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Commodity price uncertainty propagation in open-pit mine production planning by Latin hypercube sampling method

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Abstract

Production planning of an open-pit mine is a procedure during which the rock blocks are assigned to different production periods in a way that leads to the highest net present value (NPV) subject to some operational and technical constraints. This process becomes much more complicated by incorporation of the uncertainty existing in the input parameters. The commodity price uncertainty is among the most significant factors, whose effects cannot be mitigated through further exploration or investigation. The present work introduced a new approach for integration of the commodity price uncertainty into long-term production planning of open-pit mines. The procedure involves solving the problem by the integer programming method based on a series of economic block models that are realized based on the sampled prices from commodity price distribution function using the median Latin hypercube sampling method. The results obtained showed that the new methodology is able to reduce the risks and the net present value of the new approach at a confidence level 80% more than the conventional methods.

Keywords: *Open-Pit Mine Production Planning, Commodity Price Uncertainty, Uncertainty Propagation, Latin Hypercube Sampling.*

1. Introduction

A global challenge in the years to come is the environmentally-friendly and financially-attractive provision of exhaustible resources (minerals) to meet the ever-increasing demand by the today's high-tech society. Currently, surface mining accounts for a significant proportion of the produced minerals. The open-pit mining process starts with a small digging into the ground, called pit, and converts into larger and larger pits till the designed shape of the mine called ultimate pit limit [1].

The goal of an open-pit mine production planning is to find the optimum sequence of the mining blocks that leads to the highest net present value (NPV) of the annual cash flows, while meeting the technical constraints such as the mining and processing capacities and sequencing constraints [2]. Production planning for open-pit mining operations is a key factor in determining returns on investments of hundreds of millions of dollars.

In the mine production planning, the mineral deposit is represented as a 3D array of blocks, each of which represents a volume of material that can be mined. Each block has a weight and a metal content interpolated using the information obtained from exploration drilling [3]. In this regards, two distinct and important decisions must be made about each block of the model during the production planning process [4]:

- If the block should be mined by the end of mine life or not?
- If yes, when should it be mined? And once it is mined, to which destination should it be hauled?

The first of these questions is answered by the ultimate pit limit (UPL) problem in the mining literature. After determination of the ultimate pit contour, the next widely-studied mine optimization problem type is to answer the second question: when the blocks should be extracted over time periods so that the total net present value is maximized [5]. In the mining community, this problem type is called mine production planning, and is usually implemented in three levels of planning time frames:

- Long-term planning, which may cover a period of 5 to 10 or even up to 30 years to answer the overall development questions.
- Medium-term planning, which concerns a shorter period of 3 to 5 years to provide a forecast of the company's development over the coming few years in terms of the feasibility, profitability, and financing.
- Short-term planning, which focuses on a production period of some days to few years to ensure achieving the production properties.

Studies on the deterministic version of open-pit production planning have been started since 1968 [6], and several methodologies have been invented so far such as integer programing [4,7], mixed integer programing [8, 9], dynamic programing [10], and metaheuristic method [11-13], where the problem input parameters are assumed to be certain and exactly known (deterministic) in all approaches. However, in a real scale, it is a multi-variable optimization problem that requires a huge amount of computational resources to be solved, and incorporation of the uncertainties makes the issue much tougher to be overcome.

The sources of uncertainties in a mining projects can be categorized in three major classes: geological, technical, and economical. From another point of view, they could be classified as those that arise from the nature of the variables and those that are too expensive to be mitigated. For example, commodity price is a variable whose uncertainty arises from its nature, and its exact determination is not possible for the future years. In contrast, metal grade inside the ore body is a variable whose uncertainty would be diminished by spending time and money on extension of the exploratory studies [14]. Taking all these uncertainties in to account leads to a multi-criteria stochastic optimization problem that ends in a complex mathematical formulation and is very costly to be solved. In practice, mine engineers usually use heuristic approaches and their own engineering judgments to find a feasible sub-optimal solution based on the fixed input parameters. However, a rational mine design under uncertainties needs efficient algorithms to be developed in order to reduce the human factors and include the real circumstances of the mining industry.

Looking over the price fluctuation of raw minerals shows that the volatility of the mining product prices is much intensive than that of the other industrial products. For example, as illustrated in Figure 1, the price of copper has been highly volatile during the past 30 years, i.e. 1985-2014 [15]. The variations reached approximately 200% from 2004 to 2011, as shown in Table 1. Hence, the commodity price uncertainty can clearly play an important role in succeeding a production plan, and a constant-price-based planning cannot lead to an accurate answer and reduce the risks of the investment. In this work, we investigated the effects of the commodity price uncertainty on mine planning, and introduce an approach for its propagation into open-pit production planning model.

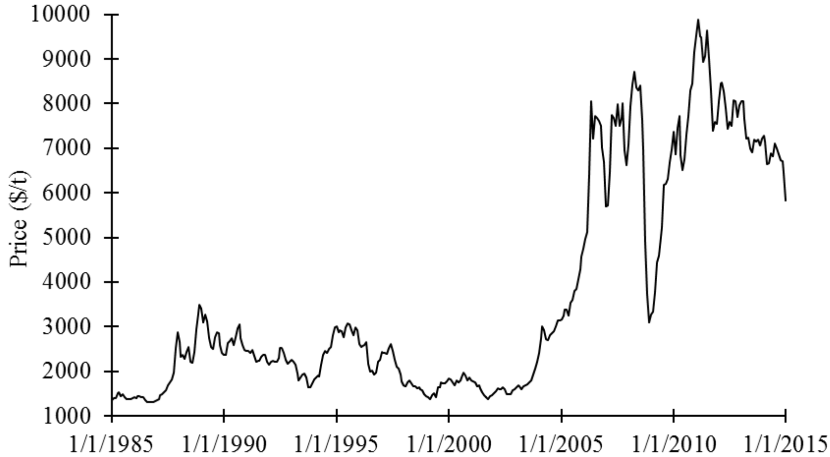


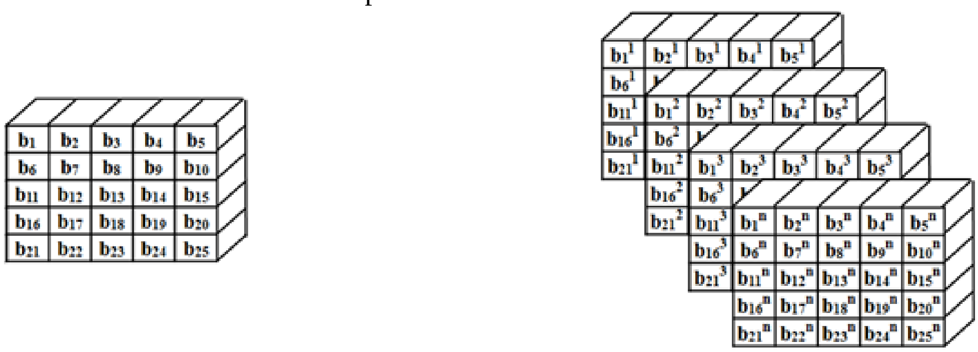
Figure 1. Fluctuation of copper price during the past 30 years [15].

Table 1. Copper price changes from 2004 to 2014.

Year	Average price ($/t)	Changes compared to previous year	Changes compared to 2004
2004	2,863.47	0.00%	0.00%
2005	3,676.50	28.39%	28.39%
2006	6,731.35	83.09%	135.08%
2007	7,131.63	5.95%	149.06%
2008	6,963.48	–2.36%	143.18%
2009	5,165.30	–25.82%	80.39%
2010	7,538.37	45.94%	163.26%
2011	8,823.46	17.05%	208.14%
2012	7,958.93	–9.80%	177.95%
2013	7,331.49	–7.88%	156.04%
2014	6,863.40	–6.38%	139.69%

2. Mine planning considering commodity price uncertainty

Unlike the conventional deterministic mine design process, which is usually implemented based on a single economic block model, stochastic planning of open pits considering commodity price uncertainty normally runs according to a series of economic block model realizations (Figure 2). The subject has been attracted by numerous researchers during the last decade, and several procedures have been developed, which can generally be divided into three main categories of mathematical, heuristic, and metaheuristic approaches. Mathematical formulations use linear programming [16], integer linear programming [17-19] or maximum flow [20] for solving a stochastic problem. The maximum upside potential/minimum downside risk method [21] is a leading development among the heuristic techniques. It takes the risks of the project failures or the potential of the over-expecting gains since the existing uncertainties are evaluated through a series of deposit realizations. Genetic algorithms [22], simulated annealing [23], ant colony optimization [1], Tabu search [24], and particle swarm [25] metaheuristic approaches have been reported to be applied on some case studies incorporating the metal grade uncertainty. As noticed, the majority of the research works have been focused on the integration of the metal grade uncertainty, and investigation in the field of commodity price uncertainty modeling seems to be still needed for further developments.



(a) (b)

Figure 2. Economic-block model a. Conventional single model, b. Multiple-block model realizations for stochastic planning.

3. Propagation of commodity price uncertainty in production planning model

The assessment and presentation of the effects of uncertainty have now become widely recognized as important parts of analyses for complex systems [26]. At the simplest level, such analyses can be viewed as the study of functions of the form:

$$Y = f(X) \tag{1}$$

where the function f represents the model or models under study, $X = [x_1, x_2, \dots, x_n]$ is a vector of model inputs, and $Y = [y_1, y_2, \dots, y_m]$ is a vector of model predictions. The goal of an uncertainty analysis is to determine the uncertainty in the element Y that results from uncertainty in the element X. Awareness about the volatility nature of the parameter under consideration is the first step in any uncertainty modeling. For this purpose, the histogram of the historical commodity price data was plotted along the mine life, and the best probability density function (PDF) was fitted on the histogram in the proposed procedure. PDF of the commodity price data is a continuous function, and production planning for all the price values is impractical or impossible. Therefore, sampling is used to represent a subset of manageable size. The process of designing and obtaining a representative sample of a desired population requires care and accuracy. In simple random sampling, there is no assurance that all points will be sampled. This problem can be addressed using Latin hypercube sampling (LHS). LHS divides each input cumulative distribution function into n equal probability intervals, and selects a sample from each interval. This can be carried out in two ways. Median Latin hypercube sampling (MLHS) uses the median value of each interval (Figure 3), whereas random Latin hypercube sampling (RLHS) picks a random point from each interval. Interested reader could refer to Mckay in 1979 for details of LHS [27].

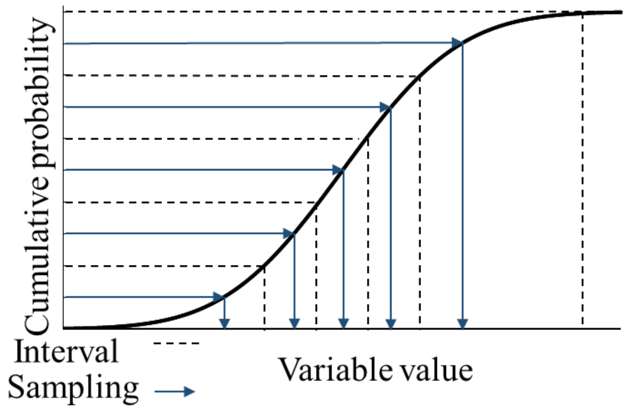


Figure 3. Median Latin hypercube sampling method.

Unlike the Monte Carlo (MC) method, the sample points in LHS, spread more uniformly over all possible values, and distribution of the sample points is much closer to the probability density function of the population. To compare the precision level of MC and MLHS, 100 samples were generated from a standard normal (0, 1) distribution using each method and computed the mean of samples. Result of sampling by MC leads to a non-zero mean value, where MLHS estimates the mean as exactly zero (Figure 4). A Monte Carlo method used for achieving a reasonably accurate random distribution need requires a very large size sample. In this research work, in order to reduce the number of runs, MLHS was used for sampling from the commodity price cumulative distribution function.

According to n selected samples from the price cumulative distribution and geological block model of the deposit, n economic block model realizations were constructed, and production planning was performed by one of the production planning problem-solving methods such as mathematical, heuristic, and metaheuristic for each created economic block model. In this research work, in order to obtain an exact solution, the binary linear integer programming (LIP) model was used. Then the most promising production plan was determined by combination of the production schedules and calculation of the extraction probability of each block at different periods. By drawing the histogram for the net present values resulting from n production schedules and fitting a distribution function on it, the most probable NPV can also be determined. Figure 5 illustrates the proposed process, in general.

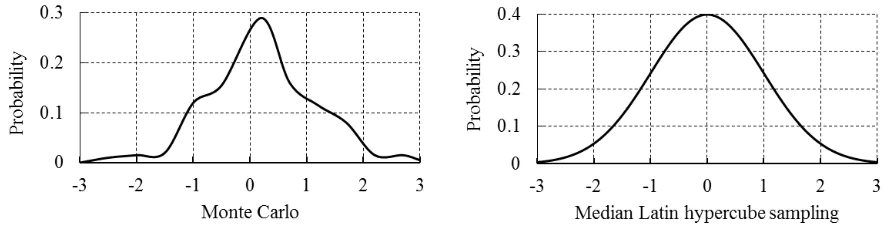
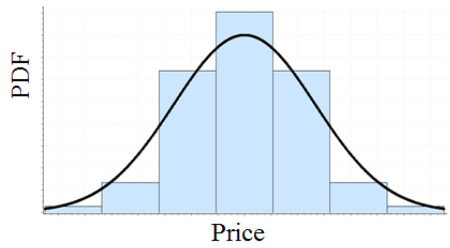
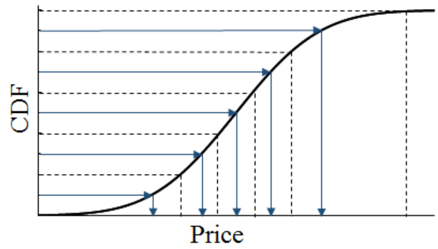


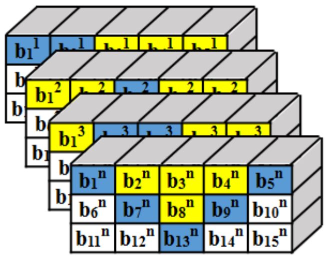
Figure 4. PDF resulting from MC and MLHS methods.



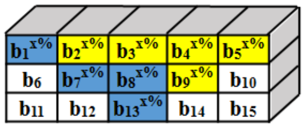
1. Drawing price histogram and fitting distribution



2. Latin hypercube sampling from distribution



3. Creating block models and production planning



4. Determining final production plan

5. Plotting net present value distribution

Figure 5. Production planning procedure under commodity price uncertainty conditions.

4. Numerical example

A hypothetical copper deposit with geological block model containing 200 blocks was assumed and subjected to scheduling for explaining the details of the proposed algorithm implementation (Figure 6). Table 2 displays the technical and economic parameters that are used for the construction of the economic block model. These parameters are general, summarized from the global data.

Mining operation was considered to run for 5 years, and the maximum and minimum mining capacities were assumed to be 24 and 18 blocks a year, respectively. The maximum and minimum processing capacities were considered to be 15 and 9 ore blocks a year, respectively, and the discount rate was presumed to be 4%. Considering the mine life, fluctuation of the copper prices were collected in the last 5 years (Figure 7).

The descriptive statistics parameters of daily copper price data are displayed in Table 3. The histogram of the price data was plotted, and the best distribution was fitted on the data (Figure 8).

The fitted distribution was a three-parameter lognormal distribution with the mean of 7.4835, standard deviation of 0.45349, and threshold (location) parameter of 5728.7. PDF and CDF of the fitted distribution can be expressed by Equations (2) and (3), respectively. To investigate the fitness of the distribution, the probability-probability (P-P) plot was drawn as Figure 9.

$$PDF\,(price) = \frac{\exp\left(-\frac{1}{2}\left(\frac{\ln(price - 5728.7) - 7.4835}{0.45349}\right)^2\right)}{0.45349(price - 5728.7)\sqrt{2\pi}} \quad (2)$$

$$CDF\,(price) = \Phi\left(\frac{\ln(price - 5728.7) - 7.4835}{0.45349}\right) \quad (3)$$

where Φ is the cumulative distribution function of the standard normal distribution.

After determination of the copper price distribution, the median Latin hypercube sampling was used for taking 50 samples from it. The statistical description of the samples was summarized in Table 4.

0.04	0.05	0.06	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
0.04	0.17	0.15	0.14	0.20	0.17	0.17	0.12	0.19	0.22	0.10	0.18	0.05	0.04	0.25	0.17	0.31	0.20	0.16	0.02
0.04	0.17	0.11	0.12	0.20	0.20	0.15	0.14	0.28	0.07	0.19	0.28	0.10	0.25	0.25	0.18	0.01	0.38	0.32	0.01
0.01	0.13	0.20	0.24	0.39	0.25	0.12	0.14	0.02	0.25	0.29	0.09	0.25	0.23	0.31	0.25	0.02	0.19	0.02	0.02
0.01	0.23	0.11	0.26	0.22	0.02	0.13	0.20	0.14	0.17	0.30	0.16	0.13	0.28	0.11	0.22	0.20	0.15	0.03	0.03
0.01	0.04	0.20	0.21	0.02	0.29	0.15	0.17	0.30	0.29	0.26	0.32	0.04	0.26	0.41	0.17	0.19	0.21	0.25	0.01
0.02	0.17	0.18	0.27	0.24	0.33	0.21	0.08	0.35	0.36	0.17	0.22	0.23	0.38	0.23	0.25	0.18	0.09	0.22	0.01
0.03	0.03	0.37	0.18	0.42	0.10	0.25	0.15	0.18	0.16	0.13	0.18	0.16	0.25	0.15	0.15	0.03	0.20	0.09	0.02
0.02	0.34	0.12	0.24	0.29	0.38	0.21	0.20	0.16	0.15	0.16	0.16	0.13	0.32	0.27	0.14	0.15	0.17	0.23	0.02
0.17	0.12	0.27	0.19	0.23	0.16	0.07	0.04	0.13	0.17	0.18	0.06	0.14	0.20	0.34	0.16	0.32	0.18	0.02	0.02

Figure 6. Geological block model of the mine.

Table 2. Technical and economic parameters required for construction of the economic block model.

Parameters	Value
Mill recovery rate	80%
Mill concentrate grade	28%
Smelting loss (kg/ton)	10
Refining loss (kg/ton)	5
Mining cost ($/ton Rock)	1.5
Milling cost ($/ton Ore)	5.5
General and administration cost ($/ton Ore)	0.5
Amortization and depreciation cost ($/ton Ore)	0.8
Transport cost of mill concentrate to the smelter ($/ton Concentrate)	30
Smelting cost ($/ton Concentrate)	92
Transport cost of the blister copper to the refinery ($/ton Blister	2
Refining cost ($/ton Blister copper)	184
Selling and delivery cost ($/kg Copper)	0.01
General plant cost ($/kg Copper)	0.01

Figure 7. Fluctuation of copper prices during the past 5 years [15].

Table 3. Descriptive statistics parameters of daily copper price data.

Parameter	Value	Parameter	Value
Sample Size	1260	Min	6091
Mean	7696	25% (Q1)	7035
Variance	7.95E+05	50% (Median)	7460
Standard deviation	891.67	75% (Q3)	8223
Coefficient of variation	0.11586	Max	10148

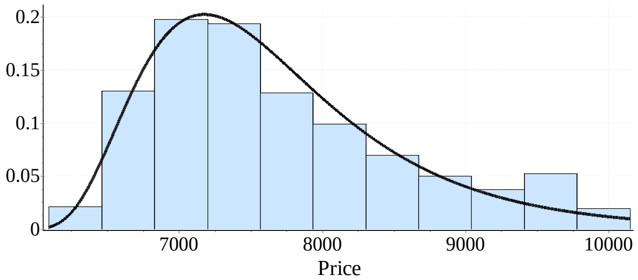


Figure 8. Histogram of the copper price data and fitted distribution.

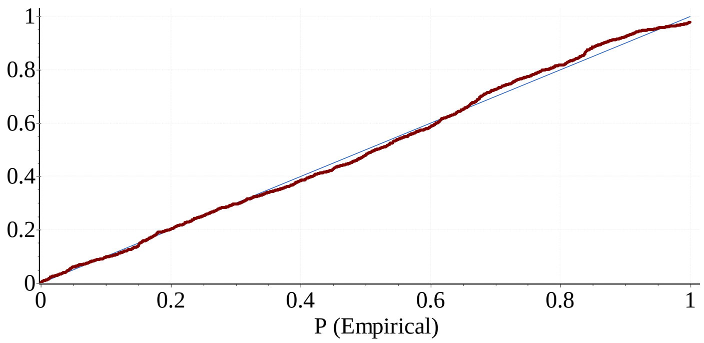


Figure 9. Probability-Probability (P-P) plot.

Table 4. Descriptive statistics parameters of the price samples.

Parameter	Value	Parameter	Value
Sample Size	50	Min	6348
Mean	7693.8	25% (Q1)	7029
Variance	8.4369E+5	50% (Median)	7507
Standard deviation	918.53	75% (Q3)	8161
Coefficient of variation	0.11939	Max	10836

The next step involved construction of the economic block model realizations according to the selected price samples. The economic value of a block is equal to the revenue earned from selling the commodity (mineral) content of the extracted block less all costs. For example, for a copper mine, the economic value of block n is calculated as follows:

$$Return_n = \begin{pmatrix} [(Copper\ \ price - Sales\ costs) \times \\ Recovery \times Tonnage_n \times Loss \times grade_n] \\ -[(Mining\ cost + Milling\ \ cost + \\ Smelting\ \ cost + Refining\ \ cost + \\ Transport\ \ cost)] \end{pmatrix} \quad (4)$$

$$v_n = \max\left[Return_n\ ,\ (-\ Mining\ cost\ of\ \ block\ \ n)\right] \quad (5)$$

where v_n is the economic value of block n.

By changing the commodity price, the block economic value will be also variable (Equation (5)), and hence, cut-off will not have a constant value. The cut-off grades are used to distinguish economical ore from non-economical ore. If the ore grade is higher than the operating cut-off grade, the mined material is sent to the mill, otherwise it is sent to a dump as waste. The cut-off should increase as commodity price falls and decrease as price rises, which implies a negative correlation between cut-off and price [28].

After construction of the economic block model realizations based on Equation (5), these models were solved by the binary linear integer programming (LIP) method. This method has been quite frequently used to solve the production planning problem of open-pit mines with the objective function to maximize the net present value while satisfying different constraints. LIP can be formulated as below [29]:

$$Maximize \quad \sum_{t=1}^{T}\sum_{n=1}^{N}\frac{v_n}{(1+d)^{t-1}}x_{tn} \tag{6}$$

where,
T: Number of time periods.
N: Number of mine blocks.
x_{tn}: Binary decision variables of the model $x_{tn} = 1$ if block n is mined in time period t, and $x_{tn} = 0$ if otherwise).
d: Discount rate.

Mining capacity constraints: Total tonnage of extracted material should be between a pre-determined upper and lower limit.

$$MC_{min}^{t} \le \sum_{n=1}^{N} W_n . x_{tn} \le MC_{max}^{t} \qquad ,\text{for } \forall t \tag{7}$$

where,
W_n: Tonnage of block n.
$MC_{max}^{t}, MC_{min}^{t}$: Maximum and minimum allowed mining capacity for the period of t.

Processing capacity constraints: Quantity of ore blocks should satisfy processing capacity:

$$PC_{min}^{t} \le \sum_{n=1}^{N} O_n . x_{tn} \le PC_{max}^{t} \qquad ,\text{for } \forall t \tag{8}$$

where,
O_n: Tonnage of ore block n. If the block economic value is greater than zero ($v_n > 0$), it will be considered as ore.
$PC_{max}^{tm}, PC_{max}^{tm}$: Maximum and minimum allowed processing capacity for the period of t.

Reserve constraints: This constraint is mathematically necessary to ensure that a block is mined only once.

$$\sum_{t=1}^{T} x_{tn} \le 1 \qquad ,\text{for } \forall n \tag{9}$$

Sequencing constraints: The sequencing constraints ensure that a block can only be removed if all the overlaying blocks have been removed in the previous or current periods.

$$\sum_{l=1}^{t}(x_{lj} - x_{ti}) \ge 0, \quad t = 1,\ldots,T \qquad ,\text{for } \forall(i, j) \in A \tag{10}$$

where A is the set of pairs (i, j) of blocks such that block j is a neighboring block to i that must be removed before block i can be mined.

The main advantage of the LIP model is its ability to solve the UPL and long-term planning problems simultaneously. The LIP model was solved using a program developed in C++ environment and CPLEX library for 50 economic block models. For instance, the solution results for the minimum, mean, and maximum copper prices are displayed in Figures 10 to 12, respectively. Then extraction probability of each block for being scheduled in different periods of the mine life were determined by calculation of the times that it has been scheduled in that period. This was shown for the block located in the most top-left position of the model in Figure 13. Finally, the most preferable production plan was constructed by combining all the individual schedules and designating each block to the maximum extraction probability period (Figure 14).

The best distribution was fitted on the net present values of the 50 production plans, as shown in Figure 15 and Table 5.

5	5	4	4	4	2	3	2	2	2	2	1	1	1	1	1	1	1	1	1
	5	5	4	4	4	3	3	2	2	2	2	1	1	1	1	1	1	1	
		5	5	4	4	4	3	3	3	3	2	2	1	1	1	1	1		
			5	5	4	4	4	3	3	3	3	2	2	1	1	2			
				5	5	4	4	4	3	3	3	3	2	2	2				
					5	5	4	4	4	3	3	3	3	2					
						5	5	4	4	5	5	5	3						
								5			5								

Figure 10. Production planning for the minimum copper price.

4	4	4	3	3	3	2	1	2	2	2	1	1	1	1	1	1	1	1	1
	4	4	4	3	3	3	2	2	2	2	2	1	1	1	1	1	1	1	
		4	4	4	3	3	3	2	2	2	2	2	1	1	1	1	1		
			4	4	4	3	3	3	2	2	2	2	2	1	1	3			
				4	5	4	3	3	3	2	2	2	2	3	3				
					5	5	4	3	3	3	2	4	3	3					
						5	5	4	3	5	4	4	4						
							5	5	5	5	5	5							
								5	5	5	5								
									5	5									

Figure 11. Production planning for the mean copper prices.

1	1	1	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	4	4
	1	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	4	4	
		1	1	1	1	1	2	2	2	2	2	3	3	3	3	4	4		
			1	1	1	2	2	2	2	2	3	3	3	3	4	4			
				4	5	4	2	2	2	3	3	4	3	4	4				
					5	5	4	2	3	3	4	5	4	4					
						5	5	4	3	4	5	5	5						
								5	5	5	5	5							
									5	5	5								
										5									

Figure 12. Production planning for the maximum copper price.

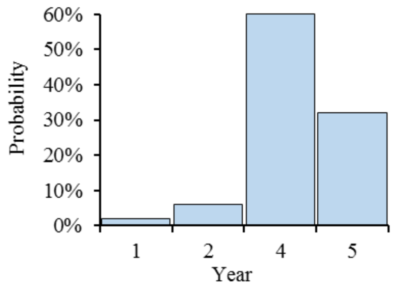


Figure 13. Extraction probability of the block located in the most top-left position.

4 60%	4 40%	4 66%	3 68%	3 74%	3 86%	2 66%	2 74%	2 84%	2 82%	2 78%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%
	4 58%	4 40%	4 66%	3 68%	3 72%	3 92%	2 74%	2 92%	2 100%	2 100%	2 100%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%	1 92%	
		4 58%	4 40%	4 66%	3 66%	3 66%	3 66%	2 82%	2 92%	2 94%	2 100%	2 92%	1 92%	1 92%	1 92%	1 92%	1 92%		
			4 58%	4 40%	4 66%	4 52%	4 52%	3 66%	2 76%	2 92%	2 68%	2 92%	2 92%	1 92%	1 92%	3 66%			
				4 60%	5 94%	4 84%	4 52%	4 52%	3 66%	2 66%	2 66%	2 68%	2 92%	3 66%	3 66%				
					5 100%	5 100%	4 84%	4 52%	4 52%	3 74%	2 66%	3 52%	3 92%	3 66%					
						5 100%	5 84%	4 84%	4 52%	5 82%	4 82%	4 46%	3 52%						
							5 72%	5 84%	5 82%	5 74%	5 86%	5 82%							
								5 64%	5 74%	5 74%	5 74%								
									5 58%	5 74%									

Figure 14. Final production plan considering commodity price uncertainty.

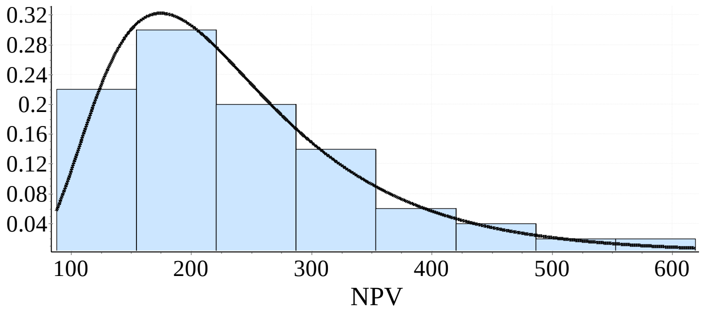


Figure 15. Net present value distribution.

Table 5. Descriptive statistics parameters of NPV.

Parameter	Value	Parameter	Value
Sample Size	50	Min	87.816
Mean	241.96	25% (Q1)	160.66
Variance	12109	50% (Median)	218.06
Standard deviation	110.04	75% (Q3)	298.9
Coefficient of variation	0.45478	Max	619.09

The fitted distribution was a three-parameter lognormal distribution with the mean of 5.2117, standard deviation of 0.5114, and threshold parameter of 33.406. PDF and CDF of fitted distribution were expressed by Equations (11) and (12), respectively. To investigate the fitness of the distribution, the probability-probability (P-P) plot was drawn, as presented in Figure 16. The most likely net present value where probability density function has its maximum value (mode) equals to $ 174.61.

$$PDF(NPV) = \frac{\exp\left(-\frac{1}{2}\left(\frac{\ln(NPV - 33.406) - 5.2117}{0.5114}\right)^2\right)}{0.5114(NPV - 33.406)\sqrt{2\pi}} \quad (11)$$

$$CDF(NPV) = \Phi\left(\frac{\ln(NPV - 33.406) - 5.2117}{0.5114}\right) \quad (12)$$

Average grade changes of the mine versus commodity price fluctuation was shown in Figure 17. As it can be seen in this figure, there is a negative correlation between average grade and commodity price.

In order to compare the new approach with the conventional constant price methods, the production planning was also performed by the conventional method (Figure 18 and 19), where the commodity price as $/t 6860.29 (equal to the mean copper price in 2014) and $/t 7696 (equal to the mean copper price in 5 recent years) were considered, and net present values of $ 142.64 and $ 153.8 were obtained, respectively, which is lower than that of the new approach ($ 174.61). According to the net present value distribution of the new approach (Figure 15), the net present value of the new approach at confidence levels of 85% and 80% were more than $ 142.64 and $ 153.8, respectively.

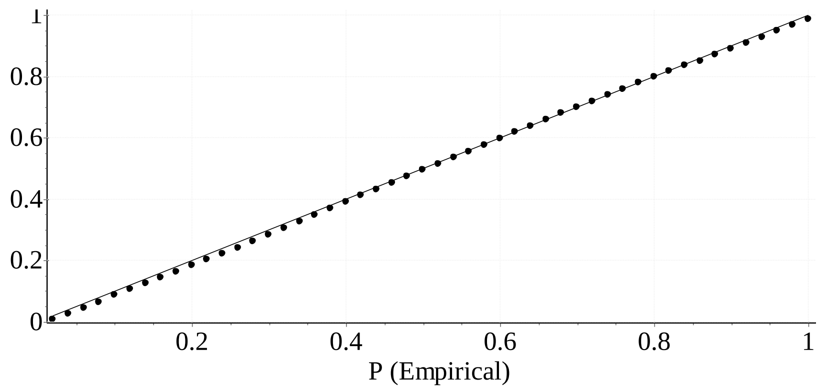


Figure 16. Probability-Probability (P-P) plot.

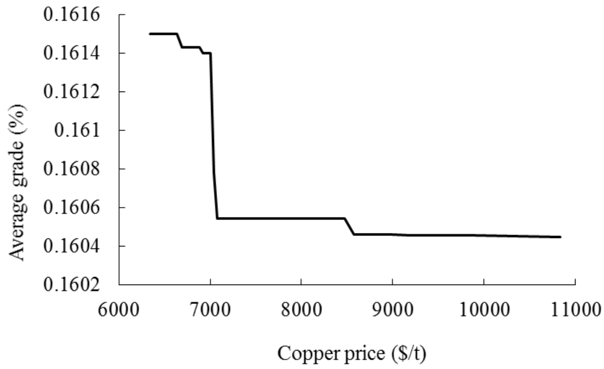


Figure 17. Average grade changes versus commodity price fluctuation.

5	5	4	4	4	3	3	2	2	2	2	1	1	1	1	1	1	1	1	1
	5	5	4	4	4	3	3	2	2	2	2	1	1	1	1	1	1	1	
		5	5	4	4	4	3	3	2	2	2	2	1	1	1	1	1		
			5	5	4	4	4	3	3	2	3	2	2	1	1	2			
				5	5	5	4	4	3	3	3	3	2	2	2				
					5	5	5	4	4	3	3	3	3	2					
						5		5	4	5	4	3	3						
											5								

Figure 18. Mine production planning by conventional method (copper price = 6860.29 $/t).

2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	4	4
	2	2	1	1	1	1	2	1	1	1	1	3	3	2	2	2	4	4	
		3	2	1	1	2	2	2	2	1	3	3	4	3	2	4	4		
			3	2	2	3	3	3	2	3	3	4	4	4	4	5			
				3	4	5	3	3	3	3	4	5	4	4	5				
					5	5	5	3	4	4	5	5	5	5					
						5		5	4	5	5	5	5						
											5								

Figure 19. Mine production planning by conventional method (copper price = 7696 $/t).

5. Conclusions

The open-pit mine production scheduling is even more difficult since the number of blocks is large and because the future economic value of the blocks is not known at the time decisions are made. This yields a large-scale stochastic optimization problem. In this work, we proposed an uncertainty propagation method based on a sampling procedure to solve an important real-world problem that arises in surface mine planning namely the open-pit mine production planning problem with commodity price uncertainty. Instead of solving a single production, the new approach was based on a series of the economic block models that were constructed based on the sampled prices from the commodity price distribution by the median Latin hypercube sampling method. Then each economic block model was solved by the integer programming method, and the schedules were combined to obtain the final preferable plan. The approach was tested through a hypothetical block model, and the results obtained revealed that the net present value of the new approach at the confidence level 80% was more than that for the conventional method.

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انتشار عدم قطعیت قیمت محصول در برنامه‌ریزی تولید معادن روباز توسط روش نمونه‌گیری مربع لاتین

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چکیده:

برنامه‌ریزی تولید معادن روباز فرآیندی است که طی آن بلوک‌هایی از سنگ معدن به فازهای مختلف تولید معدن تخصیص داده می‌شود، به‌طوری‌که بیشترین ارزش خالص فعلی با در نظر گرفتن محدودیت‌های عملیاتی و فنی حاصل شود. با لحاظ کردن عدم قطعیت موجود در پارامترهای ورودی، این فرآیند پیچیده‌تر می‌شود. عدم قطعیت قیمت محصول از جمله عوامل بسیار با اهمیت است که از بررسی و تحقیق بیشتر در ارتباط با تأثیرات آن نمی‌توان چشم‌پوشی کرد. تحقیق حاضر رویکرد جدیدی برای اعمال عدم قطعیت قیمت محصول در برنامه‌ریزی تولید بلندمدت معادن روباز ارائه می‌کند. فرآیند حل مسئله بر پایه مجموعه‌ای از مدل‌های بلوکی اقتصادی استوار است که بر اساس قیمت‌های نمونه‌گیری شده از تابع توزیع قیمت محصول با استفاده از روش نمونه‌گیری مربع لاتین میانه تحقق می‌یابند و با روش برنامه‌ریزی عدد صحیح حل می‌شوند. نتایج حاصل نشان می‌دهند که روش جدید قادر به کاهش ریسک بوده و با سطح اطمینان ۸۰ درصد ارزش خالص فعلی حاصل از روش جدید بیشتر از روش‌های متداول است.

کلمات کلیدی: برنامه‌ریزی تولید معدن روباز، عدم قطعیت قیمت محصول، انتشار عدم قطعیت، نمونه‌گیری مربع لاتین.