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KISA VE UZUN DÖNEM ÜRETİM PLANLARI ARASINDAKİ SAPMALARI DEĞERLENDİRMEYE YÖNELİK BİR HATA AĞACI ENTEGRE EDİLMİŞ SİMÜLASYON METODOLOJİSİ

A FAULT-TREE INTEGRATED SIMULATION METHODOLOGY TO EVALUATE DEVIATIONS BETWEEN SHORT- AND LONG-TERM PRODUCTION PLANS

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ÖZ

Açık ocak madenciliği, dünya çapında özellikle yüzeye yakın cevherlerin çıkarımı için kullanılan en yaygın madencilik yöntemidir. Üretim planlaması, stratejik (uzun dönem) veya operasyonel (kısa dönem) seviyelerde gerçekleştirilmekte olup, farklı ölçeklerde ve hassasiyetlerde konumsal üretim planlarının yapılmasına olanak vermektedir. Stratejik üretim planları esas olarak projenin Net Bugünkü Değerini ve maden ömrünü tespit etmeyi amaçlayan ve operasyonel planlara kılavuzluk eden daha makro ölçekli planlardır. Kısa dönemli planlar ise madencilik operasyonlarının sevk ve idaresini amaçlamaktadır. Madencilik projeleri, değişkenlerin doğası ve bunlar hakkında bilgi edinmenin maliyeti nedeniyle, üretimsel ve finansal açıdan oldukça belirsiz ve riskli olarak sınıflandırılır. Uzun dönemli planların kısa dönemli planların üzerindeki etkilerini değerlendirmek ve olabilecek riskleri azaltmak için bazı hesaplama araçları mevcut olsa da maden sahasında ihmal edilen veya hafife alınan çeşitli belirsizlikler, planlanan üretim hedeflerinden ciddi sapmalara neden olabilir. Bu belirsizliklerin altında yatan nedenler, uzun dönem planlama aşamasında yeterince açıklanmaz ve dikkate alınmaz ise, üretim alanının konumsal ilerleyişinden, hedeflenen cevher tonajından ve pasa miktarından sapma gibi olumsuz sonuçların yaşanması kaçınılmaz olacaktır. Bu nedenle belirsizlik kaynakları; rastlantısal veya epistemik olma durumları, meydana gelme sıklıkları ve üretim sapmaları üzerindeki etkileri ve planın ne kadar riskli olduğunu gösteren indikatörlerle birlikte bütüncül olarak ele alınmalıdır. Bu proaktif yaklaşım, çalışmanın temel amacını oluşturmaktadır. Bu çalışma; karar vericilerin, üretim planlarından sapmaya neden olabilecek belirsizlik faktörlerini inceleyebilecekleri ve bunların belirsizlik üzerine etkilerini ölçmeye yardımcı olabilecek, ayrık olay simülasyonu ve bulanık hata ağacı yöntemlerinin entegrasyonu ile oluşturulan bir metodolojinin geliştirilmesini amaçlamaktadır.

Anahtar Sözcükler: Açık Ocak Maden Planlaması, Belirsizlik Analizi, Karar Destek Tekniği, Bulanık Hata Ağacı Yöntemi, Ayrık Olay Simülasyonu.

ABSTRACT

Surface mining is the dominating mining method employed worldwide for near-surface deposits. Production planning plays the most vital role in different strategic or operational perspectives. Strategic plans or decisions are the ones that affect the Net Present Value of the project directly, while tactical or operational ones affect it indirectly. Mining projects are classified as highly uncertain and risky due to the nature of the variables and the cost of obtaining information about them. Although some computational tools are available to evaluate and optimize long-range plans of surface mines to facilitate operational applicability in shorter ranges, various neglected or underestimated uncertainties in mining areas can cause drastic deviations from planned production targets. Suppose the underlying factors and causes of these uncertainties are not explained and considered enough in the long-term planning phase. In that case, it will be inevitable to experience unfavorable results as deviation from the spatial advance of production area, the tonnage of targeted ore as well as waste production, and the targeted amount of final throughput. Therefore, sources and ranges of uncertainties, their aleatory or epistemic behaviors, occurrence frequencies, and their effects on the deviations should be considered holistically with factors showing how risky the plan is. This proactive approach is the primary purpose of the study. In the end, the quantification of risks could be achieved with the provided method by decision-makers so that they can clearly identify the points that have the potential to cause plan deviation with the aid of discrete event simulation and fuzzy fault tree methods.

Keywords: Uncertainty Assessment, Decision Support Technique, Fuzzy Fault Tree, Discrete Event Simulation, Surface Mine Planning

INTRODUCTION

Raw material requirements of manufacturing and other related production industries have an ascending trend in recent decades depending on the growth in the population, technology market, industrial branches, and the types of products supplied to the customer. The mining sector is a raw material supplier and necessitates continuous productivity monitoring to maintain raw material delivery to the industries. At this point, the exploitation of valuable minerals in mines has been achieved by different methods, each with different operational dynamics. Depending on the available financial constraints, mining operations can be handled as either a surface or an underground mining operation. Independent of mineral type, any mining operation is preliminarily aimed to be performed with the surface mining methods since it can provide observable financial and safety benefits and more practical monitoring of operational activities. If its feasibility cannot be verified due to the high stripping cost of exploiting deep resources, then one of the underground mining methods can be employed depending mainly on the mechanical properties of the hosting rock and valuable mineral material. Due to their advantages, over two-thirds of the mining operations are performed by surface mining methods globally.

Surface mining generally entails optimizing waste and ore material production sequence to maximize net present value (NPV) by long-term production plans. While long-term plans aim to maximize the NPV of the project, short-term scheduling is a more detailed plan on a much smaller time scale and tries to realize on-site objectives such as the planned tonnage of mill feed and target grade range estimated set by medium to long-term schedules (Chimunhu et al., 2022).

The strategic surface mine operation planning requires deciding on two main aspects: i) the ultimate pit boundaries and their associated phases, and ii) the LOM production schedule with equipment selection and sizing. As mentioned before, on the other hand, operational schedules intend to conduct these plans with day-to-day applications by up-to-date equipment positioning, reconciliation, compliances, and other on-site information.

Mining projects are considered highly uncertain and risky due to the nature of the variables and the cost of obtaining accurate information (Groeneveld and Topal, 2011). Therefore, uncertainties are involved in every aspect of a mining project. It is recommended to consider such uncertainties and support decisions with expected deviations due to involved uncertainties in every stage of mining. Even further, every strategic decision should be taken by considering quantified figures that consider day-to-day uncertainties coming from daily operations to minimize deviations from the ultimate targets. Not accounting for these uncertainties in the long-range can trigger problems in shorter ranges as well since it can lead to drastic deviation from the long-range targets (Upadhyay and Nasab, 2019). In the following, the problem statement, objective, and scope of the study are provided to detail the identified problem and steps of the study raised for the solution.

Problem Statement

Although some computational tools are available to evaluate and optimize long-range plans of surface mines to facilitate operational applicability in shorter ranges, there are still various neglected or underestimated uncertainties in mining areas that can cause drastic deviations from planned production targets. If the underlying factors with causes and consequences are not explained and considered enough in the long-term planning phase, it will be inevitable to experience unfavorable results as a deviation from the spatial advance of production area, the tonnage of ore and waste production, and the amount of final throughput. Therefore, sources and ranges of uncertainties, their aleatory or epistemic behaviors, occurrence frequencies, and their effects on the deviations should be considered holistically. Otherwise, long-range plans are expected to develop practically non-achievable plans in the mining area. For instance, it is observed that including geological uncertainty alone in the planning phase can improve the project NPV by up to 28% and mitigate the failure risk of production targets (Godoy and Dimitrakopoulos, 2004).

In brief, there should be an established bond between the long and short-range plans, including the prioritized uncertainties with their main drivers. It is seen from the literature that a systematical approach to quantify the uncertainties of production planning stages has not been concentrated enough. The uncertainty factors have generally been considered individually without assessing their mutual effects. Moreover, variability between short and long-range production plans in mines has not been investigated deeply.

Objectives and Scopes of Study

This study mainly intends to construct an event simulation model of metallic surface mine production in which stochastic behaviors of prioritized uncertainties in the model are determined previously in combination with a fault tree and the fuzzy logic analysis. Sub-objectives of the research are illustrated in Figure 1 and listed as follows:

1. Preparation and implementation of a survey. The participants should have senior-level experience in production planning of surface metal mines to detect the general attitude on priority, frequency, and severity of the production planning uncertainties,
2. Construction of a Fuzzy-Fault Tree (FFT) to a) express the dependencies between the uncertainty items that can be classified under geology, economy, operation, and external aspects and b) prioritize the uncertainties,
3. Development of a discrete-event simulation algorithm for iterative and stochastic evaluation of the variations in geological, economic, operational, and external factors and their effect on production rates and throughputs,

The study scope is limited to surface mining operations with metallic deposits. The fuzzy logic part is constructed relying on the opinions of experts experienced in the production planning of surface mines. The discrete-event simulation part is limited to the prioritized variables obtained from the fuzzy logic analyses.

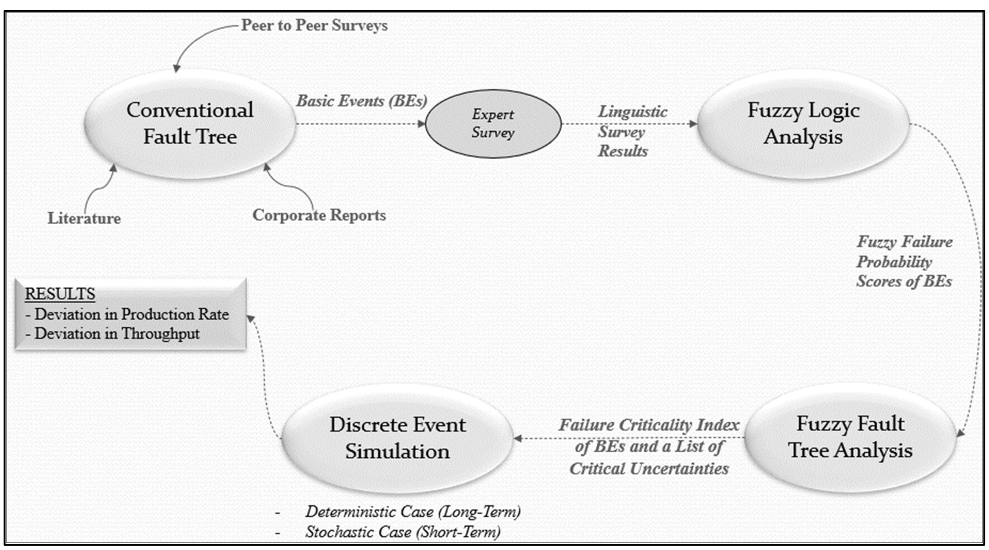

Figure 1: Sub-objectives of the Study and Their Relations with Each Other

LITERATURE REVIEW

The review is done under two sections as uncertainty factors related to long and short-term planning.

Long-Term Surface Mine Planning Uncertainties

The main subjects studied for long-term surface mining are ultimate pit boundary optimization (Learch and Grossmann, 1965; Liu and Kozan, 2016; Altuntov and Erkayaoğlu, 2021), phasing of the ultimate pit (Consuegra and Dimitrakopoulos, 2010; Farmer and Dimitrakopoulos, 2018), and scheduling (Ramazan, 2007; Sattarvand and Niemann-Delius, 2008; Farmer and Dimitrakopoulos, 2018) where equipment selection (Burt et al., 2015; Yavuz, 2015) and cut-off grade estimation (Asad and Dimitrakopoulos, 2013) are also gained attention. The first commonly studied uncertainty in long-term surface mine planning is the uncertainty of commodity prices. Grobler et al. (2011) applied a strategic mine planning optimization study with price uncertainty to show how processing and mining capacity can be changed to control the risk-reward trade-off. Groeneveld and Topal (2011) modeled the uncertainties in metal prices, capital and operating costs, and plant performance using Monte Carlo simulations with some well-known distributions. Evatt et al. (2012) have presented a methodology that can quantify the effect of price uncertainty within reserve estimates, providing both the expected reserve size and the associated distribution. Last, Saliba and Dimitrakopoulos (2019) presented an application of a stochastic framework that simultaneously optimizes mining, destination, and processing decisions for a multi-pit, multi-processor gold mining complex under commodity price uncertainty. The second common uncertainty item concentrated at the strategic level is geological and geometallurgical uncertainty. These uncertainties are discussed in the literature by referring to the uncertainties on grade and tonnage. Since there is sampling with considerably large intervals for short ranges due to the cost-intensive side of the exploration drilling (Morales et al., 2019) for constructed block models, there are uncertainties associated with that model. Due to large sample intervals, these models are hard to use directly at the tactical and operational levels (Dimitrakopoulos, 2011; Pourrahimian et al., 2015; Sarı and Kumral, 2018; Sepúlveda et al., 2018). In addition, such a model may also lead to suboptimal solutions due to its related risk of material content uncertainties (Godoy and Dimitrakopoulos, 2004; Ramazan and Dimitrakopoulos, 2007). Additionally, Morales et al. (2019) presented a two-stage methodology comprising pit optimization and stochastic life-of-mine (LOM) production schedule. Operational uncertainties, the third common uncertainty studied in long-term planning, are mainly evaluated in the literature to solve equipment selection and sizing problems. Upadhyay et al. (2021) have developed an algorithm to estimate fleet productivity and predict the required fleet size to meet the production schedules in the presence of operational uncertainties. Accordingly, Moradi Afrapoli et al. (2019) introduced an integrated simulation optimization framework to determine the haul fleet size by considering operational uncertainties in the mining and processing operations.

Short-Term Surface Mine Planning Uncertainties

Literature on short-term (tactical and/or operational) mine planning is observed to be concentrated less compared to long-term mine planning (Blom et al., 2019). Short-term surface mine planning literature focuses mainly on equipment dispatching and positioning (Dessureault et al., 2007; Erçelebi and Başçetin, 2009; Both and Dimitrakopoulos, 2020), blending problems (Chanda and Dağdelen, 1995; Matamoros and Dimitrakopoulos, 2016), scheduling (Sundar and Acharya, 1995; L'Heureux et al., 2013), and maximization of equipment utilization (Erçelebi and Başçetin, 2009; Kozan and Lui, 2018). Regarding uncertainty, scheduling, equipment positioning, and utilization topics are discussed under geological and operational uncertainties. Matamoros and Dimitrakopoulos (2016) presented a stochastic integer programming approach to optimize fleet and production schedules by considering operational considerations, such as mining width and direction of mining advance. Upadhyay and Nasab (2018) developed a discrete event simulation model for uncertainty-based short-term scheduling. However, as observed from the review process, integration of the long-and short-term mine planning is not covered. To close the gap, Jewbali and Dimitrakopoulos (2013) presented a study. The effects of short-term decisions on long-term plans under geological uncertainties were evaluated in the study. Even though this research considered both short- and long-term scheduling, only geological uncertainties were considered.

Literature has focused on different uncertainties of both long- and short-term scheduling for surface mining separately, even though they affect each other considerably under various uncertainties in mining sites. Integration of uncertainty consideration of tactical and strategic plans in a joint model is the primary intention of the current study, which has the potential to provide a source for future studies in the surface mine planning area.

METHODOLOGY

Firstly, an extensive literature review is conducted to list all uncertainty factors in short- and long-range planning. The found factors are classified as geological, economical, operational, and external factors, as done in the literature. In total, 21 factors are determined (Figure 2).

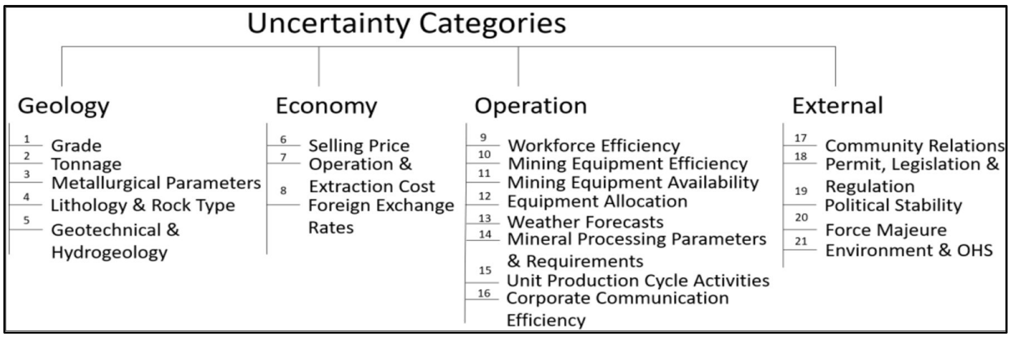

Figure 2: Uncertainty Factors Considered in the Study

A conventional Fault Tree (FT) is created by considering the uncertainty factors and their relation to the plan deviations, Figure 3, as Basic Events (BE), Sub-Events (SE), and the Top Event (TE).

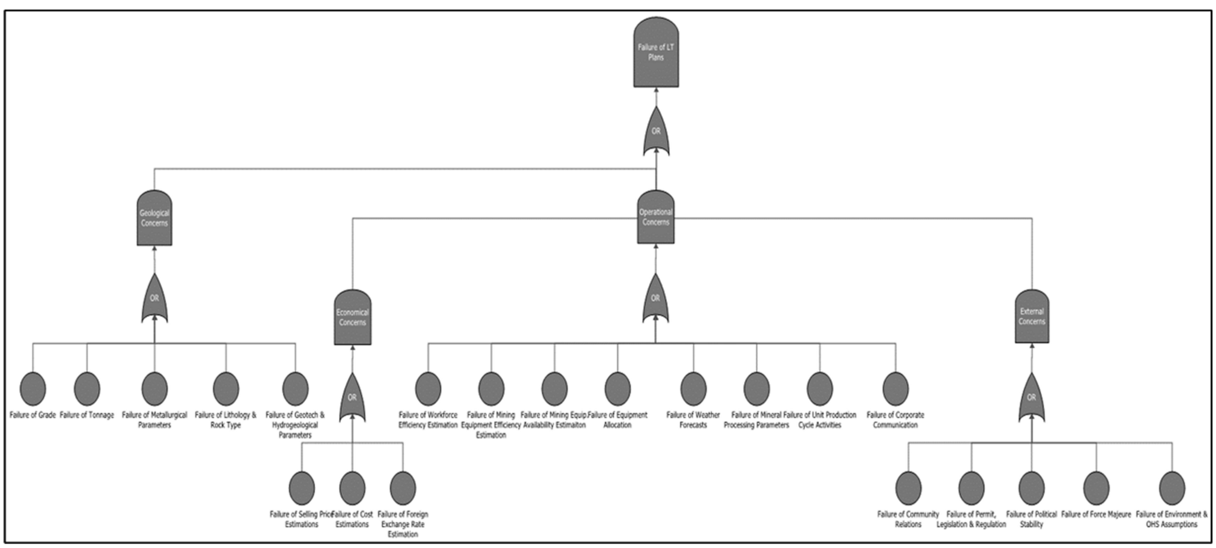

Figure 3: Conventional Fault Tree

Upon determination of uncertainty factors and conventional FT construction, a survey is prepared to gather data from mine planning experts. 11 experts have provided input to the study. In the survey, three different questions are asked to each responder for each uncertainty factor. The first answer type is linguistic to measure the combined effect of severity and frequency of the item on the contribution to the deviations. This type of answer is further analyzed in the study with fuzzy logic analysis. To input the fuzzy logic analysis for membership function creation, a rating matrix is asked to be filled in by the responders at the beginning of the survey for each linguistic term in addition to their backgrounds for responder weighting. Following the questionnaire, the results are analyzed with fuzzy logic in six steps, as listed below. Later, fuzzy logic analysis data is used to conduct Fuzzy Fault Tree Analysis (FFTA), which helps to determine the list of uncertainties to be used in the Discreet Event Simulation (DES). The results are presented in Table 1. It is important to note that the ranking is made based on the Failure Criticality Index (FCI) of each uncertainty item, which is found at the end of the analysis steps below:

1. Weighting Factor Determination: For responders, certain factors are determined so that their titles, experiences, and ages can be involved in the evaluation process with different weighting factors.
2. Fuzzy Number Type and Linguistic Variable Determination: The decided fuzzy number type is triangular, Fn={a,b,c}, and the set of linguistic variables consists of seven components, L= {very high (VH), high(H), mildly high(MH), medium(M), mildly low(ML), low(L), very low(VL) }.
3. Membership Function Determination: The membership function is one of the most critical items for fuzzy logic analysis. Therefore, its data is obtained from the questionnaire.
4. Fuzzification and Fuzzy Aggregation: By considering the expert weighting factors, linguistic response fuzzification is achieved with aggregated fuzzy numbers.
5. Defuzzification: In the defuzzification process, the left and the right fuzzy ranking method is used.
6. Conversion of Fuzzy Possibility to Fuzzy Failure Probability: The fuzzy possibility scores are converted to fuzzy failure probabilities to be used in the Fuzzy Fault Tree Analysis.

Table 01:Grouping of BE for DES and their Failure Criticality Indexes

DES Item Number	Basic Event Numer	Explanation	FCI, %	Rank
DES1		Grade Based Uncertainty	13.82	2
	BE1	Deviation in grade	13.82	
DES2		Tonnage Based Uncertainty	6.30	7
	BE2	Deviation in tonnage	6.30	
DES3		Mineral Processing Uncertainty	12.53	3
	BE3	Deviation in metallurgical parameters	7.52	
	BE14	Deviation in mineral processing parameters and requirements	5.01	
DES4		Structural Uncertainty	9.75	4
	BE4	Deviation in lithology/rock type	2.01	
	BE5	Deviation in geotechnical and/or hydrogeological parameters	7.74	
DES5		Workforce Efficiency Uncertainty	6.63	6
	BE9	Deviation in workforce efficiency	6.07	
	BE16	Deviation in corporate communication efficiency	0.56	
DES6		Mining Equipment Efficiency Uncertainty	19.05	1
	BE10	Deviation in mining equipment efficiency	7.47	
	BE12	Deviation in the equipment allocation plan	4.79	
	BE13	Deviation in the weather forecast	2.23	
	BE15	Deviation in unit production cycle activities	4.57	
DES7		Mining Equipment Availability Uncertainty	8.52	5
	BE11	Deviation in mining equipment availability	8.52	
DES8		Community Relations Uncertainty	2.34	12
	BE17	Deviation in community relations	2.34	
DES9		Permit, Legislation, and Regulation Uncertainty	5.01	8
	BE18	Deviation in the permit, legislation, and regulation	5.01	
DES10		Political Stability Uncertainty	2.84	10
	BE19	Deviation in political stability	2.84	
DES11		Force Mejaure Uncertainty	2.67	11
	BE20	Deviation in force mejaure	2.67	
DES12		Environment and OHS Uncertainty	3.96	9
	BE21	Deviation in environmental and OHS assumptions	3.96	

DES algorithm creation and analysis are the following steps after determining the factors to be considered. The main goal of the simulation is to give quantified factors/indicators of a long-term plan by considering short-term events and uncertainties associated with the resolutions of the plan to the decision-makers. In this regard, the algorithm is developed to show the effect of contributing factors on normalized production performance indicators, the tonnage of production, and metal throughput in each truck cycle. It is good to emphasize that each uncertainty-causing factor's operational detectability and measurability levels are considered for model integrity and applicability. Based on the survey results, it is found that economic concerns (deviations in commodity price, operation and extraction costs, and foreign exchange rates) are not effective in the short-term time scale for a plan deviation and are not detectable. Therefore, geological, operational, and external concerns are the primary uncertainty sources in the model presented in Figure 4 under the groups given in Table 1 and are considered to cover more than 93% of the uncertainties on a long-term plan based on their failure criticality index, FCI, %.

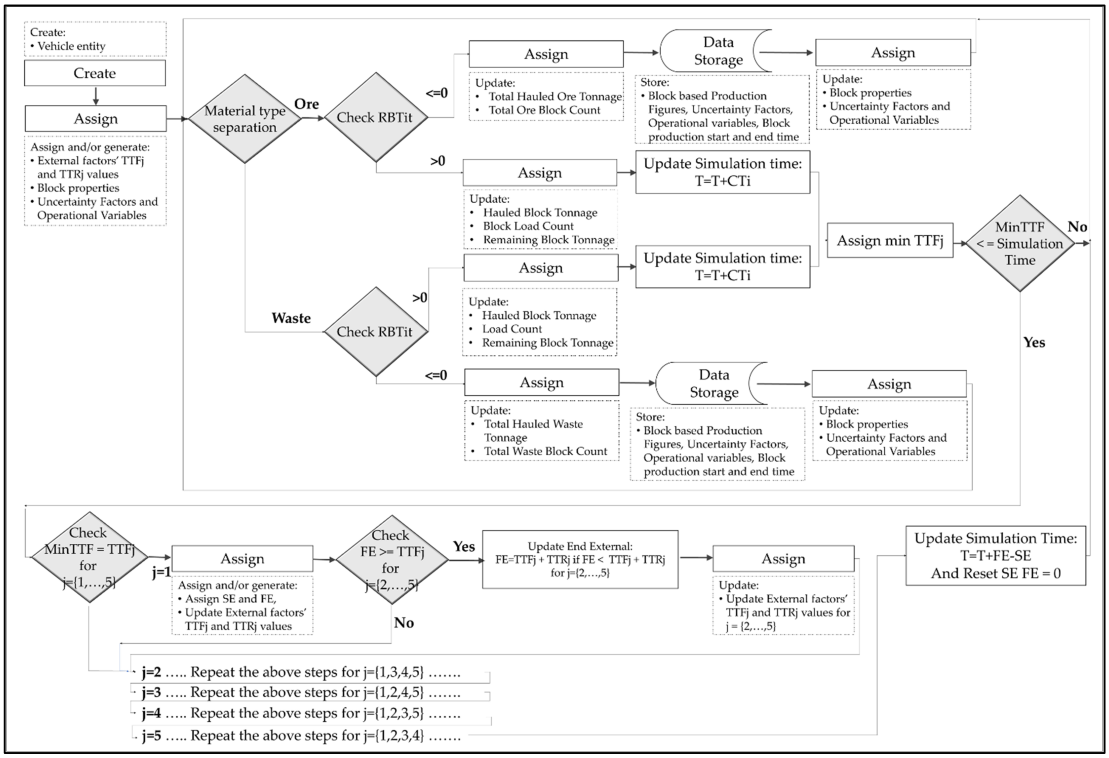

Figure 4: DES Algorithm

The model consists of two main modules, which are haulage and external factor modules. The simulation time in the model is increased with the loading time of the shovel and checks the occurrence of an external factor failure in each cycle until it reaches the simulation time. When the simulation model is used to simulate each long-term production period, expected production indicators can be obtained prior to decision-making with 93% accuracy.

The model can be used for fixed long-term schedule datasets. The blocks in the model can be fed to the simulation based on the schedule in an increasing manner. The model data and the operational parameters can be input as a distribution to assign different values in each cycle.

CONCLUSION

In the mining industry, production planning is conducted under two timeframes: long-term and short-term. The ultimate pit boundary determination, phasing, and Life of Mine (LOM) planning studies are conducted for the long-term plans of surface mines. It mainly aims to maximize the company's profit, i.e., the operation's net present value (NPV). On the other hand, tactical or operational decisions are taken in short-term plans to achieve long-term targets. Since the time discretization, level of detail, and the utilized input data do not have high resolution in long-term plans for day-to-day mining operations, deviations in the plans are observed in the short-term, which can cause drastic deviations from long-term targets and company profit at the end of the related production year. This research study intends to develop a research methodology to provide quantified measures to the decision-makers about how achievable the long-term plan is by considering short-term operations. First, a comprehensive literature survey was conducted so that 21 main uncertainty factors (shown previously in Figure 2) are observed to be effective in deviations from long-term production plans in surface metal mines. Second, a conventional fault tree was created with a top event as the failure of a long-term plan. The top event is further subdivided into geological, economic, operational, and external branches with OR gate dependency. These sub-events are further branched down to 21 basic events, each representing an uncertainty factor. Third, a comprehensive expert survey has been conducted among 11 participants working in different mining corporations that operate mines worldwide. Most of the participants have authorized signatures for international projects or have experience in various mines of different countries in the role of mine planning decision maker. Since conventional fault tree analysis cannot process linguistic data, fuzzy logic analysis was conducted, and the results (occurrence probability of uncertainty items) were integrated into the conventional fault tree. As a result of fuzzy logic analysis, failure probabilities of basic events are obtained use. Additionally, the failure criticality index (FCI) was calculated for each basic event to determine the most effective list of system failures, which is then used in DES item determination. The system failure probability is calculated as 0.1869, and geological, operational, and external factors were detected as the most influential branches with a total 93% impact on the failure according to the Fuzzy Fault Tree analysis performed. When the FCI numbers are considered, it is observed that the grade with 14% effectiveness is the most influential uncertainty item, while corporate communication efficiency with 0.6% impact is the least influential uncertainty item. Including uncertainty factors recommended by FFTA, a DES algorithm was constructed, and the model was realized in Rockwell Arena software to mimic short-term conditions in a long-term schedule period. In brief, the current study introduced an uncertainty quantification methodology that can be utilized in the production planning stages of surface metal mines and filled the gap in the corresponding literature.

REFERENCES

Altuntov F. K., Erkayaoğlu M. (2021). A New Approach to Optimize Ultimate Geometry of Open Pit Mines with Variable Overall Slope Angles. *Natural Resources Research, 30(6), 4047- 4062.*

Asad, M. W. A., and Dimitrakopoulos, R. (2013). Implementing a parametric maximum flow algorithm for optimal open pit mine design under uncertain supply and demand. *Journal of the Operational Research Society, 64(2), 185–197.*

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.*

Blom M., Pearce A. R., Stuckey P. J. (2019). Short-term planning for open pit mines: a review. *International Journal of Mining, Reclamation and Environment, 33(5), 318–339.*

Burt C., Caccetta L., Fouché L., Welgama, P. (2015). An MILP approach to multi-location, multi-period equipment selection for surface mining with case studies. *Journal of Industrial and Management Optimization, 12(2), 403–430.*

Chanda E. K. C., Dağdelen K. (1995). Optimal blending of mine production using goal programming and interactive graphics systems. *International Journal of Surface Mining and Reclamation, 9(4), 203-208.*

Chimunhu P., Topal E., Ajak A. D., Asad W. (2022). A review of machine learning applications for underground mine planning and scheduling. *Resources Policy, 77, 102693.*

Consuegra F. R. A., Dimitrakopoulos R. (2010). Algorithmic approach to pushback design based on stochastic programming: method, application, and comparisons. *Mining Technology, 119:2, pp. 88–101.*

Dessureault S., Yildirim M., Baker, M. (2007). Data mining mine data: truck-shovel fleet management systems. *CIM Magazine, 2(4), 94.*

Dimitrakopoulos R. (2011). Stochastic optimization for strategic mine planning: a decade of developments, J. *Min. Sci. 47, pp. 138–150.*

Erçelebi S. G., Başçetin, A. (2009). Optimization of shovel-truck system for surface mining. *Journal of the Southern African Institute of Mining and Metallurgy, 109(7), 433-439.*

Evatt G.W., Soltan M.O., Johnson P.V. (2012). Mineral reserves underprice uncertainty. *Resour Policy.37(3):340–345.*

Farmer I., Dimitrakopoulos R. (2018). Schedule-based pushback design within the stochastic optimization framework. *International Journal of Mining, Reclamation, and Environment, 32:5, pp. 327–340.*

Godoy M., Dimitrakopoulos R. (2004). Managing risk and waste mining in long-term production scheduling, *SME Transactions, 316.*

Grobler F., Elkington T., and Rendu J. (2011). Robust decision making-application to mine planning under price uncertainty. *35th APCOM Symposium-Application of Computers and Operations Research in the Minerals Industry, Proceedings; Wollongong. p. 371–380.*

Groeneveld B., Topal E. (2011). Flexible open-pit mine design under uncertainty. *Journal of Mining Science, 47(2), 212-226.*

Groeneveld B., Topal E. (2011). Flexible open-pit mine design under uncertainty. Journal of Mining Science, 47(2), 212–226.

Kozan E., Liu S. Q. (2018). An open-pit multi-stage mine production scheduling model for drilling, blasting, and excavating operations. *In Advances in applied strategic mine planning (pp. 655–668). Springer, Cham.*

Learchs H., Grossmann I. F. (1965). Optimum design of open pit mines. *CIM Bulletin, 58, 47–54.*

Liu S. Q., Kozan, E. (2016). New graph-based algorithms to efficiently solve large-scale open pit mining optimization problems. *Expert Systems with Applications, 43, 59–65*.

L'Heureux G., Gamache M., and Soumis F. (2013). Mixed integer programming model for short-term planning in open-pit mines. *Min. Technol. 122(2), pp. 101–109.*

Matamoros M. E. V., Dimitrakopoulos R. (2016). Stochastic short-term mine production schedule accounting for fleet allocation, operational considerations and blending restrictions. *European Journal of Operational Research, 255(3), 911–921.*

Morales N., Seguel S., Cáceres A., Jélvez E., and Alarcón M. (2019). Incorporation of Geometallurgical Attributes and Geological Uncertainty into Long-Term Open-Pit Mine Planning. *Minerals 9, 108*.

Moradi Afrapoli, A., Tabesh, M., and Askari-Nasab, H. (2019). A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. *Mining Technology, 128(1), 9-20.*

Pourrahimian Y., Ben-Awuah E., and Nasab A. H. (2015). *Mining Optimization Laboratory (MOL), Report Six, ©MOL, University of Alberta, Edmonton, Canada*.

Ramazan S. (2007). The new fundamental tree algorithm for production scheduling of open pit mines. *European Journal of Operational Research, 177(2), 1153–1166.*

Ramazan S., Dimitrakopoulos R. (2007). Stochastic optimization of long term production scheduling for open pit mines with a new integer programming formulation, Orebody Modelling and Strategic Mine Planning. *Spectrum Series AusIMM, 2nd Edition.*

Saliba Z., Dimitrakopoulos, R. (2019). Simultaneous stochastic optimization of an open pit gold mining complex with supply and market uncertainty. *Mining Technology, 128(4), 216–229.*

Sarı Y.A., Kumral M. (2018). Dig-limits optimization through mixed-integer linear programming in open-pit mines. *Journal of the Operational Research Society, 69:2, 171-182.*

Sattarvand J., Niemann-Delius C. (2008). Perspective of metaheuristic optimization methods in open pit production planning. *Gospodarka Surowcami Mineralnymi, 24(4), 143-156.*

Sepúlveda E., Dowd P. A., and Xu C. (2018). The optimization of block caving production scheduling with geometallurgical uncertainty – a multi-objective approach. *Mining Technology, 127:3, 131–145.*

Sundar D. K., Acharya D. (1995). Blast schedule planning and shift wise production scheduling of an opencast iron ore mine. *Computers & Industrial Engineering, 28(4), 927–935.*

Upadhyay, S. P., Doucette, J., and Askari-Nasab, H. (2021). Short-term production scheduling in open pit mines with shovel allocations over continuous time frames. *International Journal of Mining and Mineral Engineering, 12(4), 292-308.*

Upadhyay S. K., Nasab A. H. (2019). Dynamic shovel allocation approach to short-term production planning in open-pit mines. *International Journal of Mining, Reclamation, and Environment, 33:1, 1–20.*

Yavuz M. (2015). Equipment selection based on the AHP and Yager's method. *Journal of the Southern African Institute of Mining and Metallurgy, 115(5), 425–433.*