu_001		142	146	168	140	121	-	-
cu_002		208	257	241	208	204	-	-
Removed (tonnes)		-	-	-	-	-	8,412	-
cu_001		-	-	-	-	-	7,640	688
cu_002		-	-	-	-	-	10,136	896
Grade		-	-	-	-	-	2.14%	-
cu_001		-	-	-	-	-	1.69%	1.69%
cu_002		-	-	-	-	-	2.61%	2.61%
Cont. Cu (tonnes)		-	-	-	-	-	180	-
cu_001		-	-	-	-	-	129	12
cu_002		-	-	-	-	-	264	23
Closing Inventory (tonnes)		14,508	23,710	32,628	40,258	47,490	39,079	39,217
cu_001		14,599	23,894	32,817	40,450	47,683	40,043	39,355
cu_002		14,599	23,798	32,623	40,159	47,259	37,123	36,227
Grade		1.92%	2.02%	2.09%	2.12%	2.14%	2.14%	2.13%
cu_001		1.58%	1.58%	1.66%	1.69%	1.69%	1.69%	1.69%
cu_002		2.20%	2.43%	2.51%	2.56%	2.61%	2.61%	2.61%
Cont. Cu (tonnes)		278	480	681	852	1,014	835	837
cu_001		231	377	545	685	806	677	665
cu_002		321	578	819	1,028	1,232	967	944

Financial Analysis

Finally, a simplified before tax cash flow analysis was included to develop a range of values associated with the geologic uncertainty. Basic revenue, mining cost, processing and general administrative costs, and the cost of rehandle were included based on dollar per tonne inputs. Once again, each of these parameters is tracked for each of the 200 realizations. Before tax cash flows for each realization was calculated and summarized in a net present value form as shown in Table 9. While all of the tables presented thus far have included a measure of central tendency (mean or average), Table 9 demonstrates that with the data from all realizations available, the spread of any

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parameter can also be examined. In this case the Standard Deviation and Interquartile Range are included although any other statistical measure could be used.

Table 9. Net Present Value.

AVERAGE NPV @ 10%	$	17,240,870
CU_001	$	16,407,155
CU_002	$	16,104,002
CU_005	$	16,021,951
CU_006	$	18,115,630
CU_007	$	17,543,865
CU_008	$	17,511,088
CU_009	$	18,290,081
CU_010	$	17,578,670
STAND DEV	$	1,299,457
1ST QUARTILE	$	16,360,971
3RD QUARTILE	$	17,957,538

Dashboard

Once the spreadsheet model was complete, the author decided to develop a dashboard with various charts showing the results of several key parameters. The following figures show some of the graphs that may be of use to the user while they are modifying the schedule. The typical template for each graph includes the data from 200 realizations (gray lines), the expected value (heavy blue line), and error bars at ±10% of the expected value (red bars). Figure 3 also includes a line for the tonnes processed (orange line) that is constant as it is an input parameter.

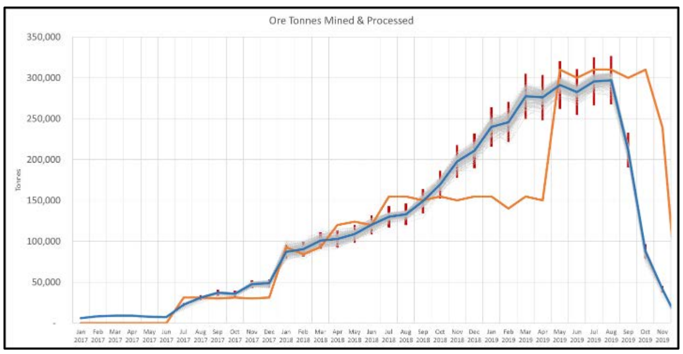

Figure 3. Ore Tonnes Mined & Processed,

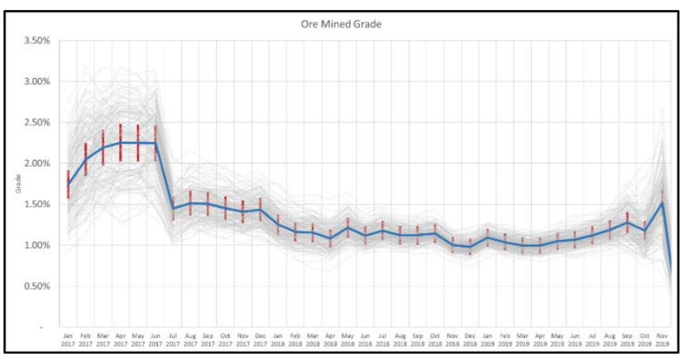

Figure 4. Ore Mined Grade.

Several other graphs include a row of percentages across the top of the graph. These values are the probability that the actual value will be within ±10% of the expected value. For some parameters, a user may wish to modify these to show another useful measure such as, the probability of exceeding the mean or the probability of being below some threshold. Due to the flexible nature of Microsoft Excel, these changes would be relatively simple.

While the author's preference is to visualize all realizations (as in Figure 7), some users or their managers may wish to reduce the amount of data being presented. One method would be to plot the minimum and maximum values (or some other quantile/quartile) with the expected value and its error bars as shown in Figure 8.

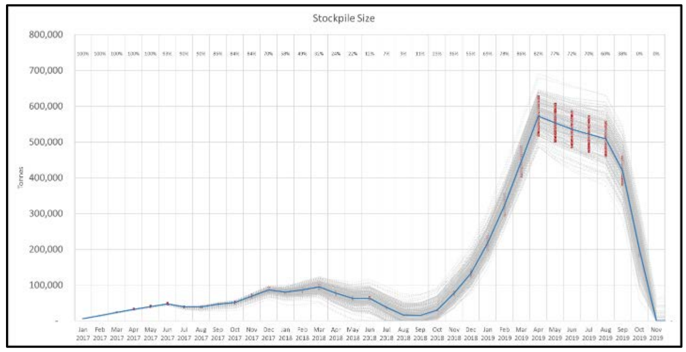

Figure 5. Stockpile Size.

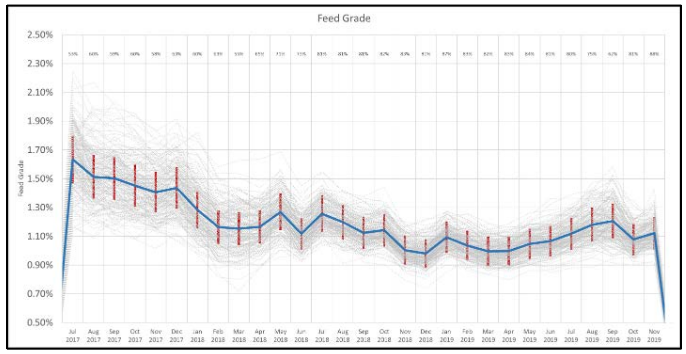

Figure 6. Feed Grade.

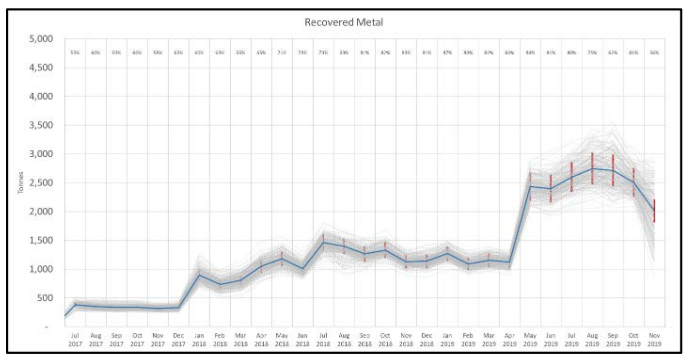

Figure 7. Recovered Metal – V1.

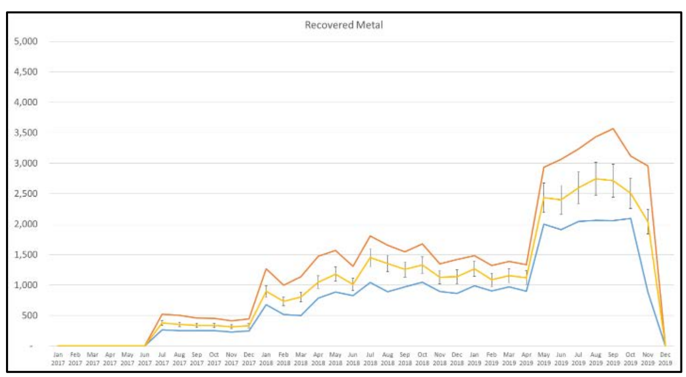

Figure 8. Recovered Metal - V2.

Another useful chart a user may wish to utilize is a histogram of any parameter in the model. This dashboard currently includes histograms of net present value (Figure 10) and of total recovered metal (Figure 11). Figure 10 was developed by specifying bins and counting the values within each bin and then plotting with a standard bar chart. Figure 11 was created using the histogram chart option

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included in Microsoft Excel 2016. The Excel 2016 tool is useful although it seems to currently lag some of the other chart types in terms of formatting and data selection options.

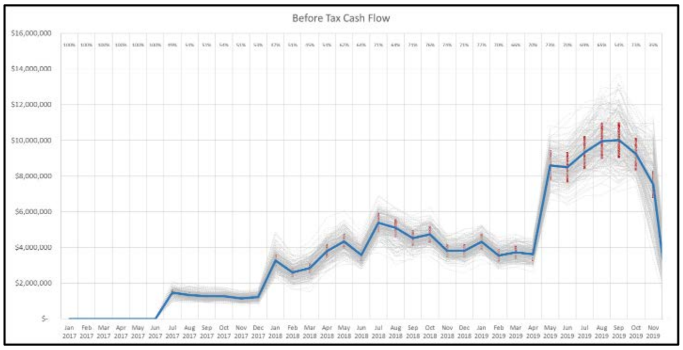

Figure 9. Before Tax Cash Flow.

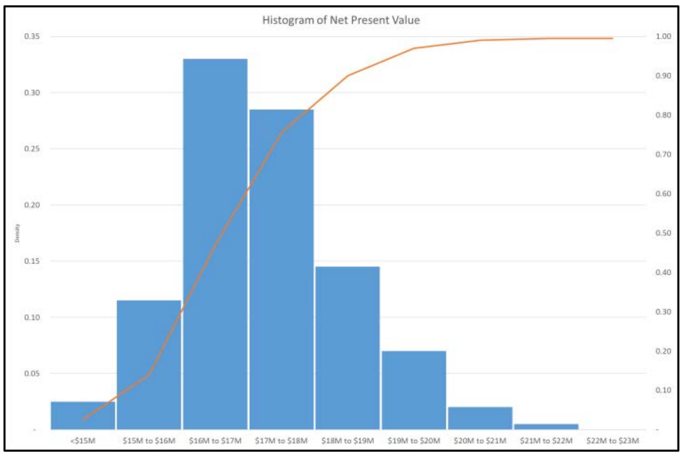

Figure 10. Histogram of Net Present Value.

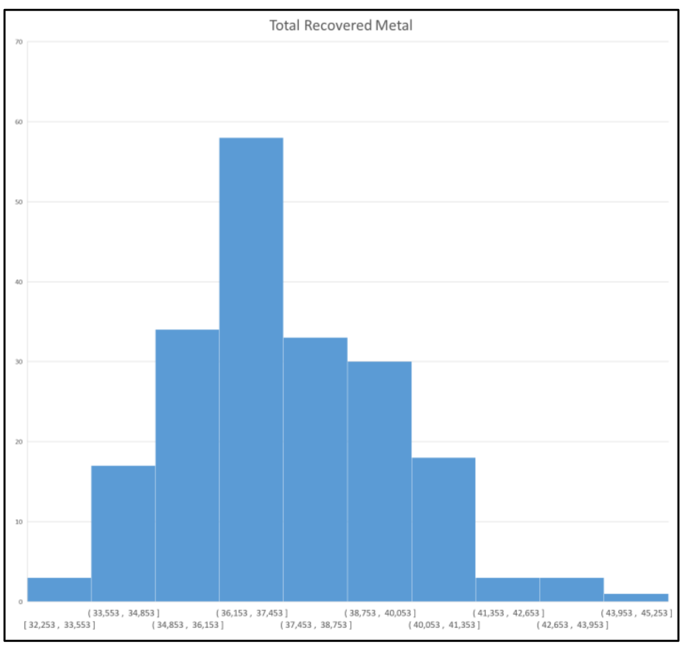

Figure 11. Histogram of Total Recovered Metal.

CONCLUSIONS & RECOMMENDATIONS

This paper has been intended to demonstrate the usefulness of a spreadsheet mine scheduling tool that quantifies the effects of geologic uncertainty through the use of multiple geologic realizations. While the proof of concept model developed for this project should be considered a work in progress, it has shown that it is possible for a mining company to develop a low-cost solution that is capable of quantifying uncertainty in a mine scheduling environment.

The author believes that while future work developing "off the shelf" solutions for uncertainty quantification in the mining industry is important, it is also critical that we begin to develop stepwise changes to our mine planning processes to improve our understanding of this field and ensure that future software and techniques can be readily accepted.

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REFERENCES

Alabert, F. G. (1987). *Stochastic Imaging of Spatial Distributions Using Hard and Soft Information.* Masters Dissertation, Stanford University.

Boland, N., Dumitrescu, I., & Froyland, G. (2008, Ocober 24). *A Multistage Stochastic Programming Approach to Open Pit.* U. of Newcastle & U. of New South Wales. Austrailia: Optimization Online. Retrieved from http://www.optimization-online.org/DB_FILE/2008/10/2123.pdf

Deutsch, M., Gonzalez, E., & Williams, M. (2015, December). Using simulation to quantify uncertainty in ultimate-pit limits and inform infrastructure placement. *Mining Engineering*, 49-55.

Dimitrakopoulos, R. (2011). Strategic Mine Planning Under Uncertainty. *Journal of Mining Science, Vol. 47, No. 2*, 138-150.

Godoy, M., & Dimitrakopoulos, R. (2011). A Risk Quantification Framework for Strategic Mine Planning: Method and Applicaiton. *Journal of Mining Science, Vol. 47, No. 2*, 235-246.

Isaaks, E. H. (1990). *The Application of Monte Carlo Methods to the Analysis of Spatially Correlated Data.* Doctoral Dissertation, Stanford University.

McGill University. (2015). Retrieved from COSMO Stochastic Mine Plannig Laboratorс: http://cosmo.mcgill.ca/index.php

Rossi, M. E., & Deutsch, C. V. (2014). *Mineral Resource Estimation.* Springer Science.

Schwenker, B., & Wulf, T. (2013). *Scenario-based Strategic Planning.* Wiebaden: Springer Gabler.

Smith, G. L., Surujhlal, S. N., & Manyuchi, K. T. (2008). Strategic mine planning - communicating uncertainty with scenarios. *The Journal of The Southern African Institute of Mining and Metallurgy*, 725-732.

Vann, J, Jackson, S, Bye, A, Coward, S, Moayer, S, Nicholas, G, & Wolff, R. (2012). Scenario Thinking - A Powerful Tool for Strategic Planning and Evaluation of Mining Projects and Operations. *AusIMM Project Evaluation Conference* (pp. 5-14). Melbourne, Austrailia: AusIMM.

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