Review of Deterministic Mathematical Models and Stochastic Optimization for Open Pit Mine Planning Problems

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ABSTRACT

Mine planning problem leads to prioritizing the extraction of blocks. Mine planning includes a wide range of processes of production planning, scheduling the mining operations, cut-off grade optimization, crusher, and conveyor location, and determining pit limits and pushbacks. Researchers in mining problems have proposed different planning problems in three levels short-term, mid-term, and long-term. Because of the nature of open-pit mine planning problems, they have some complexities and uncertainties in data. Also, the mathematical models applied to these problems include a variety of constraints relative to their assumptions. Due to the uncertainty of different parameters in mining operations, some researchers dealt with stochastic optimization in their proposed mathematical models. To solve these problems, they presented deterministic and stochastic models for mining operations. Then the applied methodologies in the last works from meta-heuristic algorithms to exact solution methods are introduced. Therefore, this paper is a comprehensive research in which different mathematical models in deterministic and uncertain conditions and related approaches to control the uncertainty of data have been compared and a conclusion based on related studies is proposed.

1. Introduction

In this section, the definition and importance of the study is mentioned. Mining is the process of extracting valuable resources from deposits. Mining can mainly be divided into two major categories, surface mining, and underground mining. Surface mining is suitable for large, low-grade ore deposits, buried not deep, and is commonly used to mine deposits such as oil sands (Kalantari et al., 2013; Nikbin et al., 2023) coal and copper. Underground mining is used for small, high-grade deposits buried deep beneath overburden and is being used for minerals like zinc, lead etc. In all methods of surface mining, first, overburden is removed by different tools such as earthmovers, draglines and bucket wheels excavators. Then, shovels extract the ore, which is loaded into haul trucks by shovel loaders (There is other types such as placer mines). Surface mining is rewarding because of its low cost and capital requirement, higher rate of recovery, and less labor intensiveness. Studies have shown that about 50% of operating costs in surface mining are allocated to haulage and materials handling (Moradi Afrapoli, A, and Askari-Nasab 2017).

The number can go up to as much as 60% in large open-pit mines (Moradi Afrapoli, A. and Askari-Nasab 2017). Therefore, hauling has the highest operating cost among all the material handling operations in open-pit mines. So, fleet management for mine planning and scheduling has always been the center of attraction for researchers in open-pit mining. In the mining industry, mine planning is considered a fundamental element aiming to obtain a feasible block extraction schedule by

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maximizing net present value and economic profit. Also, this is important to specify required constraints in mine planning such as environmental and operational ones according to the assumptions of the problem (Koushavand et al., 2014).

Mine planning and scheduling can again be divided into two categories, long-term, and short-term planning. Among the mine planning problems, long-term planning defines the sequence of extraction and displacement of material and mining operations to reach the problem's objectives. In mining research, a long-term production schedule is necessary for short-term planning and operations. So, this is required to design appropriate long-term planning to reach short-term planning. In the long-term production schedule, the capacity and expansion potential of the mine and processing are determined (Askari-Nasab et al., 2010). To reach an ideal mine design and planning, optimization is an important area for different types of mines. It considers forecasting, maximization, and control of financial flows and obtaining the best value of other objective functions in mining operations (Dimitrakopoulos, 2011).

Regarding to the literature review, the motivation of this study can be explored. In the literature, several optimization methods and mixed integer programming[1] models have been proposed in which the ore body is divided into many blocks. The majority of approaches are deterministic and do not consider the uncertainty of data. However, to make the optimization problems close to real-world conditions, some parameters should be assumed as uncertain. In this way, the optimization problem changes to a stochastic optimization problem. The uncertainty of data has several main sources including geological attributes of the deposit, geo-metallurgical properties, economic situation, and market uncertainties (Rimele et al., 2020). In the mining industry, a stochastic optimization mathematical model considers correlated random variables for some coefficients according to assumptions of uncertain parameters. These variables indicate the economic value of a mined block in a deposit (Meagher et al., 2010).

In this study, the mathematical models in long-term mine planning problems are investigated. Also, regarding to assessing the related studies and solution methods, the research gap and shortcoming of the last works are proposed. In this way, this is concluded that uncertainty of date and stochastic programming in mining problems is a vital component which last research dealt with less than expected level. In addition, two main concepts in mining problems are introduced which can be considered as uncertain parameters.

This research is organized as follows. Section 2 consists of a review of deterministic, stochastic problems, and Mixed Integer Linear Programming2 models to optimize the mine planning problem. Also, an overview of the related approaches to control the uncertainty of data and solution methods are considered. In section 3 the recommended suggestions for future research are provided. Finally, the conclusion is presented.

2. Review of the literature

According to the concept of this research, the literature review is divided to 3 main sections including deterministic and stochastic models, the role of MILP models, and importance of uncertainty of date in mining problems.

2.1. Deterministic and stochastic mine planning models

Most of the early work on the long-term planning of surface mining (open-pit mining) are linear programming (LP) based. In the long-term context, early LP-based methods focus on solving a blending problem in each time period. Blending requirements are formulated in terms of constraints,

[1] MIP
[2] MILP

putting limits on the number of relevant attributes in produced ore (Krishna Sundar and Acharya 1995; Wilke and Reimer 1977). The objective of these types of problems is to minimize the sum of deviations in the ore blend from required grades by optimizing equipment allocation (Chanda and Dagdelen 1995).

Gurgur et al. (2011) formulated an LP model for optimum shovel assignment to minimize the deviation of the production operation from the set targets in short-term and long-term schedules. This model accounts for the available trucks in each period and it considers the mine as a multi-period optimization problem, which makes it a model that lasts over the lifetime of a mine. However, this model does not consider the lost ton by shovel operation and it assumes continuous variables for discrete production systems. Most of the modern long-term planning models are MILP based with explicit precedence constraints applied.

Blom et al. (2014; 2016) presented a breakdown and MIP-based algorithm for the short-term planning of a supply chain consisting of multiple open-pit iron ore mines and multiple ports. They divided the problem into two parts: mine optimization and port blending. The mining side MIP-based optimization solves MIPs to generate a set of candidate blocks to be extracted in short-term planning horizon. The production-grade is assumed to be normally distributed about the target given as input. Ali Moradi et al. (2019) developed a multi-objective transportation model for real-time truck dispatching to minimize shovel idle times, truck wait times, and deviations from the path production requirements established by the production optimization stage. They implemented their model on a discrete event simulation model of truck-shovel operation to demonstrate that the model can meet the full capacity of the processing plants with a fleet of 30% less trucks than the desired fleet.

Linear optimization problems or linear programming only focuses on a single linear objective function with linear constraints. Goal programming is an extension of linear programming that is capable of handling multiple and conflicting objectives (Ben-Awuah et al., 2018; Maremi et al., 2020). The objective function of the model, therefore, is usually a combination of multiple objectives. It does not get a single optimal solution, but it generates the so called pareto optimal solutions, which means that there is no other solution which is better at all objectives. Only recently, Upadhaya and Askari-Nasab (2016), used goal programming for a simulation optimization-based short-term planning model, to illustrate how proactive decisions can be made in the dynamic environment of mining and operational plans can be synced with long-term planning to reduce opportunity cost, and maximize production and equipment utilization.

Noriega and Pourrahimian (2022) proposed research on a comprehensive review of data-driven and artificial intelligence methods in strategic open-pit mine planning. They identified research trends in the mine planning with data-driven approaches. Afrapoli et al. (2019) investigated a multi-objective transportation problem for a truck dispatching in open pit mines. The presented model includes the trucks to reduce shovel idle times, wait times, and deviations from the requirements of production. Their mathematical model is a benchmark model using a fleet management system in mining.

There are some important research on underground mining (Afum et al., 2021; Shuwei Huang et al., 2020). For example, Huang et al., (2020) presented a Stochastic Mixed Integer Programming Framework for Underground Mining Production Scheduling Optimization Considering Grade Uncertainty. They incorporated grade uncertainty into the strategic mine plan, and presented a stochastic mixed integer programming (SMIP) formulation to optimize an underground cut-and-fill mining production schedule.

Christian Both et al. (2020) proposed a Joint stochastic short-term production scheduling problem with a fleet management optimization for mining complexes. Also, the proposed model was to maximize the metal production and profit of the mining complex. The main methodology was a non-linear mathematical programming model and a Simulated annealing metaheuristic method. The uncertainties of the model were Geological uncertainty, uncertainty related to equipment performances, and cycle time of trucks. Liu (2021) presented a robust optimization model for mine supply chain planning and employed big data to solve the problem. In this research, he used a mine supply chain including mining, processing, and ore product transportation stages. To control the uncertainty of data he applied robust optimization in the model and several nonlinear constraints. The final results show the robust optimization model is stabilized when the model's data is under disturbance.

2.2. Mixed Integer Linear programming models to optimize mine planning problems

The complexity of the operation and dynamic nature of the mining environment force planners to make reactive decisions once production starts. However, reactive decisions cause mines to lose tons of money as opportunity costs. Therefore, a dynamic decision-making tool can make the life of mine planners easier. Many researchers have formulated models for short-term (Rahnema et al., 2023, N Al Habib et al., 2023) and long-term (Tabesh et al., 2023; Moradi-Afrapoli et al., 2022; Jelvez et al., 2020) mine planning. While some of the existing models are concerned highly about operational details, they do not account for the uncertainties involved in the process. Also, assuming constant production rates from shovels and trucks makes the generated schedule very hard to achieve, which depends significantly on the haulage network and profile, the available number of trucks in the system, and the truck dispatching efficiency.

In the related studies the practical mathematical models have been proposed to manage and optimize mining operations. Moradi Afrapoli et al. (2019) has presented a multiple objective transportation problem for dynamic truck dispatching in surface mines. Their model has three objective functions as the objective functions (1-3):

$$\boldsymbol{f_1} = \sum_{\boldsymbol{i}}\sum_{\boldsymbol{j}}\sum_{\boldsymbol{k}} \boldsymbol{S_{ijk}x_{ijk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1},\dots,\boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1},\dots,\boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1},\dots,\boldsymbol{D}\} \tag{1}$$

$$\boldsymbol{f_2} = \sum_{\boldsymbol{i}}\sum_{\boldsymbol{j}}\sum_{\boldsymbol{k}} \boldsymbol{T_{ijk}x_{ijk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1},\dots,\boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1},\dots,\boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1},\dots,\boldsymbol{D}\} \tag{2}$$

$$\boldsymbol{f_3} = \sum_{\boldsymbol{j}}\sum_{\boldsymbol{k}} \boldsymbol{c^{-}}_{\boldsymbol{jk}} + \boldsymbol{c^{+}}_{\boldsymbol{jk}} \qquad \forall \boldsymbol{i} \in \{\boldsymbol{1},\dots,\boldsymbol{N}\} \& \forall \boldsymbol{j} \in \{\boldsymbol{1},\dots,\boldsymbol{M}\} \& \forall \boldsymbol{k} \in \{\boldsymbol{1},\dots,\boldsymbol{D}\} \tag{3}$$

The first objective function indicates minimization of active shovels' idle time. The second objective function is minimization of truck wait time in the operation, and the third objective function aims to decrease deviation from flow rates of the paths. They solved the multi-objective optimization model with a goal programming method.

Also, Moradi Afrapoli et al. (2019) proposed the other paper on a multi-step approach to long-term open-pit production planning in which they dealt with the following constraints; i) The number of incoming trucks to each shovel is equal to the number of outgoing trucks from the same shovel (equation 4), ii) The tonnage a truck can transport in one payload is less that its maximum nominal capacity (equation 5), and iii) Total haulage capacity sent to a shovel is less than the nominal digging rate of that shovel (equation 6).

$$\sum_{\boldsymbol{i}}\sum_{\boldsymbol{k}} \boldsymbol{x}^{`}_{\boldsymbol{ijk}} = \sum_{\boldsymbol{i}}\sum_{\boldsymbol{k}} \boldsymbol{x_{ijk}} \qquad \forall \boldsymbol{j} \in \{\boldsymbol{1},\dots,\boldsymbol{M}\} \tag{6}$$

$$\sum_{i}\sum_{k} \boldsymbol{tc_i x_{ijk} \leq T_i} \qquad \forall \boldsymbol{i} \in \{\mathbf{1}, \dots, \boldsymbol{N}\} \tag{7}$$

$$\sum_{i}\sum_{k} \boldsymbol{tc_i x_{ijk} \leq SC_j} \qquad \forall \boldsymbol{j} \in \{\mathbf{1}, \dots, \boldsymbol{M}\} \tag{8}$$

Behrang et al. (2014) studied the linear programming model for long-term mine planning in the presence of uncertainty and a stockpile. The objective function of the model as below (9) is to minimize the NPV minus discounted cost of uncertainty which is calculated by simulated realizations.

$$Max \sum_{t} \{\underbrace{\sum_{i} v_{ti} \times z_{ti} - q_{ti} \times y_{ti}}_{NPV} - \underbrace{1/L \sum_{l} \left[C_{up}(t,l) + C_{op}(t,l) \right]}_{C_u(t)}\} \tag{9}$$

Behrang et al. (2014) conducted another research on Truck-shovel allocation optimization: a goal programming approach in which the main constraints of their model were as following: the lower limit and upper limit (target production) for the designed processing plant production, and the total tonnage of material mined is within the acceptable range of mining equipment capacity.

$$p_l(t) \leqslant \sum_{i=1}^{N} \{T(i) \times z(t;i)\} \leqslant p_u(t) \tag{10}$$

$$m_l(t) \leqslant \sum_{i=1}^{N} \{T_o(i) \times z(t,i)\} \leqslant m_u(t) \tag{11}$$

Askari Nasab et al. (2011) proposed a study on large-scale open pit production scheduling using Mixed Integer Linear Programming with a main objective function of maximizing the discounted revenue generated by selling the product minus the discounted costs involved in extracting the block.

$$d_n^t = \underbrace{\left[\sum_{e=1}^{E} o_n \times g_n^e \times r^{e,t} \times (p^{e,t} - cs^{e,t}) \right.}_{\text{discounted revenues}} - \underbrace{\left. \sum_{e=1}^{E} o_n \times cp^{e,t} \right] - \left[(o_n + w_n) \times cm^t \right]}_{\text{discounted costs}} \tag{12}$$

However, Tabesh et al. (2015) presented a multi-step approach to long-term open-pit production planning in which the profit by including the blocks with the highest value in the pushback has been maximized.

$$\max \sum_{i \in N} p_i x_{ij} \tag{13}$$

In scheduling problems, Upadhaya and Askari (2016; 2019) used goal-based mixed integer programming (MILGP) model with discrete simulation to allocate trucks and shovels in mine faces with four main objective functions as following,

- The production is maximized by optimizing shovel utilization or minimizing negative deviation in production

- Minimize deviation in production received in processing plants from desired
- Minimize deviation from the expected grade of ore
- Minimize material handling time (shovel movement time)

$$\Psi_1 = \sum_{s} x_s^- \tag{14}$$

$$\Psi_2 = \sum_{d^o} \sum_{k} \left(g_{k.d^o}^- + g_{k.d^o}^+ \right) \tag{15}$$

$$\Psi_3 = \sum_{d^p} \left(\delta_{d^p}^- + \delta_{d^p}^+ \right) \tag{16}$$

$$\Psi_4 = \sum_{s} \sum_{l} \Gamma_{F_s,l}^F \times A_s \times a_{s,l} + \sum_{t} \sum_{l} \sum_{d} n_{t,l,d} \times \Gamma_{l,d}^D \times (C_t + \bar{C}_t) \tag{17}$$

The research of S. P. Upadhyay et al., 2016 was Truck-shovel allocation optimization: a goal programming approach while the study of Upadhyay et al., 2019 was about Dynamic shovel allocation approach to short-term production planning in open-pit mines.

There are other important studies on MILP (Badiozamani et al., 2019; Hosseini et al., 2020; Afum et al., 2020 and Shamsi et al., 2022). For example, Shamsi et al. (2022) conducted research on the optimization of open-pit mine production scheduling considering an optimum transportation system in which ore and waste crushers are not located at the same location, and the grade of ore sent to the processing plant is in the acceptable range.

$$o_{t,c} + w_{t,c} \leq 1 \quad for \quad t \in T; c \in C \tag{18}$$

$$\sum_{d \in \{1,2\}} \sum_{n \in N} x_{d,t,n} * W_n * (G_n - Cap_{Min-G}) \geq 0 \quad for \quad t \in \{1, \ldots, |T|\} \tag{19}$$

2.3. Mine planning models with the uncertainty of data

The extent and sequence of mining operations are vital components of an extraction operation in a long-term mine planning problem. Since long-term mine planning includes production sequencing, scheduling, facilities' location, and other economic operations, optimizing this problem results in maximizing the net present value and the net profit (Fathollahzadeh et al., 2021; O.M Badozie et al., 2021; Amponsah et al., 2023). Table 1 proposes a summary of the research works on long-term planning which applied stochastic optimization.

Table 1. The summary of related research on stochastic optimization.

Paper	Area	Uncertain parameters	Other considerations
Gholamnejad et al., 2012	Long-term, open-pit mine	geological uncertainty	binary integer programming model
Benndorf et al., 2013	Long-term, open-pit mine	joint multi-element geological uncertainty	stochastic integer programming formulation
Koushavand et al., 2014	Long-term, open-pit mine	Grade	Linear programming

Rahmanpour et al., 2016	Short-term, open-pit mine	price uncertainty	
Morales et al., 2019	Long-term, open-pit mine	Geo-metallurgical attributes and geological uncertainty	Risk management
Rimele et al., 2020	The long-term, open-pit mine	Geological and commodity price uncertainty	Dynamic stochastic programming
Gilani et al., 2020	Short-term,open-pit mine	Geological uncertainty	stochastic integer programming with PSO[3] algorithm
Tolouei et al., 2021	Long-term, open-pit mine	Grade	Lagrangian relaxation with meta-heuristic methods, bat algorithm, and particle swarm optimization

In the following, two main concepts in which uncertainty can occur, are investigated. The first one is metal supply and the second one is mine design and production scheduling.

2.3.1. Uncertainty in metal supply

The primary attributes of mining deposits result in uncertainty in some related parameters of long-term mine planning models. To control this uncertainty, some studies apply high-order sequential simulation with spatial cumulants. This method is useful for stochastic simulation and one of its most important elements is the notion of high-order spatial cumulants. This method has some significant benefits as below (Dimitrakopoulos et al., 2010; 2011):

- This method does not require data pre-processing.
- This approach deploys high-order relations in the data dominating the simulation process.
- This method is able to generate spatial patterns reproducing distributions and variograms.

2.3.2. Uncertainty in mine design and production scheduling

Mine design and production schedules have some complexities when it comes to long-term mine planning. Due to these inevitable uncertainties, the majority of models implement stochastic optimization. The main objective of stochastic optimization in these models is to maximize the value of NPV during the planning horizon. One of the sources which make the parameters of the model uncertain is the uncertainty of mineralized materials of the mine and their supply. In the literature, there are two main approaches as follows:

- Simulated annealing which is a metaheuristic algorithm (Albor et al., 2009).
- Stochastic integer programming, an exact solution method (Leite et al., 2010).

3. Future Direction in Research

The next leap in MILP modeling should be to quantify the uncertainties present in shovel operation or grade, metal supply and production scheduling. Identifying the distribution of uncertainty present in a system can be a challenge and this is where the focus needs to be. Once the uncertainty of a certain parameter or variable (such as grade, haulage time) is quantified and incorporated, we can modify the existing models to check how they perform under a real stochastic environment.

[3] Particle Swarm Optimization

Moreover, the models can be made more pragmatic and effective by taking factors such as the effect of road conditions on equipment life and tire cost, the impact of accidents and driver behavior on production.

4. Conclusion

Mining has always dealt with minimizing risks, and costs and maximizing the production rate by proper planning in both the long and short term. This research proposed a summary of recent papers on mine planning in short-term and long-term horizons in which there is the uncertainty of data in parameters. These models have applied stochastic optimization approaches and simulation to deal with the uncertainty and manage uncertainties and risks associated with the dynamic mining environment. The models developed thus far will act as a strong basis for how to proceed through to the future of mining research and development. According to investigating the proposed stochastic model in the literature, few research works have considered uncertainty in mine design and production schedules, and supply parameters. Therefore, it is important to consider these parameters uncertain in addition to grade and other geological data in mine optimization problems.

5. References

[1] Al Habib, N., Ben-Awuah, E., & Askari-Nasab, H. (2023). Review of recent developments in short-term mine planning and IPCC with a research agenda. Mining Technology, 1-23.

[2] Afrapoli, A. M., Tabesh, M., & Askari-Nasab, H. (2019). A multiple objective transportation problem approach to dynamic truck dispatching in surface mines. European Journal of Operational Research, 276(1), 331-342.

[3] Afum, B. O., & Ben-Awuah, E. (2021). A review of models and algorithms for surface-underground mining options and transitions optimization: Some lessons learnt and the way forward. Mining, 1(1), 112-134.

[4] Afum, B. O., Ben-Awuah, E., & Askari-Nasab, H. (2020). A mixed integer linear programming framework for optimising the extraction strategy of open pit–underground mining options and transitions. International Journal of Mining, Reclamation and Environment, 34(10), 700-724.

[5] Amponsah, S. Y., Takouda, P. M., & Ben-Awuah, E. (2023). A Multiple Objective Genetic Algorithm Approach for Stochastic Open Pit Production Scheduling Optimisation. International Journal of Mining, Reclamation and Environment, 1-28.

[6] Both, C., & Dimitrakopoulos, R. (2020). Joint stochastic short-term production scheduling and fleet management optimization for mining complexes. Optimization and Engineering, 21(4), 1717-1743.

[7] Blom ML, Pearce AR, Stuckey PJ. 2016. A decomposition-based algorithm for the scheduling of open-pit networks over multiple time periods. Management Science. 62(10):3059-84.

[8] Blom ML, Burt CN, Pearce AR, Stuckey PJ. 2014. A decomposition-based heuristic for collaborative scheduling in a network of open-pit mines. INFORMS Journal on Computing. 26(4):658-76.

[9] Benndorf, J., & Dimitrakopoulos, R. (2013). Stochastic long-term production scheduling of iron ore deposits: Integrating joint multi-element geological uncertainty. Journal of Mining Science, 49(1), 68-81.

[10] Ben-Awuah, E., Askari-Nasab, H., Maremi, A., & Seyed Hosseini, N. (2018). Implementation of a goal programming framework for production and dyke material planning. International Journal of Mining, Reclamation and Environment, 32(8), 536-563.

[11] Badiozamani, M. M., Ben-Awuah, E., & Askari-Nasab, H. (2019). Mixed Integer Linear Programming for Oil Sands Production Planning and Tailings Management. Journal of environmental informatics, 33(2).

[12] Chanda EKC, Dagdelen K. 1995. Optimal blending of mine production using goal programming and interactive graphics systems. Int J Surf Mining Reclam Environ. 9(4):203-8.

[13] Dimitrakopoulos, R. (2011). Strategic mine planning under uncertainty. Journal of Mining Science, 47(2), 138-150.

[14] Fathollahzadeh, K., Asad, M. W. A., Mardaneh, E., & Cigla, M. (2021). Review of solution methodologies for open pit mine production scheduling problem. International Journal of Mining, Reclamation and Environment, 35(8), 564-599.

[15] F. Albor Consquega and R. Dimitrakopoulos, "Stochastic mine design optimization based on simulated annealing: Pit limits, production schedules, multiple orebody scenarios and sensitivity analysis," Transactions of the Institution of Mining and Metallurgy: Mining Technology, 118, No. 2 (2009).

[16] Gholamnejad J. 2008. A zero-one integer programming model for open pit mining sequences. Journal of the Southern African Institute of Mining and Metallurgy. 108(12):759-62.

[17] Gurgur, C.Z., Dagdelen, K., Artittong, S. 2011. Optimization of a real-time multi-period truck dispatching system in mining operations International Journal of Applied Decision Sciences. 4(1):57-79.

[18] Gholamnejad, J., & Moosavi, E. (2012). A new mathematical programming model for long-term production scheduling considering geological uncertainty. Journal of the Southern African Institute of Mining and Metallurgy, 112(2), 77-81.

[19] Gilani, S. O., Sattarvand, J., Hajihassani, M., & Abdullah, S. S. (2020). A stochastic particle swarm based model for long term production planning of open pit mines considering the geological uncertainty. Resources Policy, 68, 101738.

[20] Hosseini, N. S., Ben-Awuah, E., & Pourrahimian, Y. (2020). A two-step approach to incorporate cut-off grade and stockpiling in oil sands mine planning optimization framework. Computers & Operations Research, 115, 104659.

[21] Jélvez, E., Morales, N., & Askari-Nasab, H. (2020). A new model for automated pushback selection. Computers & Operations Research, 115, 104456.

[22] Koushavand, B., Askari-Nasab, H., & Deutsch, C. V. (2014). A linear programming model for long-term mine planning in the presence of grade uncertainty and a stockpile. International Journal of Mining Science and Technology, 24(4), 451-459.

[23] Krishna Sundar D, Acharya D. 1995. Blast schedule planning and shiftwise production scheduling of an opencast iron ore mine. Computers and Industrial Engineering. 28(4):927-35.

[24] Kalantari, S., Ben-Awuah, E., & Askari-Nasab, H. (2013). Towards an integrated oil sands mine plan and composite tailings plan. International Journal of Mining, Reclamation and Environment, 27(2), 103-126.

[25] Liu SQ, Kozan E. 2012. A hybrid shifting bottleneck procedure algorithm for the parallel-machine job-shop scheduling problem. J Oper Res Soc. 63(2):168-82.

[26] Leite and R. Dimitrakopoulos, “Production scheduling under metal uncertainty – Application of stochastic mathematical programming at an open pit copper mine and comparison to conventional scheduling,” The Australasian Institute of Mining and Metallurgy, Spectrum Series, 17 (2010).

[27] Morales, N., Seguel, S., Cáceres, A., Jélvez, E., & Alarcón, M. (2019). Incorporation of geometallurgical attributes and geological uncertainty into long-term open-pit mine planning. Minerals, 9(2), 108.

[28] Moradi Afrapoli A, Askari-Nasab H. 2017. Mining fleet management systems: A review of models and algorithms. International Journal of Mining, Reclamation and Environment. :1-19.

[29] Moradi Afrapoli A, Tabesh M, Askari-Nasab H. 2019. A multiple objective transportation problem approach to dynamic truck dispatching in surface mines.

[30] Meagher, C., Abdel Sabour, S. A., & Dimitrakopoulos, R. (2009). Pushback design of open pit mines under geological and market uncertainties. In Proceedings of the International Symposium on Orebody Modeling and Strategic Mine Planning: Old and New Dimensions in Changing World (Vol. 17, pp. 297-304).

[31] Moradi-Afrapoli, A., & Askari-Nasab, H. (2022). Advanced Analytics for Surface Extraction. In Advanced Analytics in Mining Engineering: Leverage Advanced Analytics in Mining Industry to Make Better Business Decisions (pp. 181-203). Cham: Springer International Publishing.

[32] Maremi, A., Ben-Awuah, E., & Pourrahimian, Y. (2020). An automated production targeting goal programming framework for oil sands mine planning considering organic rich solids. Mining Technology, 129(2), 53-67.

[33] Noriega, R., & Pourrahimian, Y. (2022). A systematic review of artificial intelligence and data-driven approaches in strategic open-pit mine planning. Resources Policy, 77, 102727.

[34] Nikbin, V., & Moradi Afrapoli, A. (2023). A Multiple Objective Hybrid Algorithm for Daily Ore Blend in Oil Sands Mines. International Journal of Mining, Reclamation and Environment, 1-16.

[35] Rimélé, A., Dimitrakopoulos, R., & Gamache, M. (2020). A dynamic stochastic programming approach for open-pit mine planning with geological and commodity price uncertainty. Resources Policy, 65, 101570.

[36] Rahmanpour, M., & Osanloo, M. (2016). Determination of value at risk for long-term production planning in open pit mines in the presence of price uncertainty. Journal of the Southern African Institute of Mining and Metallurgy, 116(3), 229-236.

[37] Rahnema, M., Amirmoeini, B., & Moradi Afrapoli, A. (2023). Incorporating Environmental Impacts into Short-Term Mine Planning: A Literature Survey. Mining, 3(1), 163-175.

[38] R. Dimitrakopoulos, H. Mustapha, and E. Gloaguen, “High-order statistics of spatial random fields: Exploring spatial cumulants for modelling complex, non-Gaussian and non-linear phenomena,” Mathematical Geosciences, 42, No. 1 (2010).

[39] S. Huang, G. Li, E. Ben-Awuah, B. O. Afum, and N. Hu, "A stochastic mixed integer programming framework for underground mining production scheduling optimization considering grade uncertainty," IEEE Access, vol. 8, pp. 24495-24505, 2020.

[40] Shamsi, M., Pourrahimian, Y., & Rahmanpour, M. (2022). Optimisation of open-pit mine production scheduling considering optimum transportation system between truck haulage and semi-mobile in-pit crushing and conveying. International Journal of Mining, Reclamation and Environment, 36(2), 142-158.

[41] Tolouei, K., Moosavi, E., Tabrizi, A. H. B., Afzal, P., & Bazzazi, A. A. (2021). An optimisation approach for uncertainty-based long-term production scheduling in open-pit mines using meta-heuristic algorithms. International Journal of Mining, Reclamation and Environment, 35(2), 115-140.

[42] Tabesh, M., Afrapoli, A. M., & Askari-Nasab, H. (2023). A two-stage simultaneous optimization of NPV and throughput in production planning of open pit mines. Resources Policy, 80, 103167.

[43] Upadhyay SP, Askari-Nasab H. 2019. Dynamic shovel allocation approach to short-term production planning in open-pit mines. Int J Min Reclam Environ. 33(1):1-20.

[44] Upadhyay SP, Askari-Nasab H. 2018. Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. International Journal of Mining Science and Technology. 28(2):153-66.

[45] Upadhyay SP, Askari-Nasab H. 2016. Truck-shovel allocation optimisation: A goal programming approach. Transactions of the Institutions of Mining and Metallurgy, Section A: Mining Technology. 125(2):82-92.

[46] Wilke FL, Reimer T. 1977. Optimizing the short term production schedule for an open pit iron ore mining operation. :425-33.