AN UNCERTAINTY ASSESSMENT MODELING FOR DEVIATIONS BETWEEN LONG- AND SHORT-RANGE PRODUCTION PLANS AT SURFACE METAL MINES

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ABSTRACT

DEVELOPMENT OF AN UNCERTAINTY ASSESSMENT MODEL FOR DEVIATIONS BETWEEN LONG- AND SHORT-RANGE PRODUCTION PLANS AT SURFACE METAL MINES

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Surface mining is the dominating mining method employed for extracting near-surface economic minerals. Production planning in surface mines plays the most vital role in different ranges of horizons that can be divided into strategic or operational levels. Strategic (long-term) plans or decisions, affecting the Net Present Value of the project directly, decide on waste or ore mining blocks to be extracted in annual periods generally, while tactical and/or operational (mid- or short-term) plans decide on their daily implementation plans in the site. Mining projects are usually considered highly uncertain and risky due to the nature of the epistemic and aleatoric 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. If the underlying factors and causes of these uncertainties are not explained and considered enough in the long-term planning phase, 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. At this point, the primary purpose of this thesis study is to develop an uncertainty assessment methodology covering fuzzy fault tree analysis and discrete-event simulation to explain quantitatively the uncertainty factors leading to deviations from long to short-range production plans of surface metal mines. In this regard, a Fuzzy Fault Tree Analysis (FFTA) has been conducted over the data collected from mine planning experts to determine the corresponding twenty-one uncertainty factors classified under geology, economy, operation, and external and their severity and frequency intervals. The analysis showed that various geological, operational, and external factors could explain 93% of the deviations in a long-term plan. In addition, grade itself can cause around 14% of deviations among all twenty-one factors. Following the FFTA, a Discrete Event Simulation (DES) algorithm was developed by considering the most effective and applicable uncertainty factors. The developed DES comparatively examines deterministic and stochastic long-term planning by monitoring production indicators. In its implementation for a hypothetical case, a drop of 0.4M tonne production and 140 koz gold were observed for 3M tonnes of production with a gold pour guidance of 435 koz where multiple influential uncertainty factors are available in the area, causing almost the worst-case short-range production scenario.

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

ÖZ

AÇIK İŞLETME TÜRÜ METAL MADENLERİNDE UYGULANAN UZUN VE KISA DÖNEM ÜRETİM PLANLARI ARASINDAKİ SAPMALARA YÖNELİK BİR BELİRSİZLİK DEĞERLENDİRME MODELİNİN GELİŞTİRİLMESİ

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Açık ocak madenciliği, yüzeye yakın ekonomik minerallerin çıkarılmasında kullanılan hakim madencilik yöntemidir. Açık ocak madenciliğinde üretim planlaması, stratejik veya operasyonel seviyelerde farklı perspektiflerde en hayati rolü oynar. Stratejik planlar veya kararlar, projenin Net Bugünkü Değerini doğrudan etkiler ve cevher veya pasa bloklarının üretim zamanlarını yıllık ölçekte kontrol eder. Taktiksel ve/veya operasyonel planlar ise uzun dönemli planların sahada günlük olarak yakalanmasını sağlar. Madencilik projeleri, tesadüfi veya epistemik değişkenlerin doğası ve bunlar hakkında bilgi edinmenin maliyeti nedeniyle oldukça belirsiz ve risklidir. Uzun dönemli planların kısa dönemli planların üzerindeki etkilerini değerlendirmek ve optimize etmek adına bazı hesaplama araçları mevcut olsa da madencilik alanlarında ihmal edilen veya hafife alınan çeşitli belirsizlikler, planlanan üretim hedeflerinden ciddi sapmalara neden olabilir. Bu belirsizliklerin altında yatan etmenler ve nedenleri uzun vadeli 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, belirsizliklerin kaynakları ve aralıkları, tesadüfi veya epistemik davranışları, meydana gelme sıklıkları ve sapmalar üzerindeki etkileri, planın ne kadar riskli olduğunu gösteren faktörlerle bütüncül olarak ele alınmalıdır. Bu noktada, tez çalışmasının birincil amacı, yer üstü metal madenlerinin uzun ve kısa dönemli üretim planlarından sapmalara yol açan belirsizlik faktörlerini nicel olarak açıklamak için bulanık hata ağacı analizi ve ayrık olay simülasyonunu kapsayan bir belirsizlik değerlendirme metodolojisi geliştirmektir. Bu bağlamda sapmaya neden olan faktörlerin belirlenmesi için maden planlama uzmanlarından toplanan veriler üzerinden Bulanık Hata Ağacı Analizi (FFTA) yapılmıştır. FFTA'nın bir sonucu olarak jeolojik, operasyonel ve dış faktörlerin sapma sebepleri olarak dikkate alınması önerilir ve bu faktörlerin, sapmaların %93'ünü açıklayabileceği gözlemlenmiştir. Örneğin, sapmaların %14 lük bir kısmının tenörden kaynaklandığı ortaya çıkmıştır. FFTA'nın ardından, en etkili ve uygulanabilir faktörler dikkate alınarak bir Ayrık Olay Simülasyonu (DES) algoritması geliştirilmiştir. Oluşturulan DES modeli ile deterministik ve stokastik uzun vadeli planlama çıktıları incelenir ve üretim göstergeleri ile planın başarısı ortaya koyulur. Uygulama kısımında oluşturulan varsayımsal maden verilerine göre, 3M ton üretim ve 435 koz altın dökümü planlanan bir durumda toplam üretimin 0.4M ton, döküm değerinin ise 140 koz düştüğü gözlemlenmiştir. Oluşturulan varsayımsal maden sonuçlarında çok sayıda etkili belirsizlik faktörünün mevcut olduğu ve neredeyse en kötü kısa vadeli üretim senaryosuna neden olduğu gözlemlenmiştir.

Anahtar Kelimeler: Belirsizlik Değerlendirmesi, Karar Destek Tekniği, Bulanık Hata Ağacı, Ayrık Olay Simülasyonu, Açık Ocak Maden Planlaması

To my beloved wife

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CHAPTER 1

INTRODUCTION

1.1 Background

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 not to interrupt raw material delivery to the industries. At this point, the exploitation of valuable minerals in mines has been achieved by different methods, and each has 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. Net annual cash flows throughout the life of mine (LOM) determine the internal rate of return (IRR) of the investment, which is supposed to be much higher than the minimum attractive rate of return (MARR) of the related company for a favorable decision on the feasibility of investment. On this basis, block models (BMs) produced from different exploration drilling datasets via geostatistical interpretations are used in financial feasibility studies. The BMs hold specific deposit attributes such as grade, density, lithology, and geo-metallurgical variables (Morales et al., 2019). These attributes help to determine the economic block model (EBM) that will be utilized in production planning at varying stages from the life-of-mine (LOM) down to the shift to make decisions about the mineralogic asset.

Mine planning is commonly performed on long-term (strategic) and short-term (tactical/operational) scales. 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). In other words, long-term plans optimize the reserve extraction with the highest NPV and IRR yearly throughout LOM, whereas short-term plans intend to fulfill long-term goals in shorter intervals like months, days, and shifts. The strategic decisions for underground mining areas can be extended by determining ground support systems, stope layout, access network design, and production sequencing between the production panels (Hou et. al., 2019). On the other hand, surface mining requires deciding on two main aspects that are i) the ultimate pit boundaries and their associated phases, and ii) the LOM production schedule with equipment selection and sizing. Conventional stages of long-term surface mine planning are illustrated in Figure 1.1. As mentioned before, 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.

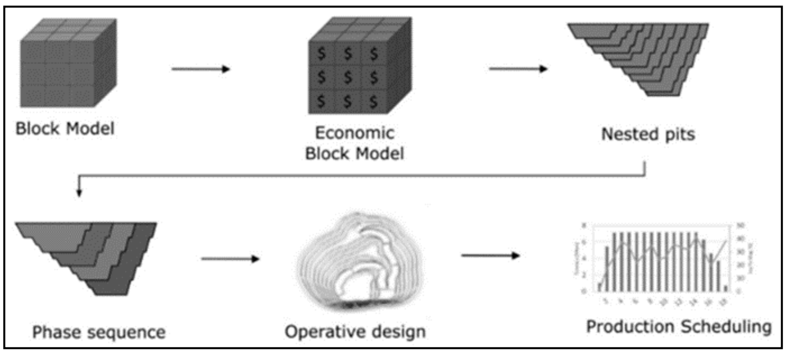


Figure 1.1: Traditional Steps of Long-Term Surface Mine Planning (Heidari, 2015)

Mining projects are considered highly uncertain and risky due to both nature of the variables and the cost of obtaining accurate information (Groeneveld and Topal, 2011). Van et al. (2012) classified the uncertainties associated with a mining project as internal and external. Internal uncertainties are generally related to geological uncertainties of the resource models and the uncertainties in mining processes such as loading, hauling, and mineral processing. On the other hand, external uncertainties are related to the variability in the values of external factors such as commodity price, cost, demand, selling cost, and weather. Although numerous risks are merging with internal and external uncertainties, Rimélé et al. (2020) pointed out that the conventional production planning methods are generally deterministic -do not account for uncertainty- and are still widely used in the industry via commercial schedulers. Therefore, ignoring uncertainties when planning and forecasting production can lead to suboptimal results with a high possibility of planning failure.

In addition, not accounting for these uncertainties in the long-range can trigger problems in shorter ranges since it can lead to drastic deviation from the long-range targets (Upadhyay and Nasab, 2019). Thus, it can be concluded that uncertainties in production planning should be regarded attentively not to deviate from optimized NPV and throughput.

1.2 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 the including geological uncertainty alone in the planning phase can improve the project NPV 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.

1.3 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 by a fault tree integrated with fuzzy logic analysis of an expert survey. Sub-objectives of the research can be listed as follows:

i. Implementation of a survey with the participants who 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,

ii. 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,

iii. Development of a discrete-event simulation algorithm for iterative and stochastic evaluation of the variations in geological, economical, operational, and external factors and their effect on production rates and throughputs,

iv. Implementing and examining the joint model with an operational and environmental dataset.

The study scope is limited to surface mining operations with metallic deposits. The fuzzy logic part will be 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.

1.4 Research Methodology

This research study entails performing the following steps:

i. Literature Review: A comprehensive literature review on uncertainties experienced in mining areas and the related uncertainty assessment methods is conducted.

ii. FFT Construction: A fuzzy-fault tree is constructed considering the dependencies between the uncertainty items that are categorized under four main groups: Geology, economy, operation, and external.

iii. Data Acquisition and Fuzzy Logic Analysis: A questionnaire is delivered to experts highly experienced in production planning of metallic surface mines to obtain linguistic knowledge about the occurrence, frequencies, and severities of the uncertainties that trigger the deviations between long and short-range plans. Then, the questionnaire is evaluated using fuzzy logic by considering the weightings of responses for experts of different experiences, ages, and seniority.

iv. FFT-Fuzzy Logic Integration: The survey results obtained by fuzzy logic analysis are converted to probabilistic values of basic events. These values are inputted into the fault tree to determine the priority rankings and levels of uncertainties. Some of the uncertainties are considered in the simulation stochastically so that the level of stochasticity in the model runs is evaluated considering their percentile priority levels.

v. Simulation Model Construction: A discrete-event simulation algorithm is developed to evaluate the effects of variations of the uncertainty factors on production rates and long-term plans. Accordingly, the model simulates an open-pit mine production cycle where the model variables are derived from the prioritized uncertainty items of the fuzzy logic analysis. The simulation achieves multiple outcome datasets of different scenarios where each is varied depending on the stochastic values of the prioritized uncertainty items.

vi. Validation and Verification: The model results will be verified and validated using expert options and hypothetical field data.

Additionally, the research methodology is summarized in Figure 1.2.

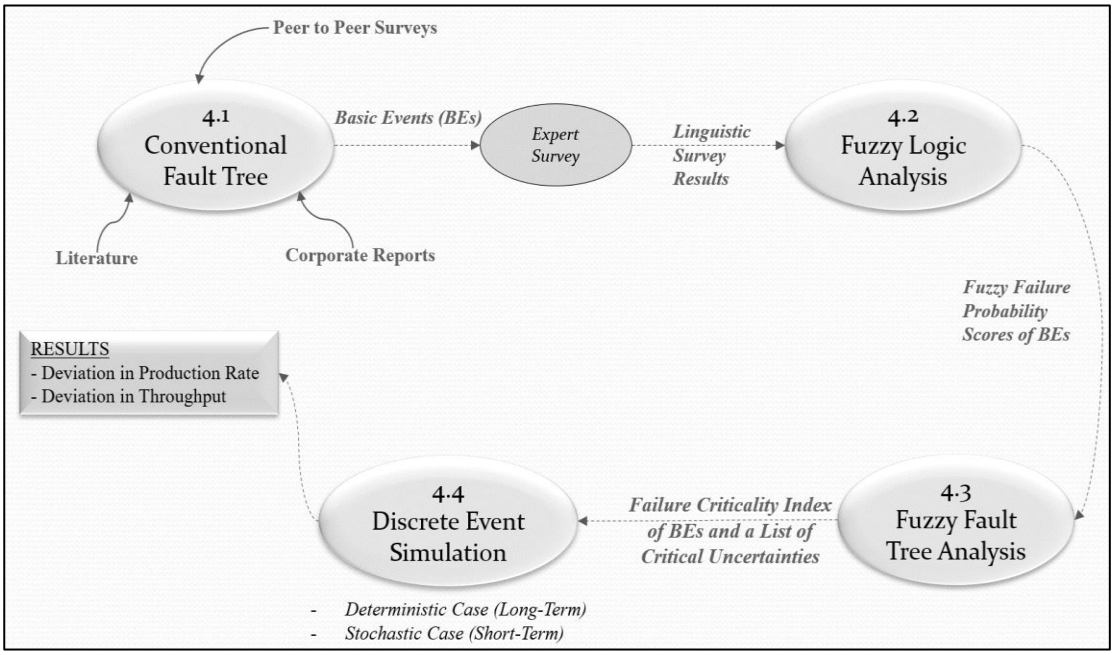


Figure 1.2: Research Methodology

1.5 Expected Contributions of This Thesis

Strategical (long-range) and tactical/operational (short-range) planning are studied independently in the literature. It is also observed from the related studies that the previous research area is limited to ultimate pit boundary determination, phasing, and scheduling without considering the transitions between long and short-range planning, including uncertainty items. In other words, a joint model with uncertainty aspects is not observed in the literature. However, a deep analysis of stochastic factors and their effects on operational planning should be evaluated attentively in the strategic planning phase not to experience unfavorable conditions during production. This research study intends to reveal and prioritize the uncertainty items that can cause variations between long and short-range production plans in surface mines. In this way, the study tries to close the gaps in the literature by developing a joint model of FFT and event simulation in quantifying the geological, operational, and external risks of production. The mining sector may benefit from the study outcomes to improve their NPV and IRR estimations more realistically.

CHAPTER 2

LITERATURE REVIEW

This chapter presents a literature review starting with a mining and uncertainty relationship investigation (Section 2.1). After giving the details with illustrative studies, underground mine planning and its link with uncertainty (Section 2.2) are presented, which is followed by surface mine planning and associated uncertainty (Section 2.3) determination. The uncertainties in surface mines are discussed regarding short- and long-term plans. Last, a general review of the decision support methods and event simulation technique are stated in Sections 2.4 and 2.5, respectively.

2.1 Mining with Uncertainty Aspects

Cambridge Dictionary defines uncertainty as *a situation in which something is not known or something that is not known or certain*. Accordingly, various uncertainties from different areas, with varying predictability levels, arise in the mining field. Aleatoric (naturally random) or epistemic (systematic ignorance) type uncertainties are prone to cause deviation from the planned NPV of the mining project. Therefore, various literature works have been conducted to analyze and estimate the effects of single or multiple uncertainties on mining operations.

At this point, the uncertainty sources in a mining project are observed to be related to geology (on grade, tonnage, and metallurgical parameters), commodity price (or mineral value chain), foreign exchange rates, cost, supply, and demand in the market, equipment and infrastructure, environment, host government policies, legislations and regulations, political risks in the host country, and social as well as human resources issues (Ajak et al, 2019). Generally, combinational effects of multiple uncertainties are handled in the relevant studies to derive joint solution. For instance, Dimitrakopoulos and Sabour (2007) focused on geological, metal price, and foreign exchange rate uncertainties. These three items holding varying levels of risks on production plans are frequently observed in the literature.

The effect of geological uncertainties has been worked on in detail individually and in combination with various subjects. Vallee (2000) emphasized the topic's importance by referring to the survey belonging to the World Bank. The survey results showed that 73% of mining projects have failed due to ore reserve estimation problems mainly related to improper analysis and identification of the geological aspects. The total was estimated at US$1.106 million for the Canadian mining industry in early 1991. Open pit ultimate limits, pit phasing and design, underground stope design, and surface and underground mine scheduling are the topics evaluated regarding geological uncertainties. Goodfellow and Dimitrakopoulos (2013) investigated the effect of metal content and material types on open-pit mine design. The study aimed to integrate grade and material uncertainties in pushback design of open pit mines by proving two formulations to reduce risk regarding the amounts of material hauled to each destination, while maintaining similar pushback sizes compared to the original design. Its implementation for BHP Billiton's Escondida Norte mine in Chile showed a 35–61% reduction in variability in quantities of material sent to the various processes. Dimitrakopoulos and Grieco (2009) developed a new probabilistic mathematical model optimizing the size, location, and number of underground stopes under the presence of grade uncertainty. It was shown that the risk-based approach could generate different designs that meet the pre-specified minimum acceptable risk with the desired risk profile accommodating the selection of designs with preferred upside/downside profiles. Koushavand et al. (2012) introduced a mixed-integer linear programming (MILP) model for long-term mine planning under grade uncertainty. The model determines the cost of uncertainty in a production schedule regarding the deviations from the target production. It was formulated with two objective functions: maximizing the NPV and minimizing the cost of uncertainty. In a joint study, Montiel et al. (2016) presented a global optimization model for a mining complex bearing surface and underground mining operations. Mining, blending, processing, and transportation decision variables are simultaneously optimized considering geological uncertainty. A higher NPV was achieved while reducing the amount of risk compared to traditional optimization methods. A set of model realizations is used with randomly generated model attributes instead of one single outcome set. Although there are numerous algorithms to create a set of the realization of the ore bodies in nearly all studies, a type of conditional sequential simulation like Sequential Gaussian Simulation (SGS) has been used as the method. These types of models consider grade uncertainty by producing different alternative designs, plans, and schedules in accordance with the distribution range of grade (Figure 2.1). Ajak et al. (2018) handled the geological uncertainty for an operating mine using data mining algorithms for quantification by using available grade control data. It was concluded that geological uncertainties could be quantified by implementing data mining and real-option analyses.

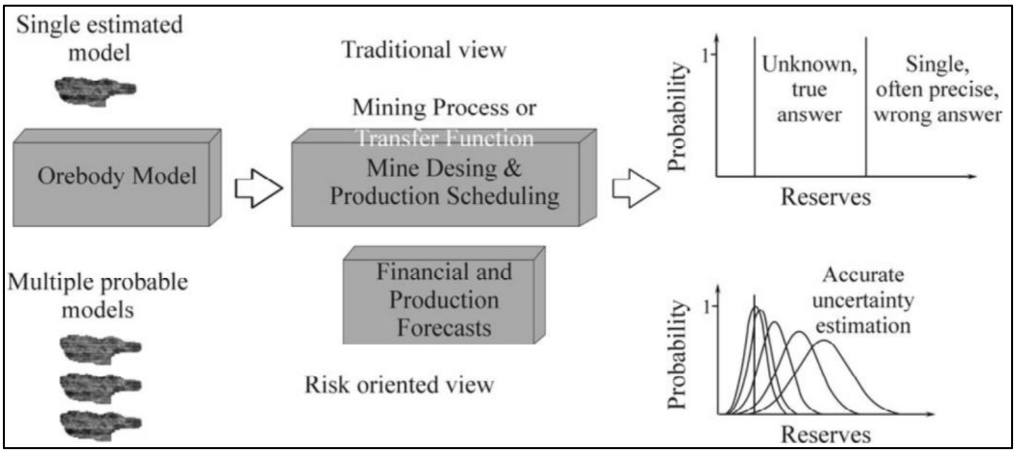


Figure 2.1: Comparison of geological uncertainty consideration in terms of input and outputs of long-term mine planning (Dimitrakopoulos, 2011)

Secondly, uncertainties sourced from commodity prices or mineral value chains have gained attention in the literature due to volatility in economical factors not following a constant trend (Figure 2.2). For example, Haque et al. (2014) presented a new valuation method for mining projects involving commodity price uncertainty. In the research, it is revealed that there is a strong correlation between the commodity price and the value of the mining project. Commodity price volatility is used as a measure. It is shown that when the gold price volatility increases, the project value of the mine decreases. Additionally, the importance of the foreign exchange rate consideration on the success of the mine valuation is outlined. The study strongly recommends continuous tracking and dynamic interpretation of commodity prices and foreign exchange rate volatility. On the other hand, Haque et al. (2017) developed a new Real Options Valuation (ROV) technique to consider combined effects of commodity price and foreign exchange rate uncertainties on the mining project valuation. The study claims that the commodity price, exchange rate, and correlation parameters between them are incorporated into the model and used in the evaluation process to assess a mining project's economic success more accurately with its inherent volatility. If commodity price uncertainty is considered alone in evaluating the project value instead of the joint effect of commodity price and exchange rate uncertainties, project values are observed to be overestimated.

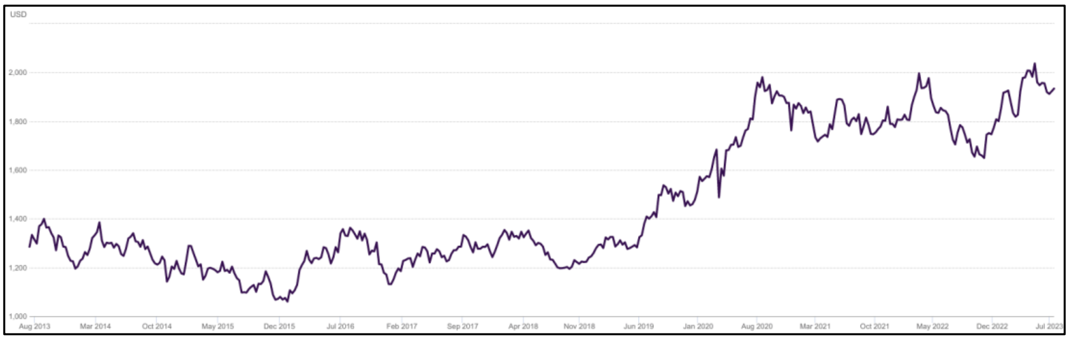


Figure 2.2: Gold price trend between July 2013 and 2023. (Data source: Gold.org. https://www.gold.org/goldhub/data/gold-prices)

Lastly, the cost is also another item considered in the literature as a part of the mining uncertainty. As an illustrative study, Topal and Ramazan (2012) considered the maintenance cost, which is crucial for determining the operating cost. While traditional planning techniques handle the maintenance cost as a specific value, the study considered the maintenance cost as a function of stochastic parameters in the model, developing a distribution of expected cost values used to calculate the confidence level, risk, and lower cost opportunities.

2.2 Underground Mine Planning with Uncertainty

Underground mining methods are used whenever the economic feasibility of surface mining operation is not satisfied for the resource beneath the surface with varying depths. Although many challenging uncertainties are effective in underground mining projects at varying levels, uncertainty studies have attracted less than surface mining applications due to their unstructured and complex behaviors changing by the employed mining method. Chimunhu et al. (2022) classified the uncertainty items for underground mining as geology (ore grades and tonnage), equipment availability, and geotechnical restrictions to ore extraction affected by unforeseen ground conditions (Figure 2.3). Among these items, geological uncertainty is focused mainly in the literature so the related studies will be discussed in the current section. Sepúlveda et al. (2018) worked on geological and geometallurgical uncertainties for block caving operations. Two-objective optimization problems were formulated to maximize economic return and minimize the risk arising from the uncertainties. Dimitrakopoulos and Grieco (2009) presented a probabilistic mixed-integer programming (MIP) model to optimize stope design, including size, location, and the number of underground stopes under grade uncertainty using stochastically simulated equally probable representations of the deposit. In addition, Kumral and Sarı (2017) utilized MIP by considering grade uncertainty in a sub-level stope layout determination and scheduling. Finally, Nesbitt et al. (2021) presented a stochastic integer programming (SIP) framework with uncertain ore grades and activity durations to maximize NPV for an underground mine.

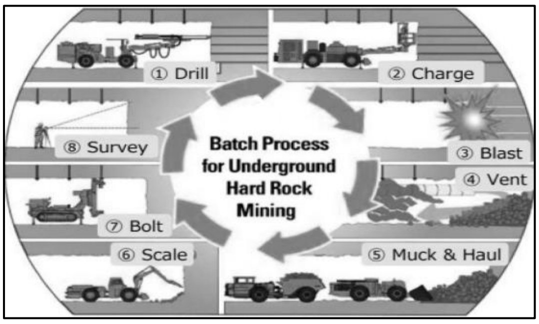


Figure 2.3: A Cyclic Underground Mining Operation (Chimunhu et al., 2022)

2.3 Surface Mine Planning with Uncertainty

Sarı and Kumral (2018) divided surface mine planning scale into three categories as long-term (strategic), medium-term (tactical), and short-term (operational) mine planning. In the literature, however, tactical, and operational plans are used interchangeably, so in the following, mine planning will be given in two main parts further as long-term and short-term plans with their associated uncertainties. An extensive literature review on surface mine planning shows that ultimate pit boundary optimization, phasing of the ultimate pits, production scheduling, equipment selection, and cut-off grade estimation are the main topics studied under long-term production planning of surface mines, while equipment dispatching and positioning, the blending of mined materials, production scheduling, and equipment utilization are the main subjects in short-term planning (Figure 2.4).

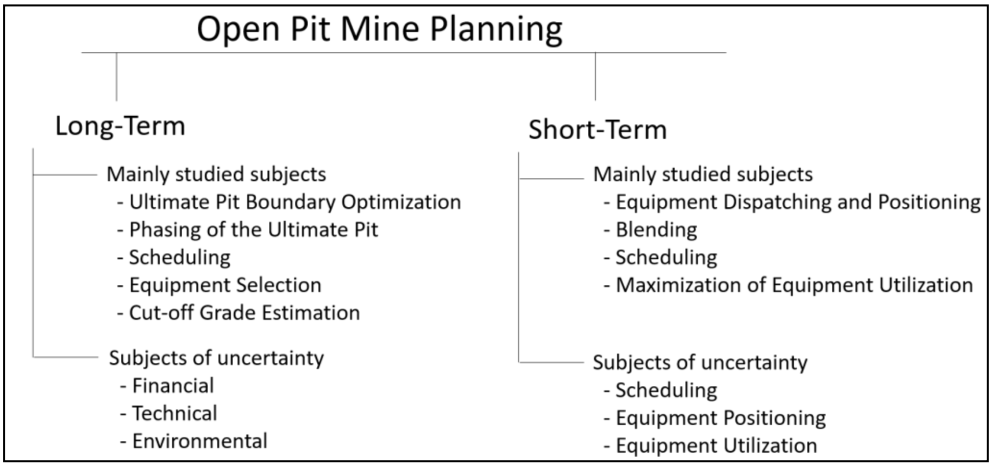


Figure 2.4: Open Pit Mine Planning Review

2.3.1 Long-Term Surface Mine Planning Uncertainties

Long-term mine planning evaluates deposits while deriving optimized indicators of the operation’s profitability, such as NPV and IRR (Newman et.al., 2010, Sarı and Kumral, 2018; Morales et al., 2019). Since optimization at an extended time frame affects the NPV of the project directly, the literature has been focused intensely on this topic. 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.

Uncertainty sources on long-range planning are grouped into three main aspects: financial, technical, and environmental (Sepúlveda et al., 2018). Commodity prices and foreign exchange rates are the most common examples of uncertain financial variables. On the other hand, geological (including geotechnical and metallurgical) and operational variables are well-known examples of technical uncertainty sources. Environmental uncertainties are expected to result in consequences related to technical, financial, organizational, and social licenses to operate aspects. Among these uncertainties, the previous studies mainly concentrated on commodity price, geological, and operational uncertainties.

The first commonly studied uncertainty in long-term surface mine planning is the uncertainty of commodity prices. The effect of commodity prices on mine plans is deeply investigated primarily in terms of its effects on ultimate pit limits and its related phases, the NPV of the project, and its effect on the feasibility of the projects. However, its extensive effect on short-range planning has not been studied. 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. It aimed to generate alternative scenarios so that operations could gain flexibility in changing conditions. 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. This work is one of the most detailed studies on price uncertainty. However, the short- or mid-range planning aspects are generally neglected in the model. It was stated that the ability to optimize mining capacity and processing rates, specifying extensions of the destination policy to consider multiple attributes in cut-off grade decisions, must be considered in future studies. As a result, the stochasticity of price uncertainty with its effect on shorter-range planning needs improvements.

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. Block models (BMs) constructed using reliable exploration drill information determine the extent of the deposit to support strategic decisions. Since there is sampling with considerably large intervals due to the cost-intensive side of the exploration drilling (Morales et al., 2019), there are uncertainties associated with that model depending on the success of the sampling process of the exploration phase. Due to large sample intervals, these models are hard to be used directly at the tactical and operational levels (Medium- to short-term plans) (Sepúlveda et al., 2018; Pourrahimian et al., 2015; Dimitrakopoulos, 2011; Sarı and Kumral, 2018). In addition, such a model also may lead to suboptimal solutions due to its related risk of material content uncertainties. Different approaches such as stochastic optimization, stochastic integer and mixed-integer programming, genetic algorithms, and discrete event simulation are used to turn deterministic conditions of block models into uncertainty-based (stochastic) estimations to solve pit phasing and production sequencing problems of long-term planning. Godoy and Dimitrakopoulos (2004) developed a multi-stage optimization approach based on a simulated annealing algorithm for long-term mine scheduling under geological uncertainty, resulting in an increased NPV compared to conventional methods with a reduced risk of meeting production targets. Ramazan and Dimitrakopoulos (2007) developed a stochastic integer programming model to generate the optimal production schedule using iteratively simulated orebody models as inputs. The proposed approach minimized the risk of not ensuring production targets as a function of ore, metal, and grade blending. Morales et al. (2019) presented a two-stage methodology comprising pit optimization and stochastic life-of-mine (LOM) production schedule. It was concluded that geometallurgical and geological data under uncertainty could change the decisions regarding pit limits and production schedules by impacting the financial outcomes. Therefore, geological and geometallurgical uncertainties should be considered attentively in the future works of long-term mine planning. Although the interactions of geological and geometallurgical uncertainties are explained more practically by including shorter-term planning aspects, related decisions at the strategic level also affect the tactical and operational levels considerably. Therefore, further integrations and considerations in the related models are needed.

Despite operational uncertainties playing essential roles at the tactical or operational level, some should also be considered at the strategic planning level. 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. It was shown that incorporated operational uncertainties help to better estimate the fleet parameters, which also affects the NPV of the mining project directly. 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. All in all, operational uncertainties not only affect mining projects in shorter runs but also affect the NPV of the operation dramatically in the long run. Therefore, it is recommended to consider operational uncertainties further in the upcoming research for long-term mine planning cases.

A highlighting example of comparing traditional and risk-based approaches regarding geological uncertainties is presented in Figure 2.5. Besides, it can be inferred that numerous other risks mainly arising due to uncertainties on foreign exchange rates, production cost items, equipment, and weather are effective in long-term planning but not discussed intensively in the literature.

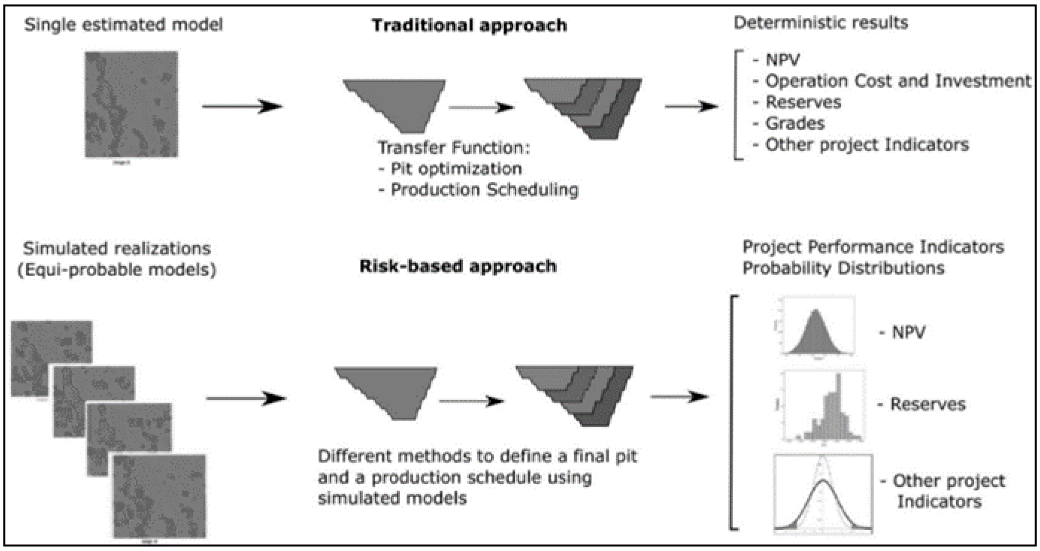


Figure 2.5: Traditional vs. Uncertainty-based Approaches to Long-term Mine Planning (Heidari, 2015)

2.3.2 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). Topics and considerations are limited to certain types. Additionally, the effects of deviations from short to long-term targets are not discussed in detail. Short-term surface mine planning literature focuses mainly on equipment dispatching and positioning (Dessureault et al., 2007; Erçelebi and Başçetin, 2009; Bosh 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). Linear programming, integer programming, mixed-integer programming, and simulation applications are the methods used widely in recent works to solve such problems. The methods used in the studies vary according to the uncertainty involved.

Regarding uncertainty, scheduling, equipment positioning, and utilization topics are discussed under geological and operational uncertainties. They are generally evaluated by stochastic integer programming and simulations. 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. The potential uncertainties of the metal grade and ore quality, fleet parameters, and availability were considered in the study. Upadhyay and Nasab (2018) developed a discrete event simulation model for uncertainty-based short-term scheduling. The model is capable of efficient short-term planning by analyzing the impact of different haul road designs, road conditions, traffic congestion, dispatching strategies, and plant requirements in mine operations. However, as observed from the previous papers, integration of the long- and short-term mine planning is not covered. To close the gap, Jewbali and Dimitrakopoulos (2013) presented a study called joint stochastic optimization of short-and long-term mine production planning: method and application in a large operating gold mine. 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, geological uncertainties were considered alone.

To sum up, as discussed in Section 2.3, the literature has focused on the 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.

2.4 Evaluation of Decision Support Techniques

Production-related decisions at the strategic level affect the overall profitability of the projects in the mining industry that should sustain operations with scarce resources; therefore, achieving the best applicable decisions is crucial for the future of company operations in the sector (Chinbat and Takakuwa, 2009). This study aims to support the decision-making process with quantified measures by considering the factors influential in production planning in surface metal mines. Therefore, this section will review the common decision support techniques so that the most proper technique to be used in the current study will be decided.

Decision-support systems (DSS) are employed to support particular decision-making processes under specific conditions for different fields with changeable purposes and applications. DSS is applied extensively in governmental, industrial, scientific, and commercial sectors. Some of the potential impacts and outcomes of an effective DSS for some application fields are listed (Burke et al., 2014):

i. More efficient production planning would lead to significant financial benefits.
ii. Better personnel rosters would lead to a more contented workforce.
iii. Efficient healthcare scheduling would lead to faster treatment (potentially saving lives).
iv. More effective cutting/packing systems could reduce waste.
v. Better delivery schedules could reduce fuel emissions.

A decision support technique's output and/or designed purpose changes with its application area. For example, an engineering project manager may ask to investigate the risk related to operational uncertainties. However, verbal result determination of a service sector review can be the driving aspect for the decision maker such as the commercial sector. Consequently, the output of a DSS diversifies with the different sectoral needs, and for an engineering project, the best way can be to present numbers for the quantified measures. Furthermore, for a mining project requiring forecasts throughout the predefined mine life, quantifying the uncertainties with the listed contributing factors can be the best way to use in the strategy development period. This requirement necessitates a detailed query on risk determination since the risk for a mining project is defined as an uncertain event or condition that positively or negatively influences the project objective (Chinbat and Takakuwa, 2009). Therefore, risk assessment techniques are comparatively discussed to determine the proper DSS to be used in the current research study. Badri et al. (2012) summarized the Risk Management Tools (RMT) under three categories: quantitative, qualitative, and semi-quantitative. On the other hand, Luo et al. (2018) grouped the RMT as quantitative and qualitative methods. Quantitative tools are further subdivided into probabilistic and deterministic, while qualitative tools are classified into expert judgment-based and prescriptive methods (Badri et al, 2012). Considering the nature of the study, probabilistic quantitative tools are observed to be properly employed (Figure 2.6).

Implementing a DSS system in the decision-making process is expected to come up with numerous benefits like saving money, natural resources, and more environmentally friendly production. Accordingly, a particular quantification is needed for the decision-maker to compare alternatives. Therefore, decision support techniques that allow the integration of mathematical models and/or simulation in a probabilistic manner with the opportunity of fuzzy logic integration are investigated to create the desired joint model.

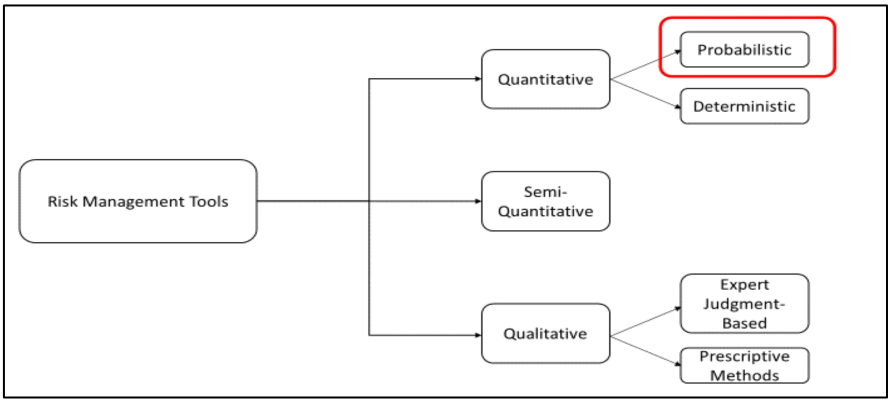


Figure 2.6: Risk Management Tools (Badri et al., 2012)

Some frequently-observed decision support techniques, fishbone analysis (FB), analytic hierarchy process (AHP), and fault-tree analysis (FTA) will be evaluated comparatively to reveal their pros and cons so that their conveniences for this research study will be understood.

2.4.1 Fishbone Analysis (FB)

Fishbone analysis is generally used for cause-effect analysis (Bose, 2012). The fishbone diagram determines the root causes of problems by indicating their interdependencies (Luo e al., 2018). It is a qualitative method that deepens the analysis with step-by-step logic. The method is generally used in the occupational health and safety area. As an illustration, Luo et al. (2018) used the method to analyze the safety of natural gas spherical tanks. The fishbone diagram of the sample engineering project is presented in Figure 2.7 and its detailed form is illustrated in Figure 2.8. Arrows in the diagram indicate small, middle, primary reasons, and their relations. Due to its qualitative structure, it will not be considered in this study

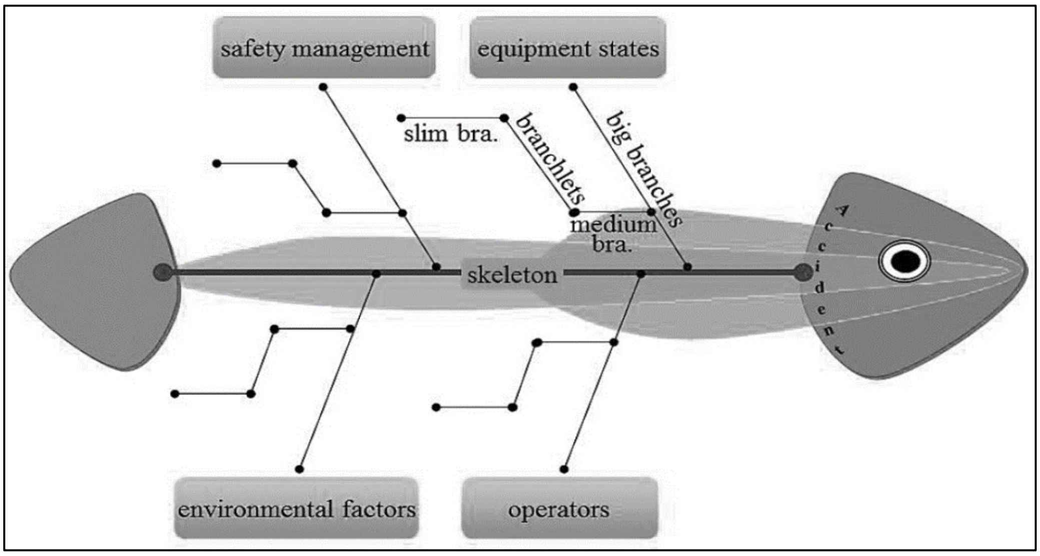


Figure 2.7: Structure of a Fishbone Diagram (Luo et al, 2018)

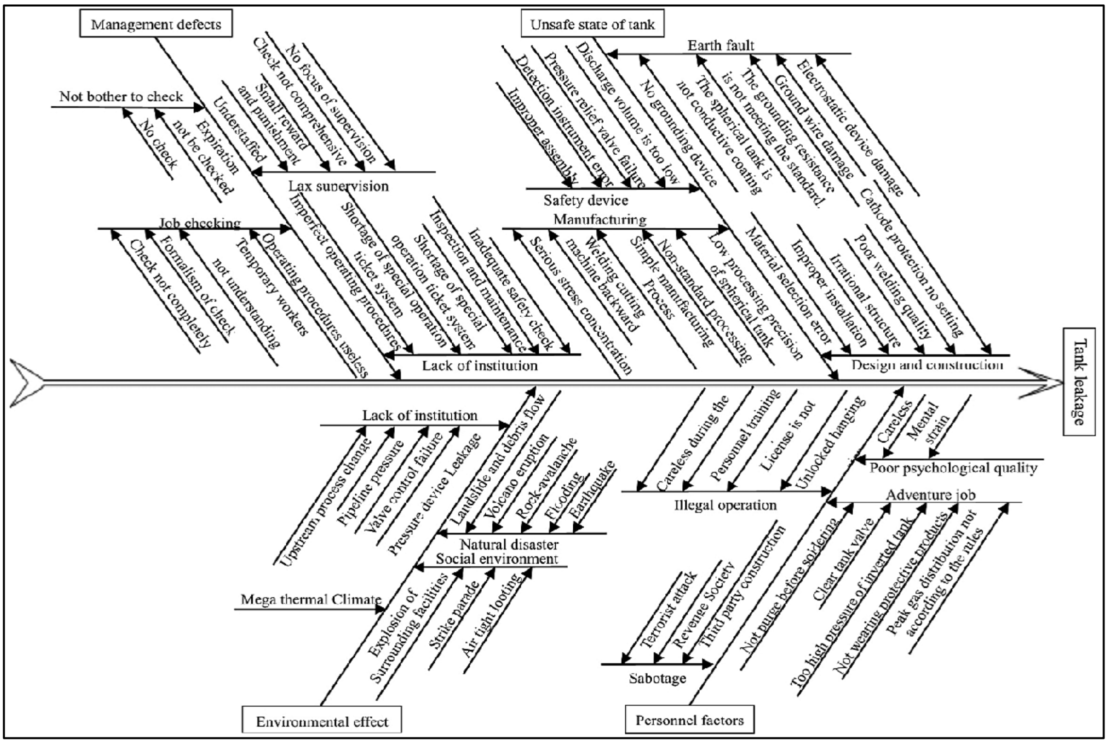


Figure 2.8: A completed Fishbone Diagram (Luo et al, 2018)

2.4.2 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is widely used in decision-making processes to compare alternative solutions (Badri et al., 2012; de FSM Russo and Camanho, 2015). It is a structured multi-attribute tool used in complex decision-making cases based on three fundamental principles: decomposition of the structure, comparison of judgments, and hierarchical composition (or synthesis) of priorities (Badri et al., 2012). It is raised that the method can be applied to cases including both qualitative and quantitative data; therefore, the method can be placed in the group of semi-quantitative risk management tools (Zhao et al., 2012). The method allows pairwise comparison and is appropriate for selecting the most advantageous solution from a set of alternatives based on their relative performances considering one or more criteria of interest (Yavuz, 2015; Spanidis et al., 2021).

For instance, Yavuz (2015) used the AHP method to compare alternative sets of mining loaders to support the decision-making process for equipment selection. A hierarchy structure was built to compare alternatives as given in Figure 2.9. After structuring the hierarchy, the pairwise comparison matrix for each level is developed by assigning scores for each alternative. The alternative with the highest priority determines the most appropriate loader for the operation under given circumstances.

Although a comparative evaluation will also be computed under the scope of this thesis, the requirement of an initial assigning failure coefficient for each case and sequential comparisons among the alternatives cannot be applied in practice when assessing the uncertainty and production correlations.

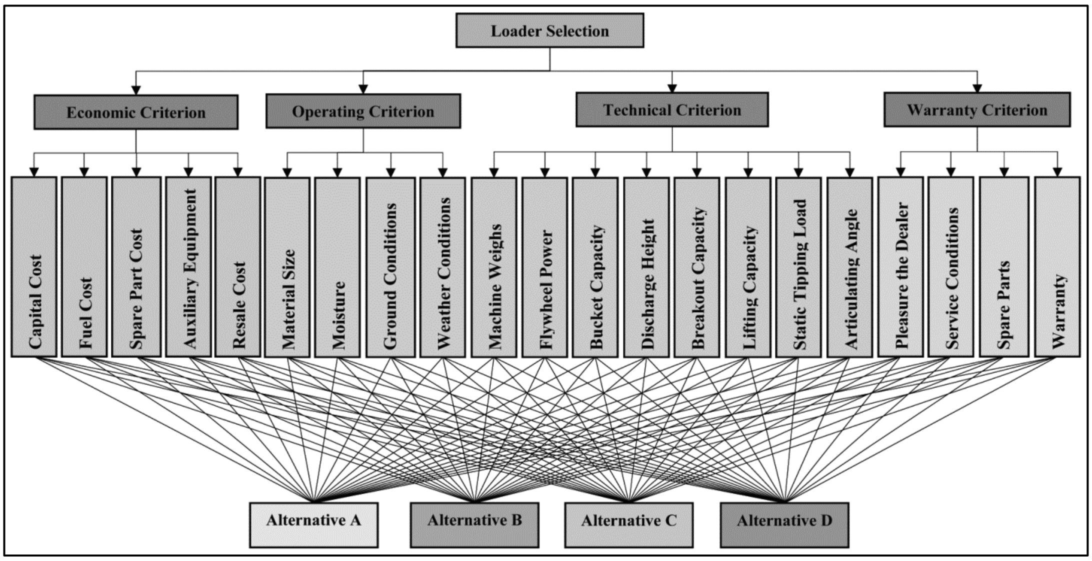


Figure 2.9: Hierarchy Structure for the Loader Selection (Yavuz, 2015)

2.4.3 Fault Tree Analysis (FTA)

Fault Tree Analysis (FTA) is a widely used systematic, analytic, top-down, and deductive system failure analysis method. In FTA, a top event is defined and deeply resolved into intermediate and basic events interrelated by particular logic gates, as illustrated in Figure 2.10 (Cheliyan and Bhattacharyya, 2018). Since FTA can be practical for any system, it is widely used in various industries, mainly in the production industry. Complex systems such as nuclear reactors, aerospace systems, electronics, electric power plants, chemical production plants, mechanical environments, civil engineering works, the petrochemical industry, and pipeline systems can be analyzed in detail to evaluate system safety and reliability (Mahmood et al., 2013). For example, Cheliyan and Bhattacharyya (2018) integrated FTA into a subsea production system to analyze the possibility of oil and gas leakage by considering different failure-triggering mechanisms.

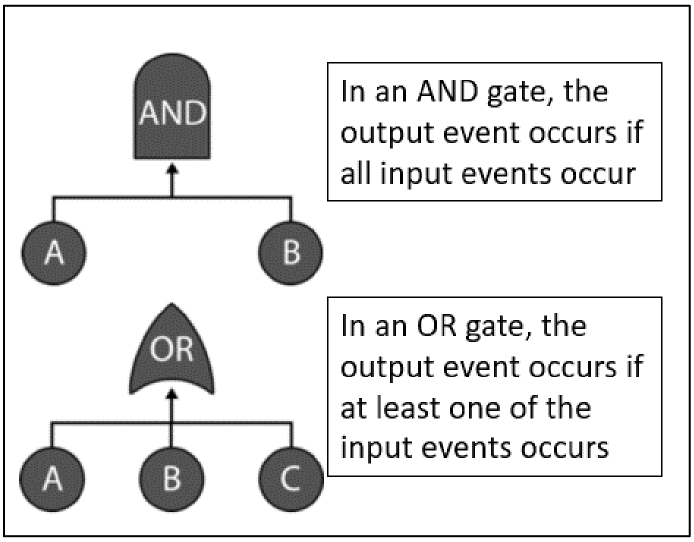


Figure 2.10: Basic AND and OR Gates Used in FTA

The use of FTA is extended by NASA (National Aeronautics and Space Administration) by integrating FTA into a Probabilistic Risk Assessment (PRA) methodology (Stamatelatos et al., 2002). The method was used firstly to calculate the probability of the mission's success in transferring and returning astronauts between the moon and the Earth. Later, the usage of the method was improved by NASA after the Challenger accident in 1986 to highlight the design and operational weaknesses of the systems. According to NASA’s handbook on FTA (Stamatelatos et al., 2002), eight steps must be taken for a successful FTA realization. The first five steps are related to problem formulation, while the remaining items aim to construct, evaluate and interpret FTA and its results (Stamatelatos et al., 2002). These steps are as follows:

i. Identify the objective,
ii. Define the top,
iii. Define the scope,
iv. Define the resolution,
v. Define ground rules,
vi. Construct the FT,
vii. Evaluate the FT,
viii. Interpret and present the results.

The symbols and gates used in defining different events in the fault trees and their inter-relationships are defined by NASA Handbook on FTA (Figure 2.11) as given in Stamatelatos et al. (2002). A typical example of FTA on evaluation of overrunning of the motor is presented in Figure 2.12. An FTA is expected to go top to down events, i.e. basic events, where dependencies between different basic events and branches in the tree are constructed using various gates of varying functionality.

In the mining industry, the method also finds a wide application area. Zhang et al. (2014) used FTA to analyze the root causes of accidents involving mining haul trucks. It was decided in the study to concentrate on accidents in West Virginia, U.S.A, by developing individual fault trees for each accident. It was concluded that the two most common root causes of the accidents are inadequate or improper pre-operational checks and poor maintenance of trucks. Gharahasanlou et al. (2014) investigated the failure occurrence probability of the crushing and mixing bed hall department at the Azarabadegan Khoy cement plant using the FTA method. Shi et al. (2018) used FTA to model the risk factors of coal dust and gas explosion in the Xingli Coal Mine. As the core part of the study, expert opinions were collected and aggregated as trapezoidal fuzzy numbers to calculate the degrees of importance of all basic events. In brief, the basic events with higher probabilities were set as hazards in daily safety management; and effective measures for preventing gas and coal dust explosions were derived. This study will be detailed more in Section 2.4.4.

To sum up, FTA is a symbolic logic analytic technique considering the failure probability of the system components when determining the top event's failure probability (Ferdous et al., 2009, Zhang et al., 2014). The other decisive property of the technique is that subjective expert opinions can be implemented in the system as a fuzzy set with triangular or trapezoidal distributions. Therefore, the uncertainties causing failure to implement long-term plans in metallic surface mines, integrated with an expert opinion, can be analyzed practically in Fuzzy Fault Tree Analysis (FFTA), a particular use of FTA. Therefore, FFTA will be discussed in Section 2.4.4 separately.

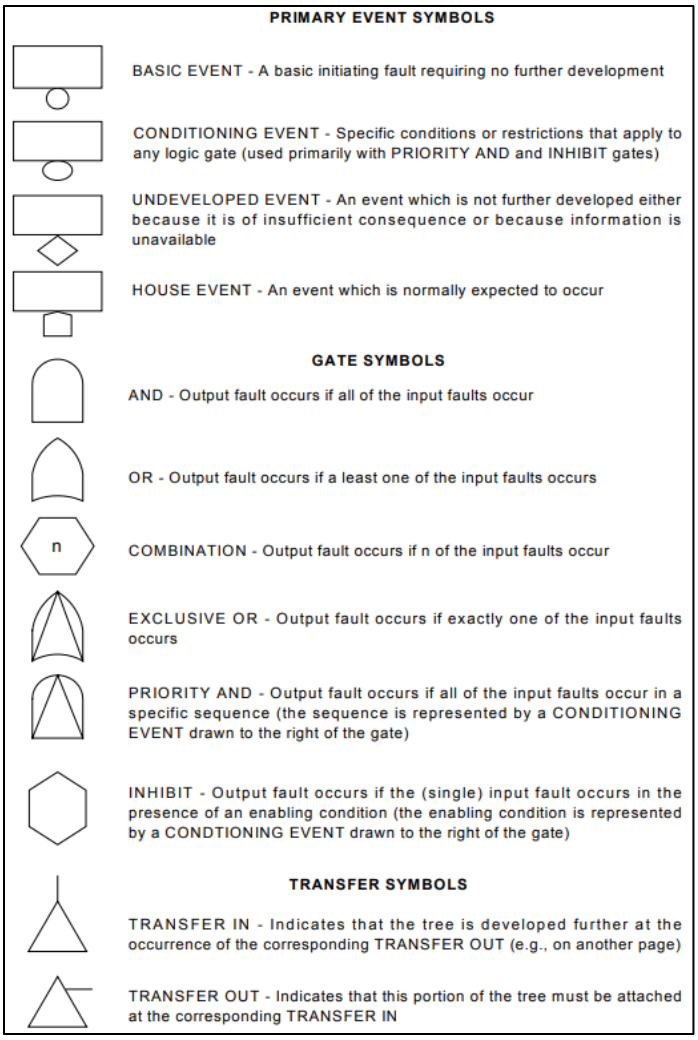


Figure 2.11: FTA Symbols According to NASA FTA Handbook (Stamatelatos et al., 2002)

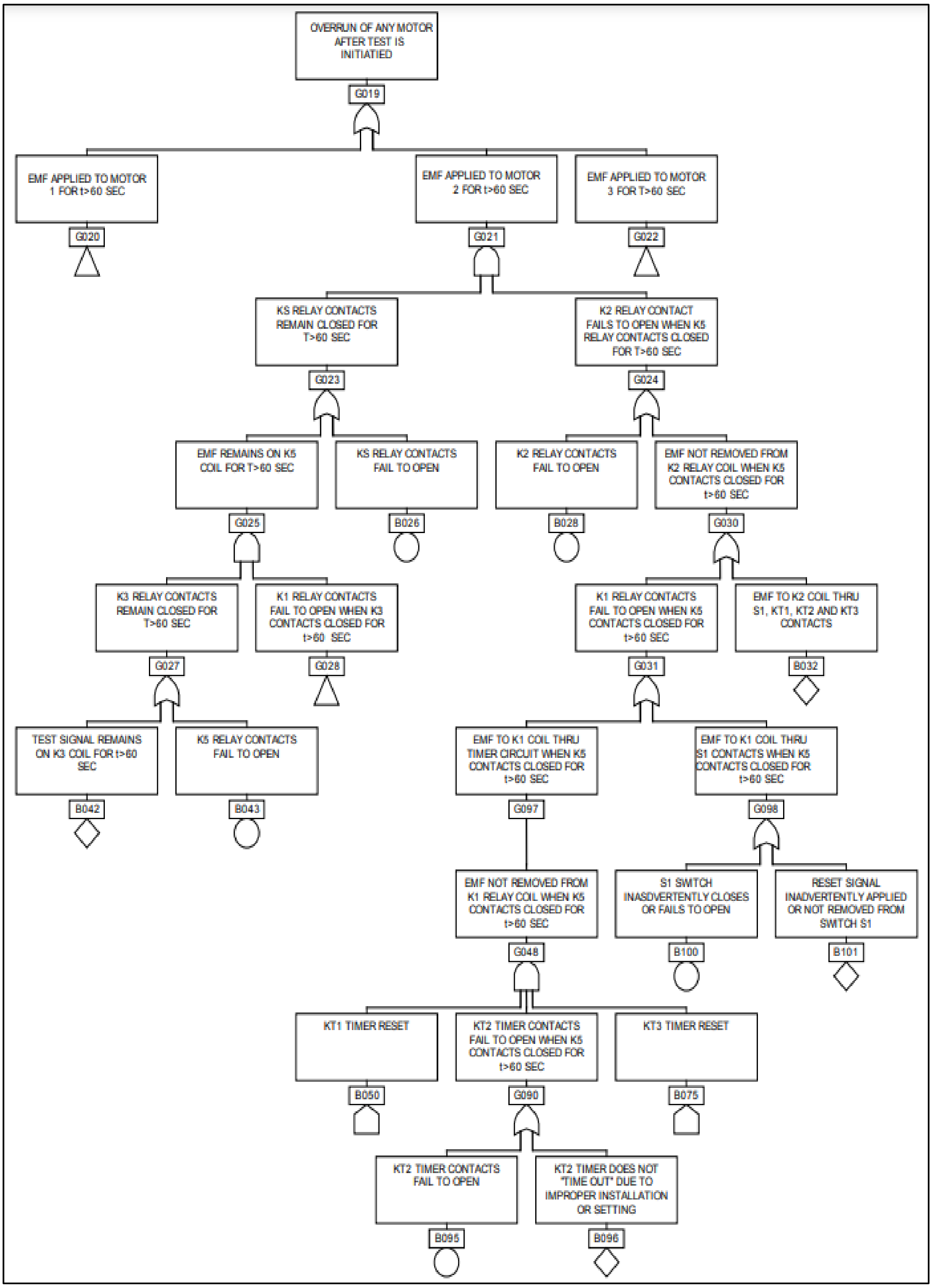


Figure 2.12: An Example of a Typical Fault Tree (Stamatelatos et al., 2002)

2.4.4 Fuzzy Fault Tree Analysis (FFTA)

Most processes and events in the real world can happen within a particular uncertainty with varying levels. Therefore, the need to express any concepts -a part of the real world- with crisp outcomes has put forward the concept of Fuzzy Set Theory, expressed by Lotfi Zadeh for the first time in 1965. The Fuzzy concept is integrated into many fields. It allows the integration of expert opinions and experience-based data, mainly in the data shortage. It obtains crisp values from vague concepts, consideration of uncertainty, and inclusion of human interpretable rules to the computer environment. Consequently, the Fuzzy concept is also integrated into the Fault Tree Analysis to improve and develop the method of supporting decisions. Therefore, fuzzy logic and set theory are required to be expressed first before detailing the fuzzy fault tree method.

Sivanandam et al. (2007) defined Fuzzy Logic as a mathematical tool to handle uncertainty by providing the concept of *computing with words*. In this context, the Fuzzy Logic method follows a sequential methodology, starting with crisp inputs' fuzzification. Fuzzification is followed by an inference process in which the fuzzy input set is mapped to the output fuzzy set based on the fuzzy logic principles. In the last sequence, the fuzzified output set of the inference process is defuzzified to obtain the crisp output so that a quantified value is obtained. In addition to these operational steps, some critical concepts, which are Fuzzy Set, Membership Function and Logical Operations should also be comprehended for better understanding of Fuzzy Logic. The Set term should first be defined to draw the boundaries for enabling combined usage with fuzzified input and output. As MathWorks (2022) indicated, there are two sets: classical and fuzzy sets. Membership criteria of classical sets are well-defined and known. For example, there is not any doubt about the membership of dogs and cats to animal class. However, there is an ambiguity about whether bacteria and starfish belong to the class of animals (Zadeh, 1965). Another example was given in MathWorks (2022) by considering weekdays and weekends. It is undoubtedly known that weekdays contain Monday, Thursday, and Saturday but do not contain the terms butter, liberty, dorsal fins, and so on (Figure 2.13). Therefore, borders are strict in a classical set and an item is either asserted or denied for the set. On the other hand, in a fuzzy set when the weekend days are inquired, the answer includes Saturday and Sunday but there is an uncertainty for Friday. Some answers would consider Friday as part of the weekend due to some participants' perceptions even though it must be excluded from the weekend in normal circumstances. Therefore, the decision on Friday becomes fuzzy (Figure 2.14), and this condition requires developing a fuzzy set, not a classical set. In brief, an item is either out or a member of a set with certainty in classical sets, while fuzzy sets include hazy boundaries.

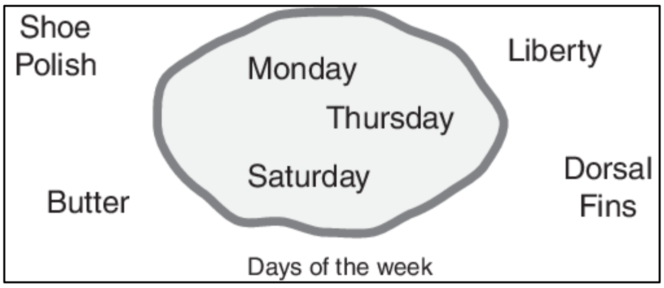


Figure 2.13: Days of the Week Classical Set (The MathWorks, 2022)

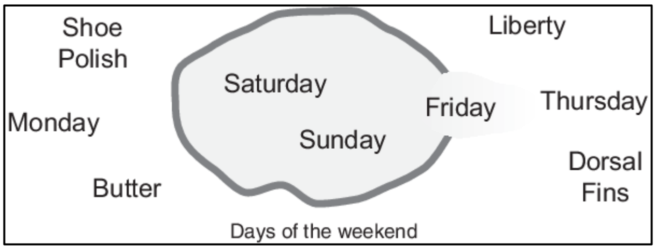


Figure 2.14: Days of the Weekend Fuzzy Set (The MathWorks, 2022)

Another critical concept in Fuzzy Logic is the definition of Membership Function. It is a function that introduces how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1 (MathWorks, 2022). The type of function is crucial since it is the backbone of the inference by affecting the format of the input and output fuzzy sets with their value determinations in the process. The function is determined based on its usage purpose and the field of interest. The most preferred types are triangular and trapezoidal, especially if expert opinion is characterized (Mahmood et al., 2013). An illustrative example of a triangular membership function is given in Figure 2.15, and the value of any *x* for the function of *f(x)* is determined with Equation 2.1.

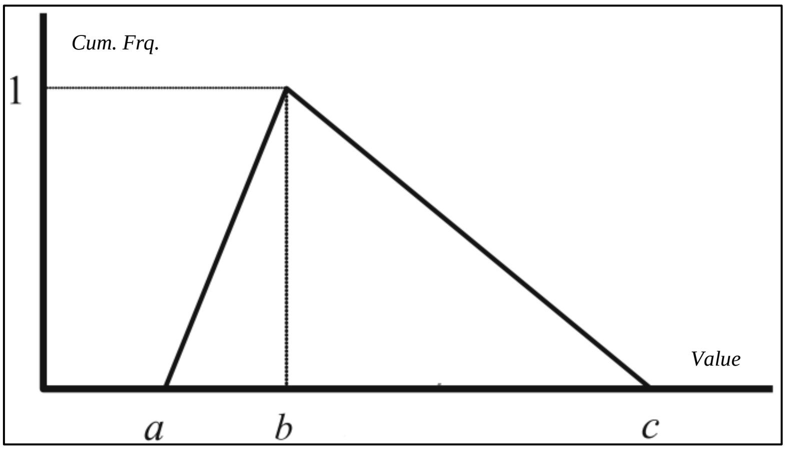


Figure 2.15: Triangular Membership Function (Mahmood et al., 2013)

$$(x; a, b, c) = \begin{cases} \dfrac{x-a}{b-a}, a \leq x \leq b \\ \dfrac{c-x}{c-b}, b \leq x \leq c \\ 0 \quad , otherwise \end{cases} \tag{2.1}$$

The last important aspect is Logical Operations that connect fuzzy inference. The most common fuzzy logical reasoning operators are AND, OR and NOT, which are analogous to the standard Boolean logic but superior to the standard. Therefore, standard logical operations hold if the fuzzy values are kept at the maximum and minimum extremes (1 and 0). The logic matrix in Figure 2.16 is used to define the fuzzy logical reasoning operators (MathWorks, 2022). As indicated in the figure, the minimum valued one is returned if the AND operator is used for two fuzzy variables. However, the maximum valued fuzzy variable's value is returned as the result of the OR statement. At last, for the NOT operator, the one minus the value is returned as the result of the operation.

A	B	min(A,B)
0	0	0
0	1	0
1	0	0
1	1	1

AND

A	B	max(A,B)
0	0	0
0	1	1
1	0	1
1	1	1

OR

A	1 - A
0	1
1	0

NOT

Figure 2.16: Fuzzy Logic Reasoning Operators AND, OR, and NOT

The concept of Fuzzy Logic has been integrated into fault tree analyses in various studies of different fields. Conventional FTA has some shortcomings, such as vagueness, absence of accurate data, and uncertainty (Mahmood et al., 2013). In addition, the failure probabilities of basic events are considered as an exact value, which is a single estimated value or crisp value in the FTA, and is not generaly representative due to insufficient data, vague characteristics of the events, and the high cost of data acquisition. Developing datasets by expert opinions can help to overcome these shortcomings. This condition requires verbal statements that must be converted to numerical representations to use the probability rate of the basic event in FTA. Therefore, conventional FTA is transformed into the FFTA. The method of FFTA is extensively used where system failures are observed for a broad range of industries and applications like image processing (Bezdek et al., 1999), risk evaluation of both upstream and downstream operations of the petroleum and gas natural sector (Rajakarunakaran et al., 2015; Cheliyan and Bhattacharyya, 2018; Badia et al., 2019), and process industries (Lavasani et al., 2015, Yazdi et al., 2017 and 2020). The mining industry is also one of these industries. As an illustrative study, Mottahedi and Ataei (2019) used FFTA to analyze the coal burst occurrence probability. In the fault tree, the occurrence of a coal burst is introduced as the top event, and occurrence probability values of a coal burst with self-initiated and remotely triggered mechanisms are compared. In the fuzzy logic part of the study, a survey was conducted among professionals from relevant field. The analysis results were inputted to the FFTA to define occurrence probabilities of some sub-events.

Similarly, Shi et al. (2018) used the FFTA method to identify the risk factors of coal dust and gas explosions in the Xingli Coal Mine, China.

In the literature, FFTA has been generally employed for OHS and equipment reliability assessments in mining; however, its use in mine planning or production has not been observed. FFTA is decided to be used as the primary method in the current study for evaluating and prioritizing uncertainties that can be effective on long-term (strategic) planning deviations. Accordingly, uncertainty occurrence frequencies and severities will be evaluated by a survey conducted with multiple experts from different metallic surface mining operations in the world. The content of the survey, its assessment using fuzzy logic, and the implementation of the fuzzy logic results into the fault tree will be discussed in detail in Section 3.

2.5 Discrete Event Simulation (DES)

The decision support methods, some of which were discussed in Section 2.4, are utilized in the decision-making period to determine the bottlenecks in an operating system and to evaluate the effects of variables qualitatively and quantitatively on the system outcomes. Therefore, these methods allow to comprehend the bounding variables and parameters to be concentrated in sequential system analysis. Since this research study will focus on understanding the uncertainty-based variations from long-term targets due to short-term results and their ranges, the outcomes of the fuzzy fault tree will specify the aspects to be considered more intensively in the following evaluations and will give the score of the doability of the plan. Since a mimic of the mining operations composed of the occurrence of sequential or independent activities and events is included in the scope of the study, event simulation is decided to be used for the production cycle of an open-pit metallic mine. In this regard, the simulation will be used to assign operation-related variations so that simulated variables will give a cluster of results. The simulation outputs and the constructed FFT will be discussed jointly to understand the range of the uncertainties and their forecasted effects on the variation between the production plans. Accordingly, this section will briefly discuss the theory behind DES, the simulation type used in the study, and its applications in mining. Development of the DES model to be employed in the current study will be detailed in Section 4.

The process of transferring the real world to the computer environment by mimicking natural laws, rules, and processes became more realistic with recent developments in the computer industry. In this way, outcomes of events or individual activities can be foreseen without the need for an actual event to be realized. This process is conducted in the computer environment with the aid of simulations. Simulation is defined as the imitation of the operation of a real-world process or system over time (Banks et al., 2014). A model is created for the system under investigation to create an artificial history considering the operating characteristics of the real system. Later, this history is used to find the solutions for the questions related to defining the most appropriate design criteria, what-if scenarios, and similar aspects. Setting the system scope and boundary is the core part of the simulation. A system is a group of objects combined with observable interactions or interdependences to achieve a joint target. Interaction between the system and its surroundings should also be defined to determine the system environment. At this point, boundary determination between the system and its environment is crucial to limit the interactions. In addition, there are system components: state and event. The state is the collection of variables required to define the system at any time, while an event is an instantaneous occurrence that might change the system's state. After defining the content and boundaries of the simulation, the simulation type should be identified according to the model interactions being static or dynamic, deterministic or stochastic, and discrete or continuous:

vi. **Static Model:** A system at a particular point in time without any variety in outcomes

vii. **Dynamic Model:** A system that changes over time with a variety of outcomes

viii. **Deterministic Model:** It represents a system containing no random variables or ineffective random variables.

ix. **Stochastic Model:** A system whose outcomes are highly affected by random values of its components

x. **Discrete Model**: A system where variables change only at a discrete set of points in time.

xi. **Continuous Model**: A system where variables change continuously over time.

Considering the nature of mining operations, the model that will be developed in this study, will be stochastic, dynamic, and discrete, generally termed Discrete Event Simulation (DES) in the literature. Simulation work has sequential steps listed below (Banks et al., 2014) and illustrated in (Figure 2.17 and Figure 2.18).

1. **Problem Definition and Formulation:** Statement of the problem.
2. **The setting of Objectives and Overall Project Plan:** Determination of questions to be answered by the simulation.
3. **Model conceptualization or Initial Design:** Construction of the model with determined system boundary, variables, sets, and assumptions.
4. **Data Collection:** Collection of the needed input data.
5. **Model Translation:** Transfer of initial model design to the computer environment via simulation software.
6. **Verification:** Control the program to see if it is working correctly.
7. **Validation:** Control and comparison of the model with the actual data.
8. **Experimental Design:** Determination of the alternative simulations
9. **Production Runs and Analysis:** Production runs and their subsequent analysis.
10. **More Runs:** Check whether additional runs are needed and what design those additional experiments should follow.
11. **Documentation and Reporting:** Documentation of program and progress.
12. **Implementation:** Realizing the simulation outcomes in the real world.

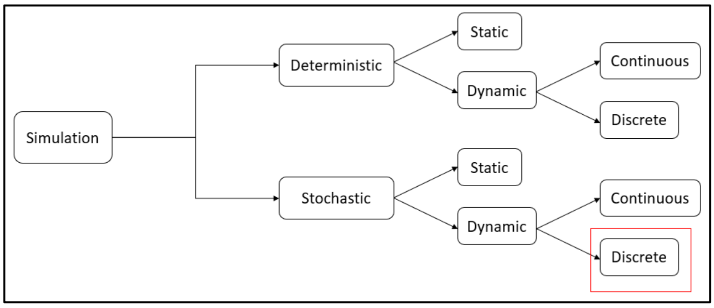


Figure 2.17: Selected Simulation Model Type

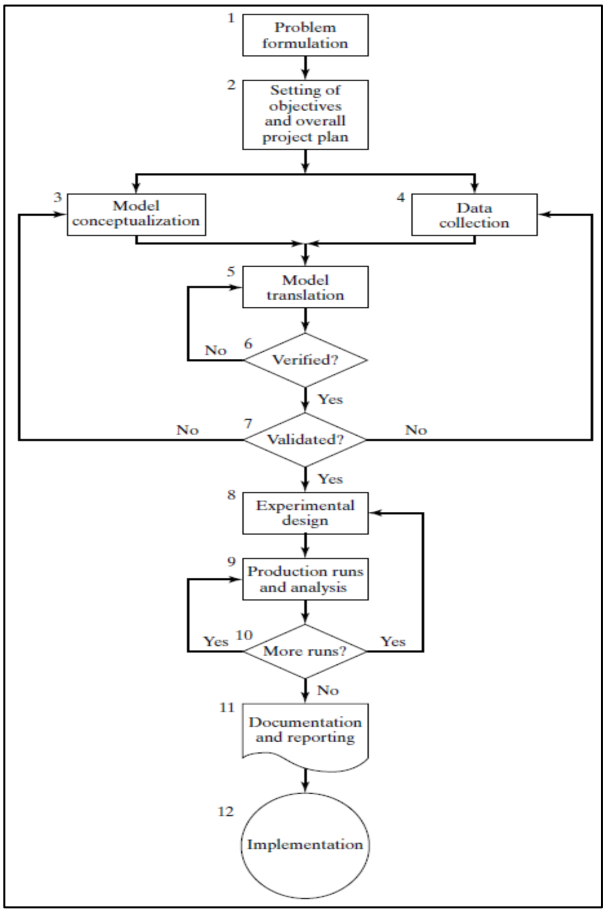


Figure 2.18: Steps in a DES Model Creation (Banks et al., 2014)

DES models are used especially in manufacturing, business processing, construction engineering and project management, logistics, transportation and distribution, military, and healthcare (Banks et al., 2014). In addition, mining is also another field where DES is used extensively due to its adequate coverage of uncertainty and dynamic processes. Equipment selection, comparison and capacity determination, real-time dispatching of truck-shovel systems, management of drilling systems, long-term and short-term production planning and scheduling, maintenance policy determination, and crew optimization are some of the application areas of DES in the mining industry for both underground and surface mining applications. Although reliability and crew optimization topics are vital for the mining industry, since it is not related to the study scope, they are not considered in the literature review.

Ben-Awuah et al. (2010) used the DES to correlate long-term predictive mine plans with short-term production schedules under uncertainty. The constructed model considers constraints and uncertainties associated with mining and processing capacities, crusher availability, stockpiling strategy, and blending requirements. An iron open pit mine case is used to show the model's effectiveness, and the resultant NPV of the simulation is compared with another commercial software. Hashemi and Sattarvand (2015) constructed a DES model for a copper mine. Match factor examination for the trucks and shovels, a dispatching simulation model creation, and ore grade blending consideration were evaluated in the study. It was concluded that a remedial action for production and hauling can improve production rates by 40%. Greberg et al. (2016) used DES to analyze ore transportation from loading points at the lower levels to the existing shaft points using trucks without employing ore passes for an operating underground mine. It is concluded in the study that haulage trucks can be used as a good alternative to the ore pass system for ore and waste transportation. Manríquez et al. (2020) utilized DES to generate short-term production schedules for improving schedule adherence. The study aims to reduce the discrepancy between the planned and actual tonnes in the short-term scheduling periods by considering the uncertainties involved in underground mining operations. The developed model is implemented to a Bench and Fill mine, and the implementation results showed a decrease in the discrepancy. Gölbaşı and Turan (2020) constructed a DES model to optimize maintenance policies for mining systems. The model incorporated corrective, preventive, and opportunistic maintenance concepts and derived comparative scenarios with their resultant cost and availability measures. The developed model was applied to mining shovels and draglines. Uğurlu and Kumral (2020) employed a DES to examine the opportunity of increasing drilling efficiency. In the study, an approach to determine the number of bits required in each period and computing the number of holes to be drilled were handled. Yılmaz and Erkayaoğlu (2021) used DES to investigate shearer performance for a longwall top coal caving operation. The daily coal production amount achieved by the shearer ans total shearer usage times were examined in the study. Gölbaşı and Kına (2022) used DES in developing a microscopic-scale fuel consumption simulator for haul trucks under load and weather uncertainties. The simulation was implemented for a large-scale cement production network where different routes having varying profiles between a clay mine, limestone mine, processing plant, fueling points, and parking spots are available.

To sum up, DES is an effective tool that can be used in different research fields where various uncertainties appearing in system components should be evaluated. To analyze and cover operational level uncertainties in metallic surface mine operations and the dynamic nature of the mining operations, a DES model with a boundary determined by fuzzy fault tree analysis will be developed under the scope of the current study.

CHAPTER 3

PRIORITIZATION OF MINE PRODUCTION PLANNING UNCERTAINTIES FOR METALLIC SURFACE MINES USING FUZZY FAULT TREE ANALYSIS

3.1 Introduction

This chapter presents a fuzzy logic-based prioritization of uncertainties in the production plans of surface mines. The prioritized uncertainty factors will be involved in developing the discrete event simulation, which will be discussed in Section 4. Accordingly, the current section briefly introduces why uncertainty prioritization is required before the simulation part and its proposed methodology. Section 3.2 will detail the preparation and evaluation method of the questionnaire to be used in the analyses. Here, fuzzy logic as the evaluation method of a part of the questionnaire will also be mentioned briefly. Later on, in Section 3.3, the fuzzy fault tree construction will be detailed so that the prescribed method can be implemented for the uncertainty items to measure their effectiveness levels. The last part, Section 3.4, will discuss how the survey results can be integrated into the fault tree by acquiring and evaluating the survey results. Additionally, uncertainty prioritization details are also given in this part.

Even though attentive long-range production plans are conducted in a mining site regarding various uncertainty factors relying on past experiences, there can still be some deviation from the target production amount and the tonnage of the final product in varying ranges since some less frequent but severe risk parameters could be neglected or not detected, or the regarded risk factors are underestimated. Therefore, the risk (uncertainty) factors must be considered holistically to evaluate expected production deviation between long and short-range plans. Since the mining production itself is a highly time-dependent series of sequential events, discrete event simulations can be utilized effectively to understand the stochasticity in the production. However, a production simulation including uncertainty factors without comprehending their effectiveness levels in the deviation cannot be practically beneficial. At this point, before constructing a discrete event simulation algorithm, it can be helpful to prioritize the uncertainty factors to be included in the simulation and estimate their range of effectiveness in the deviations. For this purpose, a questionnaire is conducted with experts highly experienced in the production planning of metallic surface mines and with a decision-making role in case of any positive or negative deviations from the target production.

The questionnaire is constructed in such a way that the participants can give some linguistic expert scores to understand occurrence frequencies (probability of failure) and severity of the uncertainty factors. These scores will be exposed to a two-level analysis. First, they will be evaluated by fuzzy logic analysis considering the participant experience and knowledge weighting factors. Second, the analysis outcomes will be inputted in a constructed fault tree to make a comparative inference on the uncertainty prioritization.

The questionnaire questions are developed following an extensive review of the available literature and annual/quarter reports of companies to branch out the uncertainties that can be observed in the production planning of surface mines. On this basis, the survey questions were classified into five main groups, as given below.

i. Background Information
ii. Geological Concerns
iii. Economical Concerns
iv. Operational Concerns
v. External Concerns

The branching of the question groups and the general framework for evaluating the questions are detailed in Section 3.2. As stated before, the prepared survey was applied to the experts generally employed in the production planning of surface metal mines with varying experience levels. Section 3.3 explains the fuzzy fault tree so that the basic events of the fault tree can be analyzed with fuzzy logic in Section 3.4.

3.2 Preparation of the Questionnaire and Its Analysis Methodology

3.2.1 Preparation of the Questionnaire

Questionnaires are widely used in data collection for social or technical complex systems. The questionnaires should be constructed consistently, and the participants should be selected carefully to produce high-quality data (Marshall, 2005). Accordingly, the questionnaire items under the scope of the current study are grouped into four main categories as geological, economical, operational, and external concerns. In addition, background information of the participants is also asked to evaluate their professional competencies.In this regard, an expert survey employing participants representing surface metal mines production planning and effective in the related decision making process from different companies worlwide, a total of eleven representative responders, was performed to reveal the common understanding on severity and frequency of each uncertainty item on production rate and throughput.

Background information: It is designed to obtain data about the relevancy and competency of the participants by blending the information on their previous experiences with mine planning and the decision-making process of productional deviations. Background information will be used when giving weights to the survey scores of participants by deriving some coefficients. On this basis, various weight rubrics deliver coefficients for expert opinions. For instance, Shi *et al*. (2018) used a 5-score rubric under three categories: participants' titles, service times, and education times, as illustrated in Table 3-1

A representative calculation of the weighting scores for five experts with different professional profiles can be examined in Table 3-2. Here, each expert gets points from the relevant groups according to their titles, service times, and education levels, resulting in a total score for the expert. Then, the weighting score is calculated by dividing the total expert point by the cumulative expert points.

Table 3-1. A Rubric for the Weighting Scores Offered by Shi et al. (2018)

Constitution	Classification	Score
Title	Senior academic	5
	Junior academic	4
	Engineer	3
	Technician	2
	Worker	1
Service Time	≥ 30 years	5
	20-29	4
	10-19	3
	6-9	2
	≤5	1
Education Time	PHD	5
	Master	4
	Bachelor	3
	HND	2
	School level	1

Table 3-2: Weighting Score Calculations for Different Experts (Shi et al., 2018)

No. of expert	Title	Service time (Year)	Education level	Weight factor	Weighting score
1	Senior	≥ 30 years	PHD	5+5+5=15	15/57= 0.263
2	Senior	6-9	PHD	5+2+5=12	12/57= 0.211
3	Junior	10-19	Master	4+3+4=11	11/57= 0.193
4	Engineer	10-19	Master	3+3+4=10	10/57= 0.175
5	Technicist	20-29	Bachelor	2+4+3=9	9/57= 0.158

Different weighting score rubrics are available in different studies, as shown in Table 3-3 and Table 3-4.

Table 3-3: Weighting Score Rubric by Cheliyan and Bhattacharyya (2018)

Attributes				Weight
Title/ Designation	Experience in Years	Education Level	Age in years	
Professor / Senior Manager	≥ 30 years	Doctoral	>50	5
Associate Professor / Manager	20-30	Masters	40-50	4
Asst. Professor / Asst. Manager	10-20	Bachelors	30-40	3
Lecturer / Sr. Officer	5-10	Technical	25-30	2
Worker / Officer	< 5	Graduate	<25	1

Table 3-4 Weighting Score Rubric by Mottahedi and Ataei (2019)

Condition	Classify	Score
Profession position	Senior academic	5
	Junior academic	4
	Engineer	3
	Technician	2
	Worker	1
Job experience	≥ 30 years	5
	20-29	4
	10-19	3
	6-9	2
	≤5	1
Education	PHD	5
	Master	4
	Bachelor	3
	HND	2
	School level	1
Age	>50	4
	40-49	3
	30-39	2
	<30	1

Title (position), experience (service time), and educational level are observed to be common for all three rubrics. Age item is also included in the last two rubrics. Accordingly, the current study will ask for background information from the participants to characterize their eligibility and competency in the survey scores. At this point, the experts will be enumerated anonymously by hiding private information. The rubric used in this study is discussed in Section 3.2.2 and can be viewed in Table 3-6. In addition to background information, expert-based questions are asked in four groups entitled geology, economy, operation, and external, as detailed below.

Question Group01 – Geology:

Geology-related uncertainties have frequently been attracted in the literature on surface mine planning. Ajak et al. (2018) stated that geological uncertainties develop inherent risks to all mining projects and lead to primary sources of uncertainties in the mining projects. Accordingly, various research studies discuss geological uncertainties, especially in strategic mine planning, and mention that a noticeable improvement in the NPV and planning of mining projects can be achieved by controlling and monitoring geological risks. In brief, geology-based uncertainties are one of the main drivers that contribute to the discrepancy between long and short-range plans, and they can be evaluated in five main sub-categories as variation in grade, tonnage (cut-off grade and specific gravity), metallurgical parameters, lithology, and geotechnical and hydrogeological parameters.

Group01-1: Variation in grade (Metal Content)

The grade values in production blocks are estimated using interpolation techniques such as distance weighting or geostatistical methods to achieve spatial grade distribution in an ore deposit (i.e. block model (BM)). The estimations use the actual but restricted data derived from the drill holes. Even though the drill holes are tried to be located with proper spacing and orientation in a way to represent the ore deposit, the long-term production plans using these estimations can deviate from short-term plans since ore-control results of daily samples can be quite different from the expectations due to increased sample numbers and decreased sample intervals. Dimitrakopoulos et al. (2002) showed that BM produced with traditional geostatistical methods generally leads to unrealistic forecasting of NPV, mine design, ore production performance, and ultimate pit limits. Based on the study, NPV relying on traditionally produced BM has a 2-4 % probability of fiting into reality. In a later study, Dimitrakopoulos (2011) further detailed the involvement of grade uncertainty in strategic open pit production planning and stated that grade uncertainty consideration is a necessity to reduce risk on production plans and to produce more reliable plans. Thus, grade uncertainty is included in the survey.

Group01-2: Variation in tonnage (or in cut-off grade or specific gravity)

Tonnage variation in the ore is another parameter that must be considered. It becomes visible in the modeling phase or when estimating specific gravity or calculating the cut-off grade. In common applications, orebody modeling is achieved with two methods. These methods are implicit and explicit modeling, and both are susceptible to human interaction and open to error.

Eventhough people who have long-time professional experience conduct the operation, there is always a risk of misjudgment. Therefore, the total tonnage can deviate due to estimation errors in the modeling phase or density assumptions. For a mining operation, certain material classifications are achieved depending on its purpose. Ore/waste distinction is one of them and is achieved via the setup of a parameter called the cut-off grade. Cut-off grade calculation is based on certain assumptions, calculations, and managemental decisions. Asad and Dimitrakopoulos (2013) defined the optimal cut-off grade strategy as maximizing the NPV of an open pit mining operation subject to the mining, processing, and marketing/refining capacity constraints. Materials having grades greater than or equal to the cut-off grade are regarded as ore, while smaller values are regarded as waste. The total amount of material above the cut-off value contributes to reserve tonnage. In the literature, there are studies about the uncertainty of cut-off grades, such as Asad and Dimitrakopoulos (2013) and Birch (2017). Overall, tonnage variation is also a topic that needs to be addressed in the questionnaire.

Group01-3: *Variation in metallurgical parameters*

Generally, the ultimate goal for metallic mining projects is to produce metal above the target degree of purity. Metal production is performed in processing plants using certain enrichment operations. Such enrichment operations usually require specific metallurgical parameters at a certain range of values for the feeding to the plant. On this basis, ore materials are blended to meet the requirements. Metallurgical parameters like grade, are also regionalized attributes of the deposit and are assigned with certain assumptions, models, and estimations over samples taken from different parts of the deposit. In an illustrative study, Rahmanpour and Osanloo (2016) developed a stochastic optimization model to reduce underproduction probability sourced from quality deviation in the plant feed. The system developed in the study is defended to reduce the underproduction probability from 87% to 13%. Since the value range of metallurgical parameters is crucial for processing operations, uncertainty on metallurgical parameters is vital for predictable continuity of a mining project. Thus, variations in metallurgical parameters are needed to be addressed in the questionnaire.

Group01-4: Variation in lithology and/or the rock type

Earth's crust consists of different minerals and rocks. From a mining perspective, these minerals have different chemical and mechanical properties, which may cause deviation in the dominant lithological properties that need to be regarded in mineral processing operations and the safety of the mining structures. Since lithological assignments are achieved with assumptions, modeling, and estimations from samples, there is uncertainty involved in the process. Therefore, the effectiveness of lithology and/or rock type on production plans is also addressed in the questionnaire.

Group01-5: Variation in geotechnical and hydrogeological parameters

Structural safety in mining operations is driven by the mechanical properties of available rock formations of pit walls and their behaviors under different loading conditions with or without the presence of water. Geotechnical parameters are assigned for the intact rocks or the rock masses after laboratory or field tests. Hydrogeological parameters are also assigned for the area under consideration. These tests are performed with the samples considered to be representative of the whole deposit. However, deviations from these parameters are often observed in the fields in the form of different scales of failures. Such failures can cause severe results for mining operations. Therefore, the deviation in production plans should be evaluated with geotechnical and hydrogeological parameters.

Question Group02 – Economy:

There is a balance between the demand and the supply of goods that designates the price in the market. Price is prone to increase if demand is increased or the supply is decreased and to decrease if demand is decreased or the supply is increased in ceteris paribus. Uncertainty of economic parameters in surface mine planning is observed to be discussed and studied from different perspectives. Supply, demand, and commodity price uncertainties have been regarded extensively for strategic mine planning. Although economic parameters can be classified under external factors since external authorities govern them in most studies (such as Ajak et al., 2019), economic factors are considered individually as a group other than the external group due to their importance for mining projects. Ramazan and Dimitrakopoulos (2013) considered the uncertainty of supply and claimed that a gold project's 10% increase in NPV can be achieved by incorporating supply uncertainty into production schedules. In another study, Senécal and Dimitrakopoulos (2020) considered the supply uncertainty to produce more stable plans over time. In addition, Chatterjee et al. (2016) evaluated the effect of commodity price uncertainty on the ultimate pit boundary problem solution. It was claimed that an increase in the NPV of an iron ore project by 48% could be achieved by including the price uncertainty. Some other studies have also investigated the combined effects of the uncertainty items. For example, Asad and Dimitrakopoulos (2013) assessed the joint effect of supply and demand uncertainties of the final product on the open pit mine design process. In addition to the effects of market price fluctuations over the production planning stages, variations in the values of mining and processing cost, and changes in the exchange rate can be other factors causing deviations from long to short-range production planning. In conclusion, uncertainties about economic parameters are considered in the literature remarkably, and recognition of these uncertainties in the planning stage is expected to contribute to the economic indicators of the mining project observably. Hence, economy-related uncertainties are given as follows.

Group02-1: Variation in the selling(market) price of the product

The commodity price is the selling price of the end product of a mining operation. It drives the company's income; therefore, the operation's cash flow is highly dependent on the commodity price. Most of the operations worldwide are highly sensitive to the commodity price. Although companies take precautions against fluctuations in commodity prices, severe price drops over a long time can turn feasible mining operations into unfeasible ones. On the contrary, severe increases in the selling price of a commodity can allow unfeasible operations to be realized or prompt capacity increments. It is concluded that mining industry investments are highly sensitive to commodity price movements (Kim et al., 2023). As an illustration, Shafiee and Topal (2010) presented an example of the metal price drop in 2008 and early 2009. It was stated that many metal mining companies had difficulties in sustaining their operations, and some of the companies had to reduce their production rates. All in all, commodity price is one of the most critical parameters in a mining operation and should be analyzed attentively to see whether strategic or short-term plans deviate from the targets due to fluctuations in commodity price. It should be noted that fluctuations in demand and supply for a commodity are regarded as joint contributors to the price, so they will not be considered separately in the other parts of the questionnaire.

Group02-2: Variation in operations and extraction cost

In general, the cost is the financial item used to refer to the expenses of a mining operation that can be divided into capital and operating costs. Capital cost is defined as the expense incurred in buying and installing fixed capital items like machinery, buildings, and site development. On the other hand, operating cost is the day-to-day expense incurred in running an operation. The total cost can also be expressed as the summation of these fixed and variable costs, where fixed cost is the cost that does not rely on production or sales levels like rent, property tax, and insurance. In contrast, variable cost is the cost that appears for the production like material purchases and is expressed mostly as per unit of product (Demirel and Güyagüler, 2008). Since capital cost is generally more predictable and not continuously spent over production time, operating cost and its associated uncertainty are more important for the cash flows of the mining operations and prone to uncertainties. Therefore, uncertainties on variable expense items in the mining operations and extraction costs are decided to be included in the questionnaire to understand their effects on production plans.

Group02-3: Variation in foreign exchange rates

Exchange rates are used to convert currencies to each other and are one of the indicators of the country's stability and economic reliability. For companies operating in undeveloped or developing countries, the local currency's stability against US$ plays a vital role in the financial predictability of projects. Revenue and operating costs currency units can be quite different from each other. Even though the selling price of the final or by-products of mining companies are rated in US$, their operating costs are generally estimated considering local currency. For example, 100,000 TL expense in August 2020 was equal to 14,286 $; however, it was equal to 5,556 $ in August 2022. As seen from the example, foreign exchange rates need to be evaluated for the long-term predictability of NPV. Therefore, its effect on production planning deviations is also analyzed under the scope of the questionnaire.

Question Group03- Operation:

Operational plans in open pits are short-range plans, and they differ from long-term plans in terms of the type and/or size of the used Block Model (BM), discretization of time, objectives, constraints, and the level of detail. BM used in strategic planning consists of mostly millions of blocks of the whole economic orebody, but BM used in operational plans consists of related portions of the orebody. Time discretization is in the shift, day, week, or month levels for short-term planning; however, it is in the degrees of month, quarter, or year for the long-term scale. Short-term planning generally intends to satisfy the total mine production and the plant feed, maximizing equipment utilization, minimizing the rehandling, and minimizing the cost. In this level of detail, truck and shovel movements, allocation, and dispatching play crucial roles, as the main constraints of a short-term plan. On the other hand, long-term plans generally aim to maximize the NPV of the project and minimize the cost. Equipment and plant capacities, blending for the plant feed and the waste dump (generally, it is the case for mines producing sulfide ore), and environmental and/or operational safety are the main constraints for long-term plans (Blom et al., 2019). Cumulative of the short-term production amounts and throughputs of processing plans for the related period is asked to serve the previously determined long-term plans.

Although mine operations need to be modeled and analyzed attentively, their associated uncertainties have been less studied in the literature. At the operational plan level, different sources of uncertainties, including geology, economy, and operations (uncertainty in cycle time, productivities, availabilities, and reliabilities) (Blom et al., 2019), can be considered. Soleymani and Benndorf (2016) evaluated the effect of geological uncertainty on pre-defined KPIs of a short-term plan. The method developed in the study is stated to forecast critical situations affecting the continuous supply of raw materials to customers and the system's performance. Li and Knights (2009) considered the fuel price uncertainty in their study for operational mine planning, which profoundly affects shovel-truck system costs and the mining economy. Since tactical-level uncertainty factors of geology and economy are already considered in the earlier sections, operation-related uncertainties are the target of this part. Tokamani and Askari-Nasab (2015) constructed a DES model for operation-related uncertainties in short-term planning for a shovel-truck system. In brief, uncertainty determination on operational parameters is beneficial to be considered in the questionnaire with the branches discussed below.

Group03-1: *Variation of workforce efficiency*

Although the mining industry has become more machine-intensive in recent decades, workforce efficiency still plays a decisive role. The workforce is used not only for force-required jobs but also to drive and/or control heavy-duty equipment. An efficiency rating is estimated to represent how the workforce is expected to be operated during the plan preparation phase. However, most of the time, deviations occur from the estimated efficiency level due to numerous reasons, which need to be considered in the plan preparation period. Therefore, variation in workforce efficiency is decided to be considered in the questionnaire.

Group03-2: *Variation of mining equipment efficiency*

Surface mining operations heavily rely on the reliability and maintainability of the equipment with a high production capacity. Main production equipment is generally responsible for drilling, excavating, and hauling waste or ore material. Auxiliary equipment is also important; they assist in the smooth and safe operation of the main equipment. For example, loaders, graders, and rollers maintain haul roads on which off-highway trucks operate, where dozers are employed to provide an even ground and advance in waste dumps. Hence, auxiliary equipment is as essential as the main production equipment to continue mining operations safely and effectively. Efficiency assignment is also performed for the mining equipment in the planning stage that relies upon certain assumptions which can change over time. Thus, changes in mining equipment efficiency should be considered in the questionnaire since all mining projects include a considerable number of equipment in varying types.

Group03-3: *Variation of mining equipment availability*

The availability of the mining equipment is correlated with the efficiency of the maintenance policy applied in the mining site. Maintenance is achieved in three common ways; corrective, preventive, and opportunistic. Corrective maintenance is performed when the system/equipment is down, while preventive maintenance is organized to reduce system/equipment halts by setting preventive component replacements and/or repairs. As a third type, opportunistic maintenance is considered to allocate preventive maintenance for non-failed components of the halted systems. The long-term planning team considers expected maintenance hours for all equipment/systems to calculate the availability factors for each. The calculated availability factor can change over time due to deviations in the base assumptions, which makes the equipment availability factor to be regarded as an uncertain item. Hence, it should be considered in the questionnaire as well.

Group03-4: *Variation in equipment allocation (spatial plan compliance)*

The equipment allocation topic has been discussed in the literature from different perspectives. Matamoros and Dimitrakopoulos (2016) considered the mining fleet allocation and developed a stochastic approach to optimize fleet and production, which resulted in lower cost, minable patterns, and efficient fleet allocation, ensuring higher and less variable utilization of the fleet. Upadhyay et al. (2021b) considered the allocation of shovels to mining faces using a MIP model. In addition to fleet allocation and shovel assignment to the working phases, determining the faces that need to be worked is also a source of uncertainty. It can cause deviation in either production rates or plant feed quality and quantity. With the increased plan resolution, the number of blocks to be scheduled increases; therefore, blocks are aggregated into mineable cuts depending on the scale of the plan to realize the solution. This aggregation is higher for long-term scheduling. For example, a whole bench can be a mining cut for LOM planning, but a couple of blocks can be the mining cut for daily/weekly planning. Production of the whole bench might take several weeks or months, so how this bench should be produced is the topic of a shorter-range plan. It can affect the KIPs of the planned long-term period, such as total plant feed and grade. Depending on the conditions in which the short-term plan is produced, the face position can deviate from the areas foreseen to be produced by long-term plans. Therefore, such differences can cause deviations from the target and should be considered in the questionnaire.

Group03-5: *Variation in weather forecasts*

Unlike underground operations, surface mining operations are open to the atmospheric condition that affect the operations. Although weather forecasts are available, they do not always offer an accurate level of estimation for mining operations. Weather forecast variations on which plans are constructed can cause production rate and product quality deviations. For example, road conditions can worsen due to heavy rain; but if road maintenance teams are ready to maintain and prepare the roads on time, time loss can be avoided. However, if the forecasts deviate, the team will not be ready, and production losses are observed due to the limited mobility of trucks with increased cycle times. Therefore, uncertainties in weather forecasts should also be considered in the questionnaire.

Group03-6: *Variation in mineral processing parameters and requirements*

Reserve parameters rely on samples taken from different resource locations with some particular assumptions. All feasibility studies are constructed on these estimations, and mining facilities, equipment, mineral processing facilities, and equipment are selected based on these reserve parameters. As discussed earlier, metallurgical parameters, lithology, and ore quality deviations are experienced when the exploitation is started. Consequently, the plant might not work as designed or require additional constraints not foreseen in the design process. Therefore, the feed requirement of the plant can change over time, although it is not considered in the long-term planning phase. Therefore, this aspect is decided to be included in the questionnaire for a holistic evaluation of the production planning deviations regarding both mining and milling considerations.

Group03-7: *Variation in unit production cycle activities*

The production cycle consists of some unit operations in surface mining operations. Depending on the company policy and ore complexity, additional unit operations may be available, but basic unit operations include drilling, blasting, loading, and hauling. The cycle starting with drilling and ending with hauling and dumping, is repeated for every production location almost every day. Such a cycle also requires interactions with professionals with different expertise, requiring high levels of communication, collaboration, and discipline. A delay or a productivity variation in one of them can affect the whole process since they are all dependent and sequential activities, resulting in production deviations due to delays. Accordingly, delays and/or deviations in the unit production cycle activities are included in the questionnaire.

Group03-8: *Variation in corporate communication efficiency*

Mining activities are engaged with each other with different but bounded work packages that different departments or sub-departments of the main and contracted companies should fulfill. Therefore, there should be a well-defined vertical and horizontal communication structure that should ensure proper managemental and technical flow. On the other hand, improper communication flow may cause descending efficiency and a lack of good information transition inside or between the divisions, resulting in a drop and interruption in production. For instance, a standard surface mining operation cycle combines the work that should be completed sequentially by the drilling, blasting, loading, and hauling divisions, where operators and administrators of each division can be separated for micro-effective control. However, they depend highly on each other regarding their duties and work efficiencies so that any communication problem may halt the whole system. As another example, any communication problem between long-term and short-term planning staff can cause misunderstanding of each other and result in a problem in the quantity or quality of the ore to be produced. Therefore, different parties of an organization are responsible for the employment of effective communication and quality control, not to interrupt operations. Therefore, communication efficiency is also considered in the questionnaire.

Question Group04- External:

High capital-required projects like mining operate over long periods. Since the durations of such projects are long, the involvement of uncertainties driven by internal or external factors is observed (Kazakidis, 2001). Such uncertainty factors result in deviations from the expected economic returns for most mining projects. Internal factors are either foreseen with higher accuracies or revealed better when the detail level increases. However, most of the external uncertainty factors are tough to be quantified with certain confidence levels since they can also be driven by external authorities unpredictably. Furthermore, although companies can evaluate internal factors with their severity and frequency levels, there is a lack of complete control over external factors since various types of local, national, or international authorities can be involved in the existence of an external event that can be effective in production plan deviations.

Previously-discussed uncertainties mainly related to geology and operation can be regarded as internal. On the other hand, external factors can be detailed under environmental, governmental, industrial, legislation/regulation, market price, political, and social aspects (Ajak et al., 2019) or market price, industrial relations, legislation/regulation, country stability, government policy, social issues, and environmental issues (Mayer and Kazakidis, 2007). The current research study will evaluate external uncertainty factors as i) community relations, ii) permit, legislation, and regulation, iii) political stability, iv) force majeure events, and v) environmental and other OHS-related issues. Although financial uncertainty factors such as commodity price, cost items, foreign exchange rate, and discount rate are also valued externally, in this study, they are evaluated under Group02- Economy to avoid underrating these factors and highlight their crucial effects on production.

Generally, external factors are underestimated or neglected during long- and short-term production planning stages. However, they can result in catastrophic damage to production. Predicting their occurrence and severity characteristics in mine production planning can be highly useful in developing a holistic approach. Details of the external uncertainties included in the questionnaire are given as follows.

Group04-1: *Variation in community relations assumptions*

As a sustainable development goal, most mining companies would like to continue their operation with the high acceptance, involvement, and development of local communities living in the mining area and close-by areas for a long time. However, some arguments or disassociations between locals and mine management might exist. In such cases, quantitative and qualitative drops in production can be observed depending on the duration and extent of the arguments or disassociations. These types of production halts are neglected in the planning stage; however, it is included in the questionnaire to quantify the effect of such cases on mining operations.

Group04-2: *Variation in the permit, legislation, and regulation assumptions*

Every mining company needs different types of permits to be authorized to operate in the area. To get such approval from the host government, the company needs to obey and follow certain rules, legislation, and regulations set by the related organizations of the host government. To be dissuasive, the host country can apply some financial and operational penalties when the rules are not followed properly. Such penalties can deeply affect the company's cash flow if production is interrupted or a delay on any permit is available. Therefore, variation in the permit, legislation, and regulation assumptions can be critical for the mining companies, and it is raised in the questionnaire with a related question.

Group04-3: Variation in the political stability assumptions

Countries have different levels of development and political stability due to their backgrounds, the structure of the society, and economic wealth. Different organizations measure the level of development and political stability with different ranking systems and variables. As an example, the World Bank provides a public database. Different subject-related data can be found in the database, such as World Development Indicators, Education Statistics, Gender Statistics, and Health Nutrition and Population Statistics. Such factors are considered, especially in the feasibility study stage of the project. For countries with higher political risks, companies are prone to desire higher profit levels than stable countries due to the possibility of even losing the operation permits with the high risk and uncertainty involved. Thus, political uncertainties are critical for mining ventures, which should be included in the questionnaire.

Group04-4: Variation in the force majeure assumptions

Force majeure is used for an event that can be realized due to uncontrollable or unpredictable circumstances, resulting in catastrophic results. Some of these events that will trigger a Force Majeure are war, terrorist attacks, strikes, pandemics, or natural disasters. Among them, natural hazards are natural phenomena like earthquakes, floods, avalanches, and drought, affecting not only the living creators but also the environment and structures. In the designing phase, predefined natural hazards are considered with their possible destructive effect on the structures. Additionally, there should be plans considering the occurrences of such events to forecast the effect of the realization. Certain measures should be taken, and alternative schedules should be prepared in the designing phase. As well known, events ending up with a force majeure have uncertainty about the hazards' time, magnitude, and exact location. Therefore, the questionnaire should consider uncertainties about such events to catch their effect on the mine production targets.

Group04-5: Variation in environmental and other Occupational Health and Safety(OHS)-related issues

In a mining area, there can happen a wide range of unwanted events with varying consequences in terms of health, safety, damage to physical assets, damage to the environment, effect on corporate image, effect on local or national community obligations and penalties according to national regulations, financial loss of productional interruption, and loss of value of a market share. Since any unwanted event may cause a single or multiple of these consequences, not all events may result in a shortage in production. The length of shortage can be affected by technical, site managemental, and external auditing aspects. For instance, if a bench-scale slope failure happens in the production area, the failed zone should be removed technically after an internal site investigation to re-prepare the area for production. Besides, this recovery process should be managed by attentively-prepared emergency response action plans and should be recorded and reported. In addition to these internal activities, external authorities can demand the completion of their inspections regarding their work schedule to allow reinitiating production. Even though the area is re-prepared for production, there can be an extended period of delay due to extended time of external investigation and approval for operation. Although technical and site managemental aspects are internal, they are also affected remarkably by external decisions and attitudes of these external authorities. Therefore, unwanted events considered under the scope of health, safety, and environment (HSE) that can result in production loss are regarded as an external uncertainty factor and included in the questionnaire.

As given in detail, uncertainties in mining operations arise from different sources that can trigger dependently or independently of each other. In this study, these sources are grouped into four main topics as summarized in Figure 3.1.

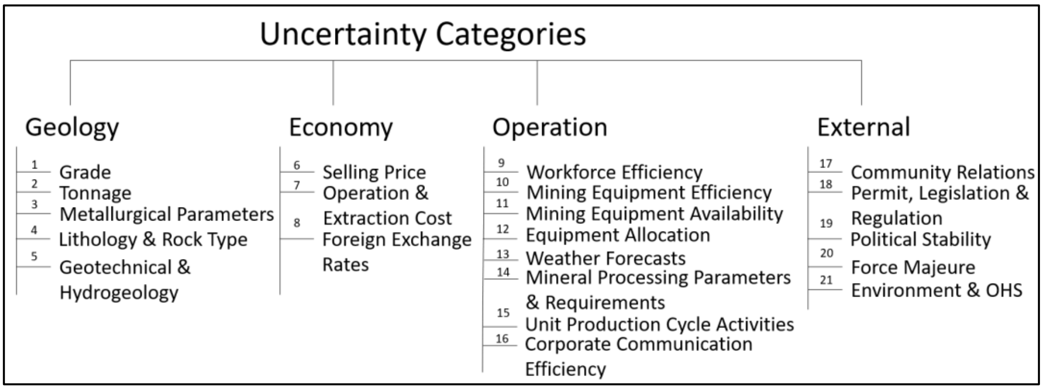


Figure 3.1. Uncertainty Categories of the Study

Within the scope of the questionnaire, two types of data can be collected to evaluate the priorities and levels of the uncertainties listed above: Objective data that can be gathered from particular operations and subjective data that can be obtained from the people experienced in mine planning. Since objective data can be site-specific without offering any holistic acceptance for the surface metallic mines with variety in geology, economic conditions, the operational environment, and external factors, subjective expert data was decided to be assessed under the scope of this study. Therefore, for a more collective and comprehensive evaluation of the uncertainties without bounding the study with a particular site, multiple experts from different mining sites of worldwide surface mining operations were informed about the questionnaire and asked to respond to the questions according to their experiences.

It is a common application in the literature to apply linguistic expressions in responses to the questionnaire questions and elaborate the responses according to the weighting scores of the participants based on some predetermined weighing criteria, as mentioned in Tables 3.1 to 3.4. Evaluation of the linguistic responses and aggregation of all experts to have a common conclusion on the uncertainties will be discussed in detail in Section 3.4.1. The evaluation will be performed using fuzzy logic and some probabilistic outcomes will be derived from the analysis to generate inputs for the fault trees. In this way, a priority matrix of uncertainties that measures their individual effects on the top event, which refers to the deviation between long and short-range production plans, will be achieved. The questionnaire is also decided to include some quantitative parts in addition to the qualitative linguistic responses. Accordingly, the occurrence frequency and the severity of each uncertainty item were asked to be answered according to their minimum, most expected, and maximum occurrence conditions. This quantitative part will be used in the event simulation, which will be discussed in Chapter 4, to generate random values on their occurrence times and their dependencies with the other operational aspects.

In brief, the questionnaire was prepared in a way that two main sections for each uncertainty should be filled using qualitative (linguistic part to be evaluated using fuzzy logic for fault tree analysis to prioritize the uncertainties) and quantitive (frequency and severity parts to be evaluated using statistical tools to generate random values later on within the event simulation model) responses. Table 3-5 illustrates the questionnaire window where some drop down menus of some uncertainty items are visible. In addition, representative views of the questionnaire window presented to the responders are added to the Appendix A.

Table 3-5. A Representative Illustration of the Questionnaire Questions

QUESTION GROUP	QUESTION ID	QUESTION	RESPONSE TYPE
G1 BACKGROUND INFORMATION			
G1Q1 Background Information	G1Q1.0	Name and Surname	Short Free Text
	G1Q2.0	Age	Short Free Text
	G1Q3.0	Educational Level	List (Dropdown)
	G1Q4.0	Professional Experience in Surface Mine Planning	Array of Experiences (Text)
G2 GEOLOGICAL UNCERTAINTIES			
G2Q1 Grade Uncertainty	G2Q1.1	Deviation in grade causes a change in either the short-term production plan or the plant feed plan *...linguistic variable...*	List of Linguistic Variables (Dropdown)
G2Q2 Tonnage Uncertainty	G2Q1.2	Deviation in grade causes a change in either the short-term production plan or the plant feed plans every *...# of day to the below table...*day.	Array of Lowest, Most Expected, and Highest Values (Text)
G2Q3 Metallurgical Parameters Uncertainty	G2Q1.3	In cases where the short-term production plan or the plant feed plan is affected by the deviation in *grade*, what is *the amount of this deviation in percent* you experienced before? (can be positive or negative)	Array of Lowest, Most Expected, and Highest Values (Text)
G2Q4 Lithology/Rock Type Uncertainty			
G2Q5 Geotechnical and/or Hydrogeological Parameters Uncertainty			
G3 ECONOMICAL UNCERTAINTIES			
G3Q1 Commodity Price Uncertainty	G3Q1.1	Deviation in commodity price causes a change in either the short-term production plan or the plant feed plan *...linguistic variable...*	List of Linguistic Variables (Dropdown)
G3Q2 Operation and Extraction Cost Uncertainty	G3Q1.2	Deviation in commodity price causes a change in either the short-term production plan or the plant feed plans every *...# of day to the below table...*day.	Array of Lowest, Most Expected, and Highest Values (Text)
G3Q3 Foreign Exchange Rates Uncertainty	G3Q1.3	In cases where the short-term production plan or the plant feed plan is affected by the deviation in *commodity price*, what is *the amount of this deviation in percent* you experienced before? (can be positive or negative)	Array of Lowest, Most Expected, and Highest Values (Text)

Table 3-5. A Representative Illustration of the Questionnaire Questions (cont'd)

QUESTION GROUP	QUESTION ID	QUESTION	RESPONSE TYPE
G4 OPERATIONAL UNCERTAINTIES			
G4Q1 Workforce Efficiency Uncertainty	G4Q1.1	Deviation in workforce efficiency causes a change in either the short-term production plan or the plant feed plan *...linguistic variable...*	List of Linguistic Variables (Dropdown)
G4Q2 Mining Equipment Efficiency Uncertainty	G4Q1.2	Deviation in workforce efficiency cost causes a change in either the short-term production plan or the plant feed plans every *...# of day to the below table...*day.	Array of Lowest, Most Expected, and Highest Values (Text)
G4Q3 Mining Equipment Availability Uncertainty	G4Q1.3	In cases where the short-term production plan or the plant feed plan is affected by the deviation in *workforce efficiency*, what is *the amount of this deviation in percent* you experienced before? (can be positive or negative)	Array of Lowest, Most Expected, and Highest Values (Text)
G4Q4 Equipment Allocation Plan Uncertainty			
G4Q5 Weather Forecast Uncertainty			
G4Q6 Mineral Processing Parameters and Requirements Uncertainty			
G4Q7 Unit Production Cycle Activities Uncertainty			
G4Q8 Corporate Communication Efficiency Uncertainty			
G5 EXTERNAL UNCERTAINTIES			
G5Q1 Community Relations Uncertainty	G5Q1.1	Deviation in community relations causes a change in either the short-term production plan or the plant feed plan *...linguistic variable...*	List of Linguistic Variables (Dropdown)
G5Q2 Permit, Legislation, and Regulation Uncertainty	G5Q1.2	Deviation in community relations causes a change in either the short-term production plan or the plant feed plans every *...# of day to the below table...*day.	Array of Lowest, Most Expected, and Highest Values (Text)
G5Q3 Political Stability Uncertainty	G5Q1.3	In cases where the short-term production plan or the plant feed plan is affected by the deviation in *community relations*, what is *the amount of this deviation in percent* you experienced before? (can be positive or negative)	Array of Lowest, Most Expected, and Highest Values (Text)
G5Q4 Force Majeure Uncertainty			
G5Q5 Environmental and OHS Uncertainty			

3.2.2 The Questionnaire Analysis Methodology

As mentioned in Sections 2.4.3 and 2.4.4, the fault tree method integrated with fuzzy logic analysis will be used to evaluate the questionnaire results. Conventional fault tree basic events require using exact values; however, integration of fuzzy logic allows the usage of a fault tree when there is no or enough data to determine and introduce the failure rate of the basic events with collected expert data. First, a conventional fault tree should be constructed, as will be detailed in Section 3.3. Then, fuzzy logic results will be input into the conventional fault tree. The ultimate purpose of the current section is prioritizing, ranking, and quantifying the uncertainty items to be regarded in the discrete event simulation. Therefore, the steps below are followed in the evaluation of the questionnaire that requires linguistic responses:

Step 1: Weighting factor determination for each participant
Step 2: Fuzzy number type and linguistic variable determination
Step 3: Membership function determination
Step 4: Fuzzification and fuzzy aggregation
Step 5: Defuzzification
Step 6: Conversion of fuzzy possibilities to fuzzy failure probabilities

Step 1. *Weighting Factor Determination*: Although the eleven participants are selected from people who are experts in surface mine planning, their background, working experiences, and their approaches to different cases show variations. Therefore, certain weighting factors will be assigned to each expert when weighing their responses to the questions. There are various studies using similar weighting factors (Liu et al., 2012; Cheliyan and Bhattacharyya, 2018; Shi et al., 2018; Suh et al., 2021). Different attributes of experts are evaluated to achieve the weightings. The most commonly used attributes used are title/position, experience (total years), education level, and age (in years), as detailed in Section 3.2.1. When the participant profiles are examined, it is observed that the vast majority have BSc degrees; just one expert has a Ph.D., and one has an M.Sc. degree. Therefore, excluding the educational degree, current professional title, experience in mine planning, and age are decided to be used in the expert weighting process. 5-score weights are used for each attribute, where scores of 1 and 5 refer to the maximum and minimum contribution to the weighting score of each attribute, respectively (Table 3-6). For instance, a participant with a senior mine planning manager title, an experience of over 25 years, and an age over 50 will have a total score of 15.

Table 3-6: Expert Weighting Factors of the Study

Attributes			**Weight**
Title	**Experience in Years**	**Age in years**	
Senior Mine (Planning) Manager	≥ 25 years	>50	5
Mine (Planning) Manager	20-25	40-50	4
Mine Planning Superintendent	10-20	35-40	3
Mine Planning Chief/ Senior Mine Planning Engineer	5-10	30-35	2
Mine Planning Engineer	< 5	<30	1

The years of experience of the eleven participants can be observed in Figure 3.2. The data are clustered as <5, [5, 10), [10, 20), [20, 25), and >=25.

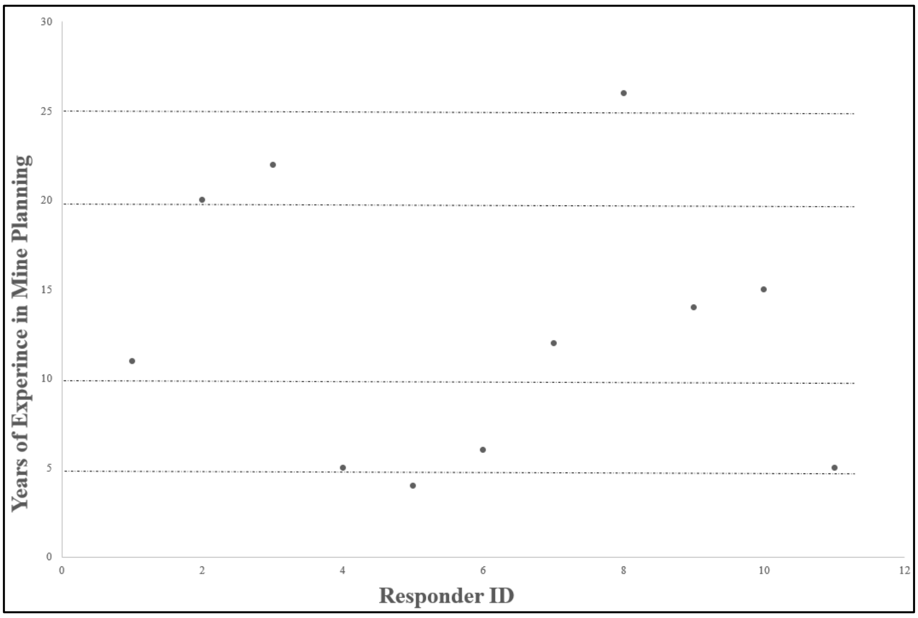


Figure 3.2: Available Data of Experience in Mine Planning

To determine the age extremes, the age information of the junior engineers in the mining sector was concluded by statistical evaluation of 520 people who graduated from a mining engineering department between 2010 and 2022. The statistical outcomes determined a lower bound for the starting employment age to be used in Table 3-6. Accordingly, the data was first exposed to outlier testing via box and whiskers analysis, as illustrated in Figure 3.3. Outlier values are extremely high and low values that can disturb the general behavior of the dataset. The data out of the whiskers can point to the outlier availability and may need elimination from the data.

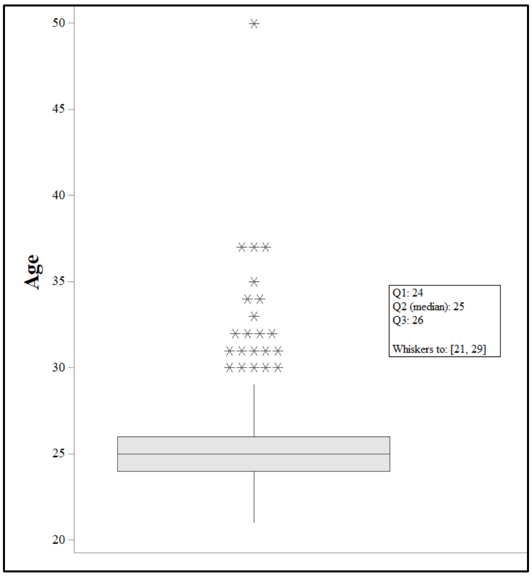


Figure 3.3: Box and Whiskers Plot of Available Data for Age

After eliminating twenty-two outlier values from the data set, the age histogram of the freshly graduated mining engineers is obtained in Figure 3.4. Owning symmetrical behavior in frequencies, normal distribution was fitted into the values with a mean value of 25.1 and a standard deviation of 1.6. It can be concluded that the average graduation age is 25, and a mining engineer with five years of experience is assumed to be around 30 years old. Therefore, the equivalence of <5 years experience was taken as < 30 years old as the minimum extreme of the age attribute in Table 3-6. Regarding the questionnaire data, the remaining extremes are also assigned for the final table of weighting factor determination.

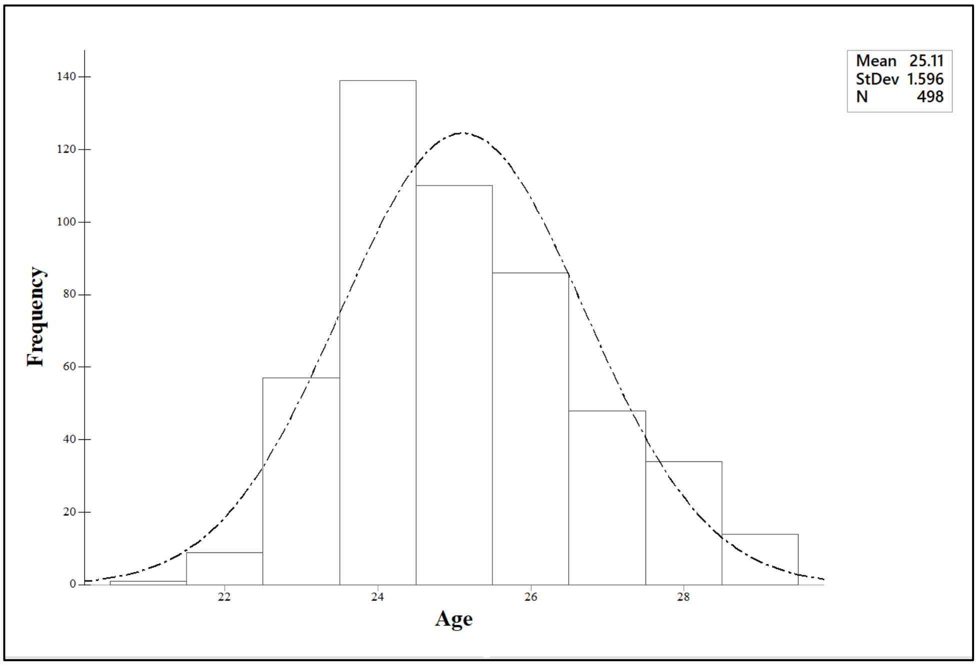


Figure 3.4. Histogram of Available Data for Age

Step 2. *Fuzzy Number Type and Linguistic Variable Determination*: Crisp inputs are transferred into fuzzy numbers at the end of the fuzzification process, which is the first stage of fuzzy logic analysis. Therefore, selecting the fuzzy number is crucial for the results. Different fuzzy numbers are in use in the literature; however, trapezoidal and triangular ones have the most significant usage frequency (Liu et al., 2012). Triangular fuzzy numbers are a special form of trapezoidal fuzzy numbers used in most FFTA applications. Consequently, triangular fuzzy numbers are decided to be used in the study, so there will be three components of the used fuzzy number as $F_n=\{a,b,c\}$ where a represents the minimum, b represents the most expected, and c represents the maximum value as represented in Figure 2.15.

Within the scope of the study, regarding the multiplication of occurrence frequency and severity of an uncertainty item, a linguistic choice is asked from the participants, necessitating a linguistic variable. The values of this linguistic variable are expressed as linguistic terms. According to Suh et al. (2021), the typical estimation of human working memory capacity follows the concept of seven plus minus two score ranges. Therefore, the suitable number of comparisons for a human being to judge simultaneously is expected to be between five and nine. In this regard, a seven-score linguistic choice was selected, covering the words *very high*, *high*, *mildly high*, *medium*, *mildly low*, *low*, *and very low*.

Step 3. *Membership Function Determination:* The membership function is the function used to relate input linguistic variables to a membership value between 0 and 1. In other words, the membership function helps to convert input linguistic fuzzy sets to a numeric output fuzzy set at the end of the fuzzification process. Since it determines the degree of membership, it is vital for fuzzy logic analysis. A membership function needs to be in place for each determined linguistic variable. The membership function values can be determined from historical data or a detailed questionnaire. Since no historical data is available, the membership functions in the study were determined with a generic approach instead of using already available membership functions in the literature. Accordingly, the extremes of the linguistic variables were also asked of the questionnaire responders. Since the determined fuzzy number was triangular, responders were asked to fill a table for each linguistic variable's minimum, maximum, and most expected values out of ten to fully understand what they meant with their linguistic responses to the questions. The collected responses from eleven responders are presented in Table 3-7. When the descriptive statistics of data are examined, it is observed that the mean, median, and mode values are similar for most linguistic variables (Table 3-8). In addition, mean value ± 1.96 standard deviations can also be estimated to see the 95% confidence interval range of the responses. The resultant fuzzy membership function can be investigated in Figure 3.5.

Table 3-7: Responses for Membership Function

Responder ID		Linguistic Variable						
		Very High	High	Mildly High	Medium	Mildly Low	Low	Very Low
1	Min	8	7	5	4	3	2	1
	Most Exp.	9	8	6	5	4	3	2
	Max	10	9	7	6	5	4	3
2	Min	8	7	5	4	3	2	1
	Most Exp.	9	8	6	5	4	3	2
	Max	10	9	7	6	5	5	3
3	Min	8	7	5	4	3	2	1
	Most Exp.	9	8	6	5	4	3	2
	Max	10	9	7	6	5	5	3
4	Min	8	8	7	5	3	1	1
	Most Exp.	9	8	7	5	4	2	2
	Max	10	8	7	6	5	3	3
5	Min	8	7	6	5	4	3	2
	Most Exp.	9	8	7	6	5	4	3
	Max	10	9	8	7	6	5	4
6	Min	9	8	7	5	4	3	1
	Most Exp.	9	9	8	7	5	3	2
	Max	10	9	9	8	7	4	2
7	Min	9	8	7	5	3	2	1
	Most Exp.	9	8	7	5	4	3	1
	Max	10	9	8	5	4	3	2
8	Min	8	7	5	4	3	2	1
	Most Exp.	9	8	6	5	4	3	2
	Max	10	9	7	6	5	4	3
9	Min	8	7	6	5	4	3	1
	Most Exp.	9	8	7	6	5	4	2
	Max	10	9	8	7	6	5	3
10	Min	8	6	5	4	3	2	1
	Most Exp.	9	7	6	5	4	3	2
	Max	10	8	7	6	5	4	3
11	Min	8	7	6	5	4	3	2
	Most Exp.	9	8	7	6	5	4	3
	Max	10	9	7	7	6	5	4

Table 3-8: Descriptive Statistics of Extreme Values of Linguistic Variables

	Very High			High			Mildly High			Medium		
	Min	Most Exp.	Max	Min	Most Exp.	Max	Min	Most Exp.	Max	Min	Most Exp.	Max
Mean	8.2	9.0	10.0	7.2	8.0	8.8	5.8	6.6	7.5	4.5	5.5	6.4
StDev	0.4	0.0	0.0	0.6	0.4	0.4	0.8	0.6	0.7	0.5	0.7	0.8
Median	8.0	9.0	10.0	7.0	8.0	9.0	6.0	7.0	7.0	5.0	5.0	6.0
Mod	8.0	9.0	10.0	7.0	8.0	9.0	5.0	6.0	7.0	5.0	5.0	6.0

	Mildly Low			Low			Very Low		
	Min	Most Exp.	Max	Min	Most Exp.	Max	Min	Most Exp.	Max
Mean	3.4	4.4	5.4	2.3	3.2	4.3	1.2	2.1	3.0
StDev	0.5	0.5	0.8	0.6	0.6	0.7	0.4	0.5	0.6
Median	3.0	4.0	5.0	2.0	3.0	4.0	1.0	2.0	3.0
Mod	3.0	4.0	5.0	2.0	3.0	5.0	1.0	2.0	3.0

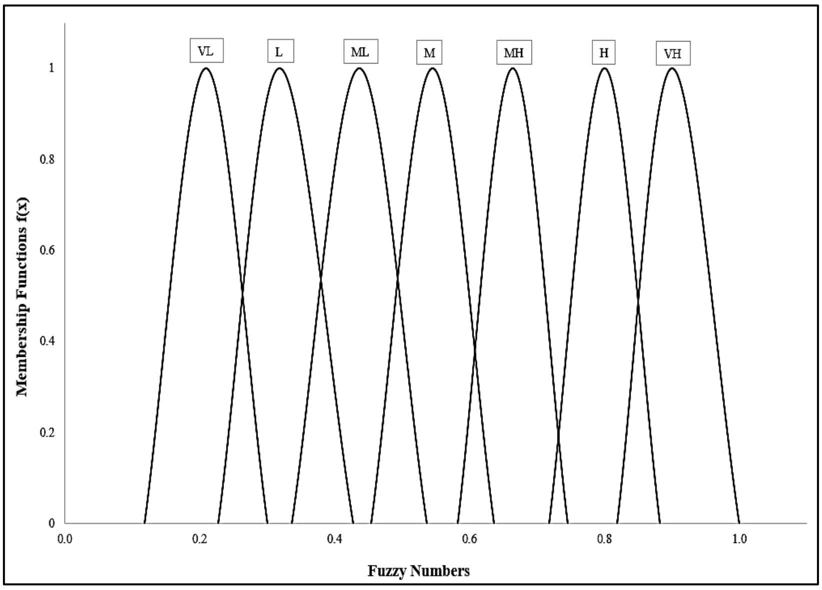


Figure 3.5: Fuzzy Membership Function of Fuzzy Numbers

Step 4. *Fuzzification and Fuzzy Aggregation:* As mentioned in the earlier step, the membership function helps to convert linguistic variables into fuzzy numbers. The ranges in Table 3-9 obtained from the Fuzzy Membership Function in Figure 3.5, can be used for transition.

Table 3-9: Fuzzy Number Conversion Scale

Linguistic Term	**Fuzzy Set**
Very High	(0.8, 0.9, 1.0)
High	(0.7, 0.8, 0.9)
Mildly High	(0.6, 0.7, 0.7)
Medium	(0.5, 0.5, 0.6)
Mildly Low	(0.3, 0.4, 0.5)
Low	(0.2, 0.3, 0.4)
Very Low	(0.1, 0.2, 0.3)

The extreme values in the table are used regarding the linguistic response of the responder first. For example, if there were not any aggregation, the answer of VH by a responder would be turned into the fuzzy number of (0.8, 0.9, 1). However, eleven experts have different linguistic responses for the same uncertainty items, with different weightings in the system. Hence, these weightings must be considered as well. Accordingly, the linear opinion pool method, one of the most successful and widely used methods, is used (Cheliyan and Bhattacharyya, 2018). The method is defined as the following:

$$M_i = \sum_{j=1}^{Ne} A_{ij} w_j \qquad \text{for } \forall \text{ i=(1,..., N)} \tag{3-1}$$

where N is the number of basic events of the fault tree, N_e is the number of experts, w_j is the weighting factor of the expert j, A_{ij} is the corresponding linguistic expression fuzzy number conversion scale of the i^{th} basic event given by j^{th} expert, and M_i is the resultant aggregated triangular fuzzy number of the BE_i.

For such aggregation to be achieved, the weighting factors of eleven responders must be known before the process. Table 3-10 the weighting of each responder calculated in accordance with the Expert Weighting Factors stated in Table 3-6. The responder names and profiles are kept anonymous; therefore, they are called with unique IDs.

Table 3-10: Responder Weights

Responder ID	Title	Title Score	Experience	Experience Score	Age	Age Score	Total	Weight
1	Senior Mine Planning Engineer	2	11	3	34	2	7	0.07
2	Senior Mine Planning Manager	5	20	4	42	4	13	0.14
3	Mine Manager	4	22	4	47	4	12	0.13
4	Mine Planning Chief	2	5	2	31	2	6	0.06
5	Mine Planning Engineer	1	4	1	31	2	4	0.04
6	Mine Planning Chief	2	6	2	30	2	6	0.06
7	Mine Planning Superintendent	3	12	3	39	3	9	0.09
8	Senior Mine Planning Manager	5	26	5	51	5	15	0.16
9	Mine Planning Superintendent	3	14	3	35	3	9	0.09
10	Mine Planning Superintendent	3	15	3	35	3	9	0.09
11	Senior Mine Planning Engineer	2	5	2	34	2	6	0.06
						Sum	96	1

The related weights can be used for fuzzification and fuzzy aggregation.

Step 5. *Defuzzification:* In a study by Cheliyan and Bhattacharyya (2018), the left and the right fuzzy ranking method is used for defuzzification which is the method used to convert fuzzy numbers into single crisp output. The left and right fuzzy ranking method is one of the most common methods to obtain the possibility scores. In the related study, this single crisp output is called a fuzzy possibility score (FPS), representing the possibility of the basic event of the fault tree. The left and right utility scores for the trapezoidal fuzzy set number of F_n = (a, b, c, d) is expressed as:

$$FPS = \frac{\mu_r + (1 - \mu_l)}{2} \quad \text{where} \quad \mu_l = \frac{1-a}{1+b-a} \quad \text{and} \quad \mu_r = \frac{d}{1+d-c} \tag{3-2}$$

If the FPS is reformulated for a triangular fuzzy set number of F_n = (a, b, c), the following equations can be followed.

$$FPS = \frac{\mu_r + (1 - \mu_l)}{2} \quad \text{where} \quad \mu_l = \frac{1-a}{1+b-a} \quad \text{and} \quad \mu_r = \frac{c}{1+c-b} \tag{3-3}$$

As a result, with the above formulation, the defuzzification of all basic events can be calculated in the form of a fuzzy possibility score as a single crisp output.

Step 6. *Conversion of Fuzzy Possibility to Fuzzy Failure Probability:* The previously calculated FPS can be converted to fuzzy failure probability, $P(X_i)$, using the following formula (Cheliyan and Bhattacharyya, 2018):

$$P(X) = \begin{cases} \frac{1}{10^k} & for\ FPS \neq 0 \\ 0 & for\ FPS = 0 \end{cases} \quad \text{where } k = 2.301 \left(\frac{1-FPS}{FPS}\right)^{1/3} \tag{3-4}$$

Fuzzy failure probabilities of all basic events of the fault tree can be calculated using the six steps explained above. Upon the calculation, the prioritization ranking can be achieved so that the most contributing basic events to the top event, which is the deviation from long-term production plans, can be detected with their contribution percentages. The major uncertainty items with their effectiveness levels will be evaluated in the discrete event simulation discussed in Section 4.

3.3 Construction of the Conventional Fault Tree

The fuzzy fault tree method was selected as the decision support method to evaluate why long-term production plans deviate from short-range plans in metallic surface mines. The details of these methods were already discussed in Sections 2.4.3 and 2.4.4. Two major strengths of these methods are to provide quantitative measures and reveal the most contributing events in the failure of the top event. In this sense, a conventional FFT was created after deciding on the scope of the questionnaire, as discussed in Section 3.2.1. The basic events of the FFT are related to each uncertainty item evaluated in the questionnaire.

Complete fault tree construction requires various steps, such as problem formulation, actual construction, evaluation, and interpretation of the result. This section will concentrate on the problem formulation and actual construction steps, while the evaluation and interpretation steps of the fault tree will be detailed in Section 3.4.2.

The problem definition of the fault tree accepts that a long-term schedule (all strategic decisions) is already available in an open-pit metal mine and is a fixed plan. After the long-term plan is already prepared under certain practical assumptions, on the short-term scale, the plan is investigated with the aspects where uncertainties cause deviations. Therefore, the problem statements that should be responded under the scope of the current thesis study when constructing a fault tree are as follows:

i. What are the branching structure and inter-dependencies of the uncertainties leading to deviations from short to long-term production plans?
ii. How can the occurrence frequencies and severities of these factors be evaluated to have a holistic approach to reveal their comparative effectiveness on the top event, which is the observable deviations in production plans?
iii. What are the levels of impact of uncertainties on production planning in a percentile weight to prioritize the least number of factors with the highest effectiveness to be simulated?

The top event of the fault tree was defined as the failure of a long-term plan in short-range (in-place) applications. It is divided into sub-components as geological, economic, operational, and external concerns with a dependency on the OR gate (Figure 3.6). It means that any of these uncertainty branches can cause the occurrence of the top event independently. These branches were in line with the questionnaire question groups previously discussed in Section 3.2.1.

Firstly, geological concerns are further divided into the following basic events: failure of i) grade, ii) tonnage, iii) metallurgical parameters, iv) lithology & rock type, and v) geotechnical & hydrogeological parameters combined with OR gate (Figure 3.7).

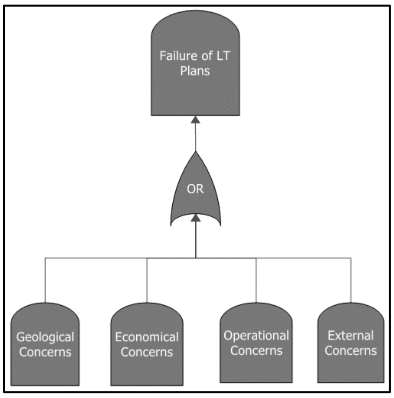


Figure 3.6: Top event of the Fault Tree

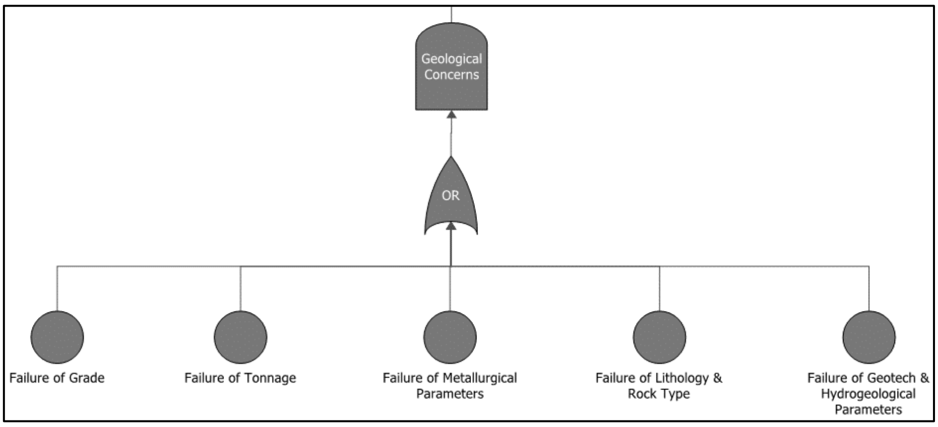


Figure 3.7: Geological Concerns of Fault Tree

Second, economic concerns are further divided into basic events of failure of i) selling price estimations, ii) cost estimations, and iii) foreign exchange rate estimation with a dependency of the OR gate (Figure 3.8).

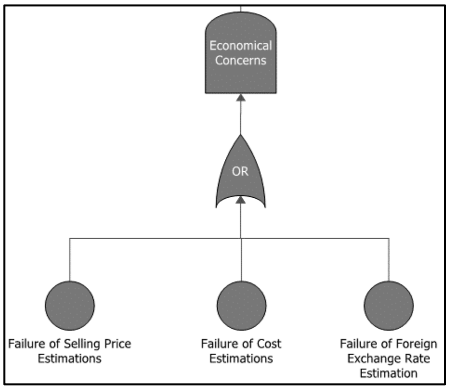


Figure 3.8: Economical Concerns of Fault Tree

Third, operational concerns are further divided into basic events related to the estimation and expectations failures of i) workforce efficiency, ii) mining equipment efficiency, iii) mining equipment availability, iv) equipment allocation, v) weather forecasts, vi) mineral processing parameters, vii) unit production cycle activities, and viii) corporate communication, connected to the Operational Concern with OR gates (Figure 3.9).

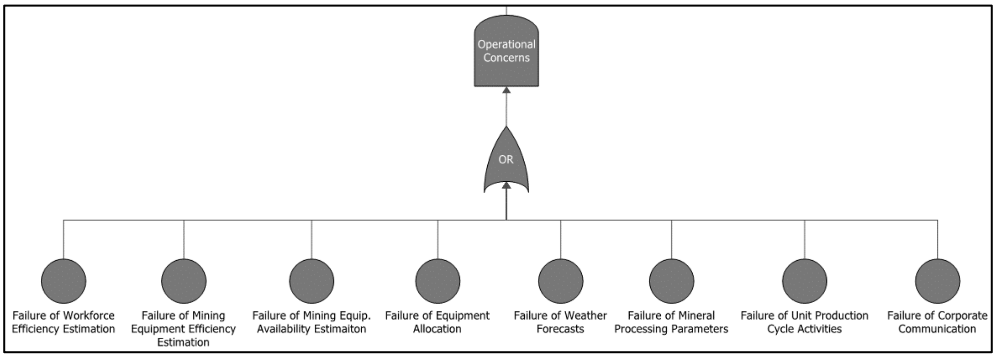


Figure 3.9: Operational Concerns of Fault Tree

Last, external concerns can be classified into basic events of failure of i) community relations, ii) permit, legislation & regulation, iii) political stability, iv) force majeure, and v) environment & OHS (HSE: health, safety, and environment), with an interdependency of OR gate (Figure 3.10).

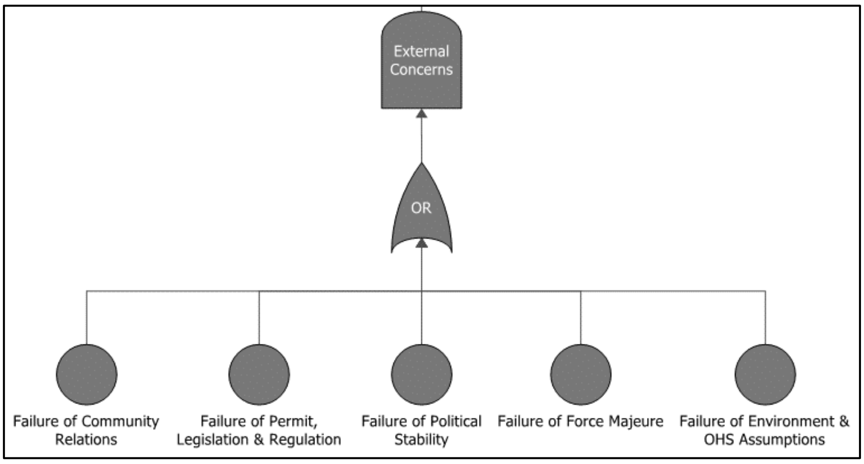


Figure 3.10: External Concerns of Fault Tree

The general look of the FFT is given in Figure 3.11 and the basic events are listed in Table 3-11.

Table 3-11: List of Basic Events of Fault Tree

Basic Even ID, BE_i	Basic Event
BE_1	Deviation in grade
BE_2	Deviation in tonnage
BE_3	Deviation in metallurgical parameters
BE_4	Deviation in lithology/rock type
BE_5	Deviation in geotechnical and/or hydrogeological parameters
BE_6	Deviation in commodity price
BE_7	Deviation in operation and extraction cost
BE_8	Deviation in foreign exchange rates
BE_9	Deviation in workforce efficiency
BE_{10}	Deviation in mining equipment efficiency
BE_{11}	Deviation in mining equipment availability
BE_{12}	Deviation in the equipment allocation plan
BE_{13}	Deviation in the weather forecast
BE_{14}	Deviation in mineral processing parameters and requirements
BE_{15}	Deviation in unit production cycle activities
BE_{16}	Deviation in corporate communication efficiency
BE_{17}	Deviation in community relations
BE_{18}	Deviation in the permit, legislation, and regulation
BE_{19}	Deviation in political stability
BE_{20}	Deviation in force mejaure
BE_{21}	Deviation in environmental and OHS assumptions

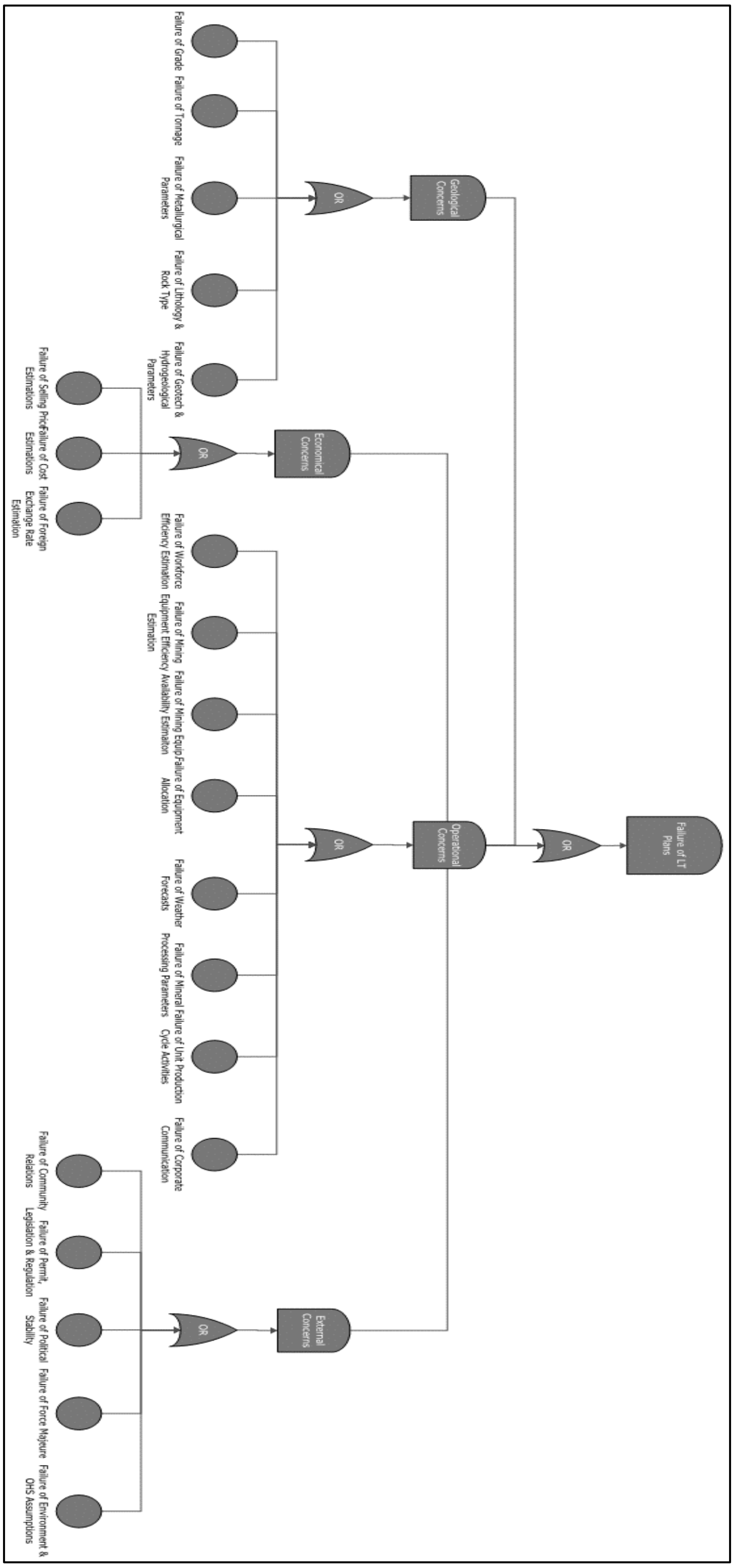


Figure 3.11: The General Look of Fault Tree

3.4 Integration of Questionnaire Outcomes and Conventional Fault Tree: Development of the Fuzzy Fault Tree Analysis

The questionnaire outcomes are evaluated in Section 3.4.1, while integrating the outcomes into the conventional fault tree to develop a fuzzy fault tree for analysis of uncertainty prioritization is given in Section 3.4.2. As mentioned previously, the quantified uncertainties with their effectiveness levels will be used as stochastic variables in the discrete event simulation that will be concentrated in Section 4.

3.4.1 Evaluation of the Questionnaire Results

There are six steps to convert linguistic fuzzy terms into fuzzy failure probabilities, already defined in Section 3.2.2, so that they can be used for the fuzzy fault tree analysis (FFTA). The calculation steps are followed as given below for each basic event listed in, Table 3-11.

Step 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, as discussed previously in Table 3-10.

Step 2. Fuzzy Number Type and Linguistic Variable Determination: The decided fuzzy number type is triangular, $F_n=\{a,b,c\}$, and the set of linguistic variables consist of seven components, L= {*very high (VH), high(H), mildly high(MH), medium(M), mildly low(ML), low(L), very low(VL)* }.

Step 3. Membership Function Determination: The membership function is one of the most critical items for fuzzy logic analysis. The membership function data is obtained from the questionnaire, Table 3-7, and the extremes for the seven linguistic variables are provided in Table 3-9 and illustrated in Figure 3.5.

Step 4. Fuzzification and Fuzzy Aggregation: By considering the expert weighting factors, linguistic response fuzzification is achieved with aggregated fuzzy numbers. The responses of the experts involved in the questionnaire are presented in Table 3-12 for each basic event, and calculations are done with Equation 3-1. In this regard, the resultant aggregated fuzzy numbers are obtained as given in Table 3-13.

Step 5. Defuzzification: In the defuzzification process, the left and the right fuzzy ranking method is decided to be used. In this regard, for the fuzzy numbers given in Table 3-13, Equation 3-3 is applied, which resulted in fuzzy possibility scores as given in the Table 3-14.

Step 6. Conversion of Fuzzy Possibility to Fuzzy Failure Probability: The fuzzy possibility scores are converted to fuzzy failure probability using Equation 3-4. The conversion results are provided in Table 3-14 in addition to a ranking based on the failure probability scores.

In the following part, the fuzzy failure probability scores for each basic event are used to calculate the failure probability of the top event and execute related analyses.

Table 3-12: Expert Linguistic Responses for Basic Events of the Study

BEi/Expert ID	1	2	3	4	5	6	7	8	9	10	11
1	MH	H	M	VH	H	VH	VH	H	H	H	VH
2	M	MH	ML	MH	VH	H	M	H	MH	MH	H
3	VH	H	VL	H	H	MH	L	VH	M	MH	H
4	L	M	L	ML	MH	MH	MH	MH	L	L	ML
5	VH	VH	ML	H	MH	H	ML	MH	MH	MH	VH
6	VL	L	VL	MH	MH	ML	L	ML	MH	MH	VH
7	VL	H	ML	H	MH	ML	ML	ML	ML	ML	M
8	L	ML	VL	H	ML	M	L	VH	M	L	ML
9	MH	MH	MH	MH	H	MH	MH	H	M	L	VH
10	VH	M	H	H	H	MH	VH	M	MH	VL	VH
11	VH	M	H	VH	H	H	VH	M	H	L	VH
12	ML	L	ML	H	H	M	M	MH	H	M	H
13	L	L	ML	M	H	MH	MH	L	M	VL	H
14	M	M	L	VH	VH	H	L	MH	H	MH	H
15	M	ML	M	H	H	M	H	MH	VH	ML	MH
16	VL	VL	ML	M	M	M	L	L	VL	M	M
17	MH	ML	VL	MH	ML	H	L	VL	M	MH	VH
18	VH	ML	H	VH	H	VH	L	M	ML	MH	VH
19	M	ML	M	H	M	ML	L	M	VL	MH	VH
20	VH	L	MH	MH	MH	H	L	VL	L	M	H
21	VL	ML	MH	H	MH	VH	M	ML	ML	MH	VH

Table 3-13: Aggregated Fuzzy Numbers of the Study

	Aggregated Fuzzy Numbers		
BE_i	Min	Most Exp.	Max
1	0.70	0.79	0.87
2	0.58	0.66	0.75
3	0.57	0.66	0.75
4	0.40	0.49	0.58
5	0.61	0.69	0.79
6	0.37	0.46	0.55
7	0.41	0.51	0.60
8	0.40	0.49	0.59
9	0.58	0.66	0.75
10	0.59	0.67	0.76
11	0.62	0.71	0.80
12	0.49	0.58	0.67
13	0.37	0.46	0.56
14	0.53	0.62	0.71
15	0.54	0.63	0.72
16	0.28	0.37	0.47
17	0.39	0.48	0.57
18	0.56	0.64	0.74
19	0.43	0.52	0.61
20	0.42	0.50	0.60
21	0.48	0.57	0.66

Table 3-14: Fuzzy Possibility Scores, Fuzzy Failure Probability, and Ranking of Basic Events of the Study

BE_i	Aggregated Fuzzy Numbers (a,b,c)	FPS	P(Xi)	Rank
1	(0.70, 0.79, 0.87)	0.7649	0.0280	1
2	(0.58, 0.66, 0.75)	0.6509	0.0135	5
3	(0.57, 0.66, 0.75)	0.6472	0.0132	7
4	(0.40, 0.49, 0.58)	0.4887	0.0046	17
5	(0.61, 0.69, 0.79)	0.6802	0.0162	3
6	(0.37, 0.46, 0.55)	0.4641	0.0039	20
7	(0.41, 0.51, 0.60)	0.5074	0.0053	14
8	(0.40, 0.49, 0.59)	0.4919	0.0047	16
9	(0.58, 0.66, 0.75)	0.6499	0.0134	6
10	(0.59, 0.67, 0.76)	0.6590	0.0142	4
11	(0.62, 0.71, 0.80)	0.6941	0.0177	2
12	(0.49, 0.58, 0.67)	0.5719	0.0081	11
13	(0.37, 0.46, 0.56)	0.4670	0.0039	19
14	(0.53, 0.62, 0.71)	0.6095	0.0104	10
15	(0.54, 0.63, 0.72)	0.6196	0.0111	9
16	(0.28, 0.37, 0.47)	0.3853	0.0020	21
17	(0.39, 0.48, 0.57)	0.4780	0.0043	18
18	(0.56, 0.64, 0.74)	0.6342	0.0121	8
19	(0.43, 0.52, 0.61)	0.5191	0.0057	13
20	(0.42, 0.50, 0.60)	0.5054	0.0052	15
21	(0.48, 0.57, 0.66)	0.5645	0.0078	12

3.4.2 Evaluation of the Fault Tree Analysis Results

The conventional fault tree constructed in Section 3.3 and illustrated in Figure 3.11 covers 21 basic events with OR-gate dependency. Therefore, probabilities of the four different branches of the Top Event and their basic events can be multiplied as given in Equation 3-5 to find out the probability of occurrent of the Top Event, which refers to the occurrence probability of the deviation from long-term production plans in short-range (in-place) application.

$D_1 = P_{\text{Failure of Grade}} * P_{\text{Failure of Tonnage}} * P_{\text{Failure of Metallurgical Parameters}} * P_{\text{Failure of Lithology \& Rock Type}} * P_{\text{Failure of Geotech \& Hydrogeological Parameters}}$

$D_2 = P_{\text{Failure of Selling Price Estimations}} * P_{\text{Failure of Foreign Exchange Rate Estimation}} * P_{\text{Failure of Cost Estimations}}$

$D_3 = P_{\text{Failure of Workforce Efficiency Estimation}} * P_{\text{Failure of Mining Equip. Availability Estimation}} * P_{\text{Failure of Equipment Allocation}} * P_{\text{Failure of Mining Equipment Efficiency Estimation}} * P_{\text{Failure of Weather Forecasts}} * P_{\text{Failure of Mineral Processing Parameters}} * P_{\text{Failure of Unit Production Cycle Activities}} * P_{\text{Failure of Corporate Communication}}$

$D_4 = P_{\text{Failure of Community Relations}} * P_{\text{Failure of Political Stability}} * P_{\text{Failure of Force Majeure}} * P_{\text{Failure of Permit, Legislation \& Regulation}} * P_{\text{Failure of Environment \& OHS Assumptions}}$

$$P_{\text{System}} = D_1 * D_2 * D_3 * D_4 \tag{3-5}$$

As an alternative and more generic way of calculating the top event failure probability, P(T), of a system consisting of AND and OR logic gates is the following:

$$P(T) = \begin{cases} \Pi_{i=1}^{N} P(X_i) & \text{for ANG gate} \\ 1 - \Pi_{i=1}^{N}\{1 - P(X_i)\} & \text{for OR gate} \end{cases} \quad \text{where N is the number of BEs} \tag{3-6}$$

In the constructed fault tree, the OR gate is used; hence the OR gate function of Equation 3-6 is active. The calculated fuzzy failure probability scores are inputted into the equation, and the failure probability of the top event and sub-events are calculated as tabulated in Table 3-15.

Table 3-15: The Failure Probability of the Top Event And Sub-events

Event	Explanation	Failure Probability
	Sub-Events	
D_1	Failure in Geological Concerns	0.0734
D_2	Failure in Economical Concerns	0.0138
D_3	Failure in Operational Concerns	0.0782
D_4	Failure in External Concerns	0.0346
	Top Event	
Psystem	Failure of Long-term Plans	0.1869

It was stated that the ultimate goal of the FFTA is determining the most influential uncertainty items. In other words, in addition to the top event failure probability calculation, found as 0.1869, the effect of the basic event failure on the system failure should also be investigated. In this way, events that contribute to the failure of the top event can be determined and ranked.

A ranking list of the basic events was provided in Table 3-14 according to the fuzzy probability scores. These ranks consider the failure rates of the events. However, the consideration should be made based on the system manner, where the effect of the event failure on the system failure should also be considered. Therefore, the following equation is used to calculate the failure criticality index (FCI), which is a relative index showing the percentage of times that a failure of a component caused a system failure:

$$\mathrm{FCI}_j = \frac{\text{Number of System Downing Failures (NSDF) by Comp. j}}{\text{Number of Failures (NF)}} \qquad (3\text{-}7)$$

where NSDF is the number of times a component's downtime causes the overall system downtime, and NF is the total number of system downs. In this sense, the calculations are conducted for each sub-event and basic event to see their effect on the system failure behavior. The rankings of the uncertainty items (basic events) according to both failure criticality index (FCI) and Fuzzy Probability (FP) scores are presented in Table 3-16, Figure 3.12, and Figure 3.13.

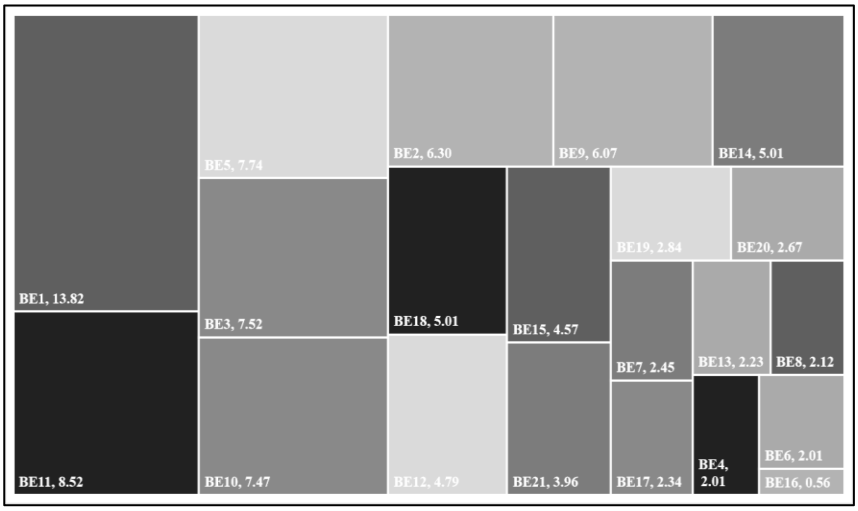


Figure 3.12: Treemap of Basic Event FCI

Table 3-16: Failure Criticality Index for Each Sub-Event and Basic Event

Event	Explanation	FCI, %	FCI Based Rank	FP Based Rank
Subevents				
D1	Failure in Geological Concerns	37.38	-	-
D2	Failure in Economical Concerns	6.57	-	-
D3	Failure in Operational Concerns	39.22	-	-
D4	Failure in External Concerns	16.82	-	-
Basic Events				
BE1	Deviation in grade	13.82	1	1
BE2	Deviation in tonnage	6.30	6	5
BE3	Deviation in metallurgical parameters	7.52	4	7
BE4	Deviation in lithology/rock type	2.01	19	17
BE5	Deviation in geotechnical and/or hydrogeological parameters	7.74	3	3
BE6	Deviation in commodity price	2.01	20	20
BE7	Deviation in operation and extraction cost	2.45	15	14
BE8	Deviation in foreign exchange rates	2.12	18	16
BE9	Deviation in workforce efficiency	6.07	7	6
BE10	Deviation in mining equipment efficiency	7.47	5	4
BE11	Deviation in mining equipment availability	8.52	2	2
BE12	Deviation in the equipment allocation plan	4.79	10	11
BE13	Deviation in the weather forecast	2.23	17	19
BE14	Deviation in mineral processing parameters and requirements	5.01	8	10
BE15	Deviation in unit production cycle activities	4.57	11	9
BE16	Deviation in corporate communication efficiency	0.56	21	21
BE17	Deviation in community relations	2.34	16	18
BE18	Deviation in the permit, legislation, and regulation	5.01	9	8
BE19	Deviation in political stability	2.84	13	13
BE20	Deviation in force mejaure	2.67	14	15
BE21	Deviation in environmental and OHS assumptions	3.96	12	12

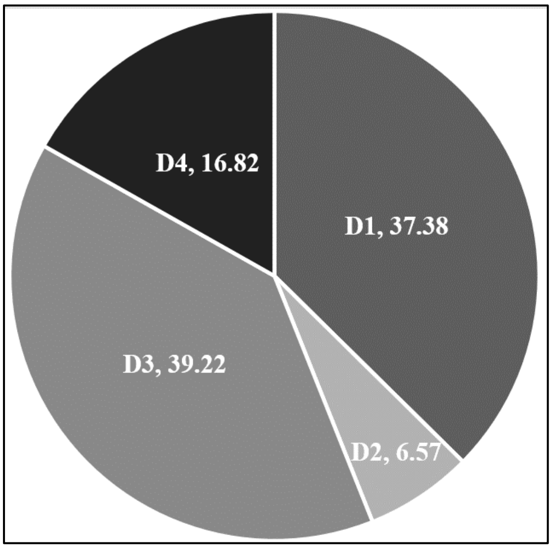


Figure 3.13: Pie Chart of Sub-Event FCI

As observed from Figure 3.12, deviation in production plans that was stated as the Top Event in the fault tree is expected to occur due to grade variability by 14 percent, with the highest priority. In second place in both rankings, mining equipment availability is observed with nearly 9% criticality. These two uncertainties alone can cause a deviation in the long-term plans by nearly 23%, which is about one-fourth and considerably high. Additionally, deviations in geotechnical & hydrological, and metallurgical parameters are the sources of nearly 15% of the deviation. As the fifth and sixth critical basic events, mining equipment efficiency, and tonnage deviations take up nearly another 14%. More than 50% of the uncertainties can be explained with the explanation and consideration of these six events. Alternatively, it is seen that the geological, operational, and external concerns cover more than 93% of the uncertainties, Figure 3.13. Therefore, it can be concluded that uncertainty in long-term plans is mainly caused by geological, operational, and external factors, and they should be addressed attentively in the planning phase. It is observed that time, economic and human resources related to mine planning should be allocated to solve the uncertainties of geological, operational, and external factors rather than concentrating on the other risk factors of economic concerns since economic factors, as a result of the conducted FFTA, are found the least criticality with nearly only 7%

FCI value, meaning that only 7 out of 100 production deviations are due to economic concerns. Because economic parameters in the long-term planning phase are generally included conservatively, and any cut-off grade change throughout the planned year is not expected in general. Anyway, the cut-off estimations can be renewed in the long-term production planning stages of the new production years and generally kept stable through the relevant year.

In the development of the discrete event simulation (DES) model in Section 4, implementation of the geological uncertainties, Basic Events from 1 to 5, can be prioritized. Deviation in grade, tonnage, and metallurgical parameters, BE1 to 3, directly affect the production rates and/or the total metal amount. Grade deviation and metallurgical parameters deviation factors can be assigned in the DES per block randomly, while tonnage uncertainty can be implemented to the model by random assignment of specific gravity over distributions to determine the block tonnage. Deviation in lithology and geotechnical and/or hydrogeological parameters, BE4 and 5, affect the structural safety and mineral processing performance. These parameters' deviation factors can also be assigned in the DES blockwise. In the end, when all of these geological items are included in the model, nearly 37% of the failure sources can be identified using DES.

Secondly, operational factors can also be implemented in the DES practically. When the basic events covering operational concerns, from BE9 to BE16, are considered, it is seen that all events are related to the mine production/output other than the BE14, deviation in mineral processing parameters and requirements. Therefore, BE14 can be jointly regarded with the earlier given mineral processing performance, BE3. The rest of the items can be summarized under three main headings: deviation in workforce efficiency, BE9 and BE16; deviation in mining equipment efficiency, BE10, 12, 13, and 15; and deviation in mining equipment availability, BE11. In this way, the efficiency concept is divided into two for workforce and equipment, while availability is presented for the equipment. These three factors can be used to determine the normalized production rates which are affected by uncertainty items in each cycle as a result of increased cycle times and/or decreased output per cycle.

For instance, let us assume that a mine is considering 320 days of operating time in a year and 21 working hours per day. The excavators will be available throughout this operating period with a pre-estimated cycle time. In that case, a total operating time of 6,720 hours should be achieved with 8,960 cycles/shovel and a total output of 89,600 tonnes, assuming 45 seconds of cycle time and 10 tonnes/cycle production. However, due to mismanagement or lack of proper planning that can be classified by uncertainties listed from BE9 to BE 16, either normalized cycle time is extended, leading to a drastic drop in the number of cycles like 8,064 cycles/shovel for the cycle time of 50 seconds or normalized output of the system per cycle is dropped by a reduction in the production per cycle like 71,680 tonnes of total output for 8 tonnes/cycle for one year period. Therefore, if the operational uncertainty factors can be included in the DES, nearly 39% of the uncertainties can be explained.

Last, the external factors (BE17 to BE21) have a high potential to be implemented in the DES. These events can occur independently of each other, and the occurrence of one does not affect the occurrence of the other; however, any external factor can interrupt production majorly in case of their existence.

In brief, using FFTA, the failure probability of the top event and the most effective basic event are presented in the current section. The effect of each item's failure on the top event is investigated, and further recommendations are made for their usage in developing a DES model. To accumulate more than one basic event and use them jointly, weighting their contribution to the joint item can be achieved using the FCI values. The joint interactions of the relevant basic events can be viewed in Table 3-17. These joint interactions will also be benefitted in the DES model for better applicability of the simulation model by combining basic events with similar sources of uncertainties and/or operational consequences under particular DES Items.

Table 3-17: Grouping of BE for DES

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	

CHAPTER 4

DEVELOPMENT AND IMPLEMENTATION OF A SIMULATION-BASED UNCERTAINTY QUANTIFICATION MODEL

4.1 Development of the Simulation Algorithm

To navigate day-to-day productions in operating mines, mine plans with different detail levels are employed to catch operational targets. Specific inputs are used to constitute plans, and outputs of these plans are generally production performance indicators of a mine as tonnage and grade for different material types. These values are calculated with the aid of inputs coming from quantitative data, assumptions, and subjective perspectives. Ultimately, such assumptions, quantitative and qualitative data with expert opinions jointly produce production indicators. Since surface metal mining operations with a truck-shovel haulage system consist of sequential and recursive cyclic events, discrete event simulation is a good candidate for modeling such stochastic operations, as discussed in detail in Section 2.5 so as to analyze deviations of production plans stochastically (under uncertainty) and iteratively (with all possible combinational scenarios). The main goal of the simulation will be 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, a discrete event simulation 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. In Section 3, the uncertainty items were categorized and analyzed using FFTA under geological, operational, external, and economic groups. The categories excluding economic factors were highly recommended to be used in the DES. Economic factors are not recommended to be included in the simulation model since their conservative estimations and the resultant cut-off grade values are recursively included in the long-term planning of each year and kept stable through the related production year in general. Although related reasons were already discussed in Section 3.4.2, 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 within the groups given in Table 3-17, and are considered to cover more than 93% of the uncertainties on a long-term plan based on their failure criticality index, FCI, %.

Before introducing the model’s computational steps, it is decided to introduce parameters, sets, and variables to be used in the model with the system's boundary. Afterward, algorithm logic will be given to increase awareness about the model. In addition to the logic, the details of the model computational steps will be mentioned. The last part will give step-by-step algorithm implementation in a discrete event simulation software (Rockwell Arena).

The model starts with introducing information about sets/parameters, probability density functions, and variables to be used in the model. For this purpose, two different tables are constructed with related explanations. Table 4-1 details the model's variables and probability distribution functions (PDF), while Table 4-2 provides sets/parameters not changed over the computational time. Parameters and sets are defined as deterministic values. On the other hand, variable values are over-written during computation, and their values change in time whenever any related process is triggered. PDFs are used to generate random values for the uncertainty items and contribute to the stochastic environment of the model.

Table 4-1: Variables and PDFs Used in the Simulation Algorithm

Variable/PDF	Description
D_i	The PDF of the density for the i^{th} block (Triangular Distribution (TRD))
GVF_i	The PDF of the grade variance factor for the i^{th} block (TRD)
MP_i	The PDF of the mineral processing-related deviation factor for the i^{th} block (TRD)
SU_i	The PDF of the structural uncertainty-related deviation factor for the i^{th} block (TRD)
OBC_t	Total produced ore block count at time t
TOH_t	Total hauled ore tonnage at time t
WBC_t	Total produced waste block count at time t
TWH_t	Total hauled waste tonnage at time t
BT_i	Calculated block tonnage of the i^{th} block where $BT_i = DX_i * DY_i * DZ_i * D_i$
LC_i^t	Total loads delivered to the crusher or to the waste dump from the i^{th} block at time t
CT_i	The PDF of the cycle time of shovel (loading time) assigned for the i^{th} block (TRD)
TC_i	The PDF of the truck capacity determined for the production of the i^{th} block (TRD)
WE_i	The PDF of the workforce efficiency factor for the i^{th} block (TRD)
MEE_i	The PDF of the mining equipment efficiency factor for the i^{th} block (TRD)
MEA_i	The PDF of the mining equipment availability factor for the i^{th} block (TRD)
HBT_i^t	Total hauled block tonnage of the i^{th} block at time t where $HBT_i^t = HBT_i^{t-1}+(TC_i*WE_i*MEE_i*MEA_i)$
RBT_i^t	The remaining block tonnage of the i^{th} block at time t where $RBT_i^t = BT_i - HBT_i^t$
ST_i	The loading start time of the i^{th} block
FT_i	The loading finish time of the i^{th} block
SE	The start time of downtime due to an external event(s) occurrence
FE	The end time of downtime due to an external event(s) occurrence
TTFj	Time to Failure for external factors occurrences (TRD) (j={ 1, …, 5}) j=1 represents community relations j=2 represents permit, legislation, and regulation j=3 represents political stability j=4 represents force mejaures j=5 represents environment and OHS
TTRj	Time to Recover for external factors occurrences (TRD) (j= {1, …, 5}) j=1 represents community relations j=2 represents permit, legislation, and regulation j=3 represents political stability j=4 represents force mejaures j=5 represents environment and OHS

Table 4-2: Set and Parameters Used in the Simulation Algorithm

Set/Parameter	Description
ID_i	Block ID of the i^{th} block
DX_i	X dimension of the i^{th} block
DY_i	Y dimension of the i^{th} block
DZ_i	Z dimension of the i^{th} block
MTY_i	The material type of the i^{th} block (ore or waste)
G_i	The grade of the i^{th} block

The simulation system boundary is determined with the following assumptions:

- The model is designed for surface metal mines with a shovel-truck haulage system,
- Block Model (BM) input deviation factors are assigned for each block individually,
- The block tonnage and truck output are assigned randomly,
- The majority of the 21 basic events are joined by considering the FCI factors,
- Operational factors are considered to have a normalized effect on the production performance indicators, and the uncertainty factors are assigned for each block separately,
- Input block IDs are given according to their production sequence,
- Active block production should first be completed before passing to the sequential block. In compliance with the practical applications in mines, the last load less than the truck capacity is also hauled individually without mixing it with the sequential block, even if the remaining tonnage is small,
- Block Model and operation based variables are assumed to realize continuously during the operation, so their values are assigned per block,
- External basic events are assumed to be independent of each other. Therefore, their occurrence frequencies do not affect each other.

After drawing the simulation boundary, the simulation algorithm logic can be constructed. The general framework of the simulation algorithm is given in Figure 4.1.

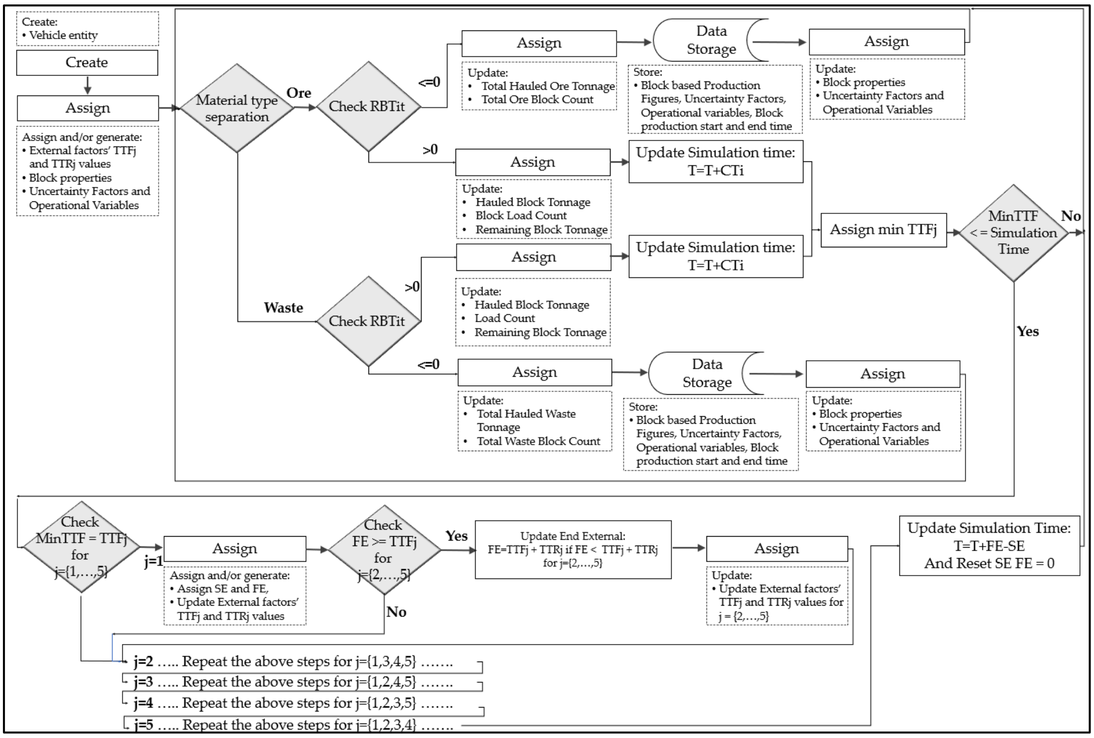


Figure 4.1: The Algorithm Logic Employed in the Simulation Model

Implementation of the logic flow illustrated in Figure 4.1 is performed in a discrete event simulation environment. The developed model will be at a macroscopic scale regarding equipment interactions (entity: truck and source: shovel) with each other. For example, instead of concentrating on the dumping, spotting, queuing, loading, and traveling times for a cycle by evaluating the behaviors of each piece of equipment at each position, the total simulation time is increased with the amount of cycle time of the shovel (loading time) without concentrating on equipment side in each state. In other words, the behavior of the overall system of a mine, including external and internal factors and their effect on production, is considered in the model.

The model introduces the following items as the input data into the system:

- Block model (BM) information, variance factors of BM data, and production sequence (Block ID in a sequential manner, material type information, x, y, and z dimensions of the block, density of the block in triangular distribution form, BM grade of the block, and variance factors of grade, mineral processing, and structural in triangular distribution form),
- Operational variance factors (workforce efficiency, mining equipment efficiency, availability) in triangular distribution form,
- Truck capacity and shovel cycle time (loading time) in triangular distribution form for each block,
- TTF_j and TTR_j variable factors for five external factors in triangular distribution form.

Considering the model components discussed in Table 4-1and Table 4-2 and the general framework illustrated in Figure 4.1, the algorithm steps are summarized as follows:

i. The model starts with the creation of the entity that is truck in this model, meaning that the truck is the unit traveling in the system, being affected by the changes in the system, and its state is changed,

ii. As the second step, initial assignments are achieved. First, blocks' properties are introduced into the system by assigning the related operational factors of that block. Additionally, occurrence intervals of the external events and their effective durations on production (TTF and TTR) are generated randomly for the first time.

iii. At the end of the second step, the entity can start the operation by reducing tonnes from the block tonnage in each cycle by hauling material from the block to either the crusher or the waste dump. To determine the destination, material type separation is achieved in the system. The logic of these two sub-modules is the same, but if the entity enters the waste sub-module, waste counters in the system are increased, whereas ore counters are increased if the entity activates the ore sub-module. Since these two modules have similar functionality but different purposes, only the ore sub-module will be discussed later.

iv. The classified block is then started to be hauled. A remaining tonnage of the block check station is used right after material type separation to check whether the block tonnage is reached.

v. If the remaining block tonnage is greater than zero, hauled block tonnage and load count variables are increased (HBT_i^t and LC_i^t). The hauled block tonnage is increased with the normalized output calculated for that block (TC_i * WE_i *MEE_i * MEA_i), and the ore load count is increased by one. The remaining block tonnage (RBT_i^t) is also calculated for the following tonnage check.

   However, when the remaining block tonnage is equal to zero, total hauled ore tonnage and block count (OBC_t and TOH_t) are increased with the block tonnage being produced and by one, respectively. After these updates, block-based production figures, uncertainty factors, operational variables, and block production start and end times are stored. Following this, block id is increased by one to switch the following block, and the simulation returns to step iii.

vi. Upon hauled block tonnage and load count increments, the simulation time needs to be increased with the loading time assigned from a triangular distribution for the block, so the simulation time increaments are achieved following the tonnage increament.

vii. Since the model proceeds discretely, external events' TTF values are examined at the end of each loading time to check if an external downtime occurs in the system. Accordingly, the minimum of the five external factors' TTF values is assigned to a variable as the earliest external event occurrence, and the simulation clock is examined after each cycle against this variable. The examination is achieved by checking whether the minTTF is less than or equal to the simulation clock. The system continues with the material type check if the external factor query is false. However, if it is true, the external factor module is activated.

viii. When the external factor module is activated, the entity comes to the first checkpoint to detect which type of external factor failure occurred. Then, the entity follows the signal point that verifies the failure. Upon verification, SE and FE variables representing the start and end times of the downtime caused by this external factor are assigned. SE is assigned to the TTF of the verified external factor, while FE is assigned to the summation of TTF and TTR values. Since the failure of the external factor verified is achieved, new TTF and TTR value re-assignments are also achieved.

ix. After SE and FE assignment, before delaying simulation time, also other external factors' TTF values are checked. The purpose is to catch if there is another failure within the period of the TTR. To illustrate the situation, an extreme case is presented in Figure 4.2. As observed in the figure, political stability fails with the min TTF value, so SE=80 hrs and FE=130 hrs values with an expected system downtime of 50 hrs are assigned. However, within this duration, community relations, permits, legislation, regulation, and force majeure factors also failed. Since the political stability failure cannot happen earlier, the initial SE is not changed, but the FE value should be updated with the value coming from the latest-ending force majeure. Ultimately, SE=80 hrs and FE=150 hrs values are the final values, and the expected simulation downtime is 70 hrs. Due to these conditions, another checkpoint is introduced to the system, which checks if FE is greater than or equal to the TTF_j for external factors other than the one with the min TTF value. If the query holds, FE is updated with the summation of the TTF and TTR values of the external factors if the FE is less than that summation; if not, FE is not changed. TTF and

TTR values are re-assigned for the ones holding the FE greater than or equal to the TTFj condition at the end of the check for the other external factors.

x. The last piece of the external factor module is updating the simulation time. The simulation time is increased with the difference between the start time and end time of the downtime caused by external factors (FE-SE). After this update, SE and FE values are reset, and the simulation continues with item iii.

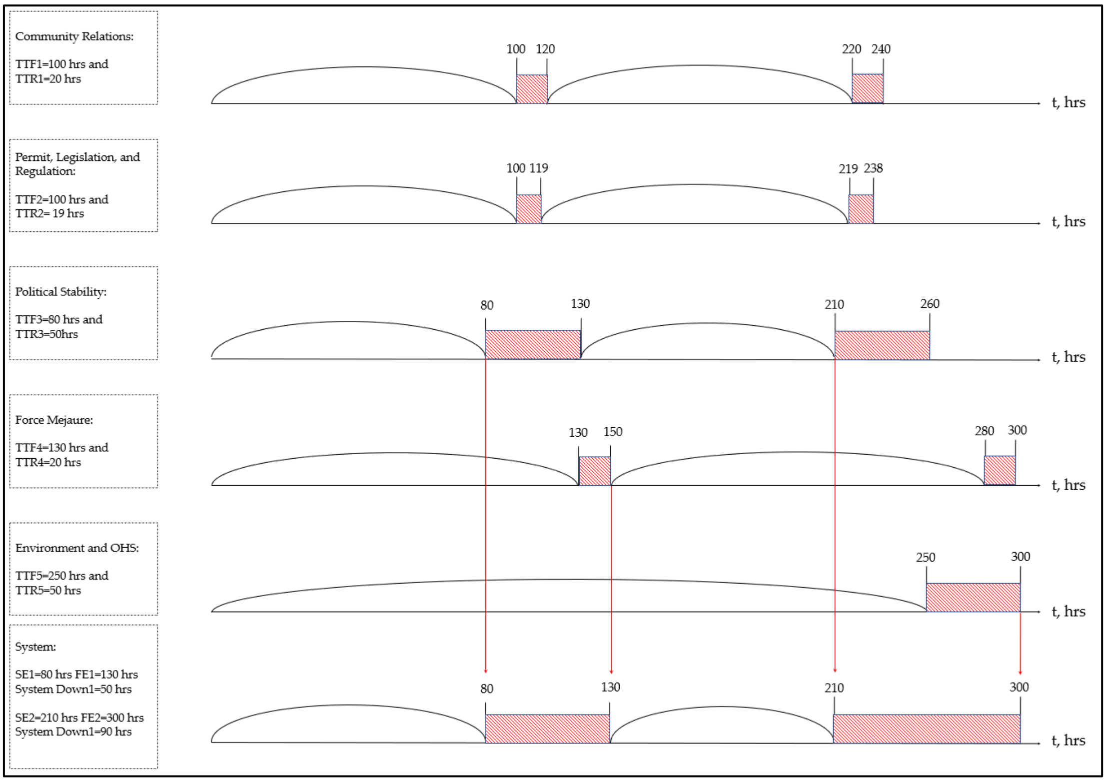


Figure 4.2: Illustration of How External Factor Module Works

At this point, the implementation of the algorithm in the Rockwell Arena software environment will be introduced briefly. Arena software is a simulation package built on SIMAN general-purpose simulation language. Using a general-purpose simulation language provides various advantages, including reduced programming effort and time, a user-friendly interface, acceptance from the authorities, and flexibility. Flowcharts and data modules are used to simulate a DES model in Arena.

Flowchart modules are objects in the model window to describe the simulation process. In contrast, data modules are the set of objectives in the spreadsheet view of the model that defines the characteristics of various process elements, such as resources and queues (Automation, 2004). The widely used flowchart and data modules are given in Table 4-3and Table 4-4 with their explanations and usage in this study.

Table 4-3: Commonly used Flow Chart Modules of Arena

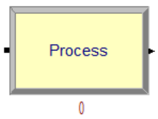
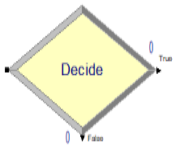
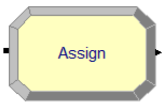
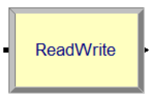
Flowchart Module	Name	Explanations	Usage
	Create	Entities are created with either a schedule or a constant time	To create truck entities
	Process	The processing method in the simulation. Allows seize, delay, and release	To delay the simulation time
	Decide	Allows decision-making based on one or more query	To separate material, check remaining tonnage, simulation time, and external factors occurrence
	Assign	Used for assigning new values to variables, entity attributes, and types	To manipulate variable values
	Read Write	Used for reading from an input file and writing to an output file	To read data from the input file and print output to an output file

Table 4-4: Commonly used Data Modules of Arena

Data Modules	Name	Explanations	Usage
Entity	Entity	Used to define entity types that move in the system and change state	To define truck entities
Variable	Variable	Used to define a variable’s dimension and initial value	To define variables
Expression	Expression	Used to define expressions and their associated values. An expression value can be in the form of integers or statistical distributions.	To define sets in the distribution form
File	File	Used to access external files with the use of the Read-write module.	To in/out input/output files

The model in the Arena can be divided into two main modules. The first is the haulage module, and the second is the external factors module. Figure 4.3, presents the complete module; however, since the external factors module has multiple flow chart modules, a partial section of this module is presented in Figure 4.4 for external factors.

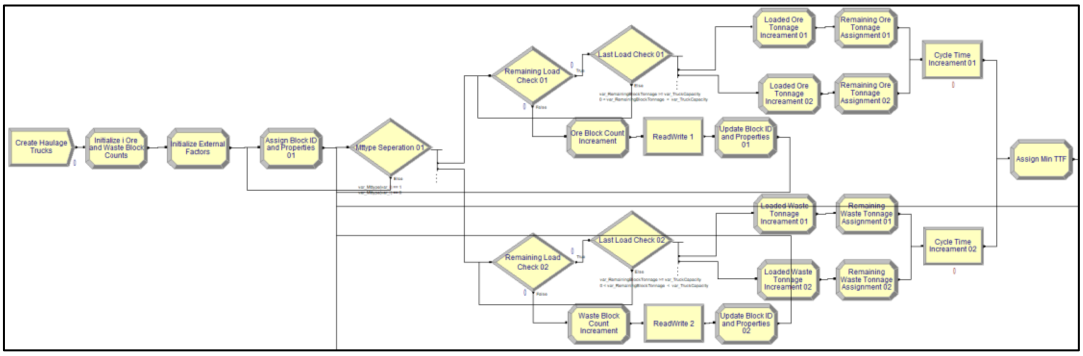


Figure 4.3: Haulage Module in Arena

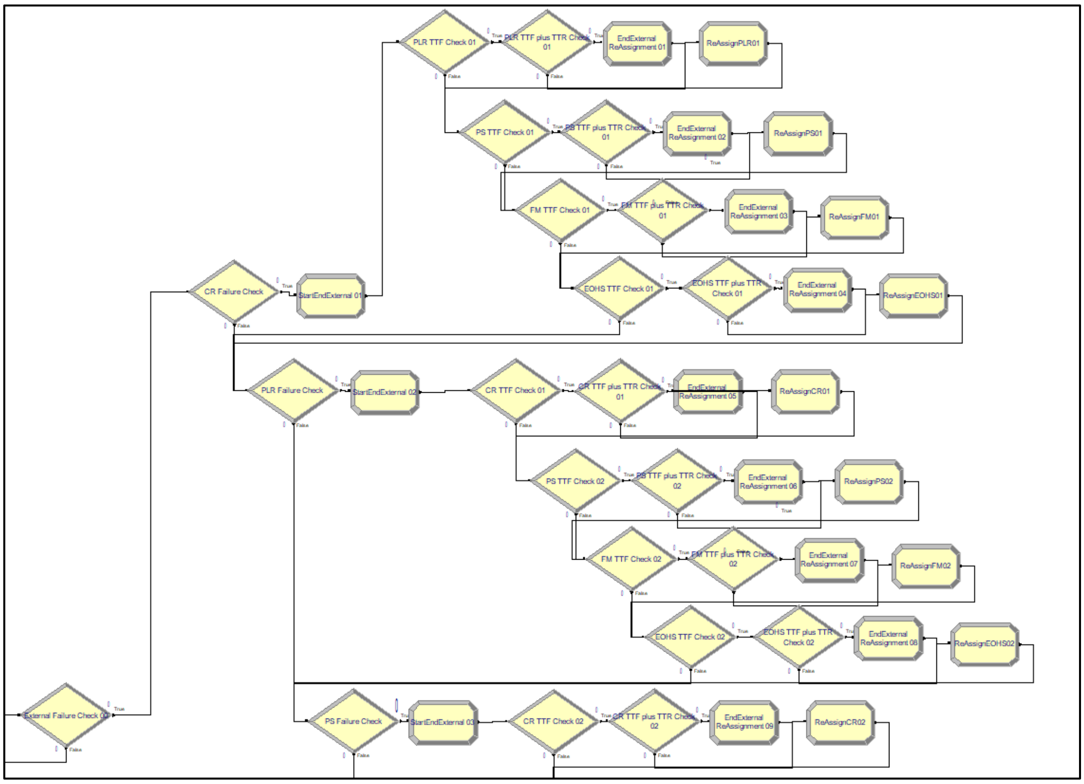


Figure 4.4: External Factor Module in Arena

As indicated in the model step (i) and illustrated in Figure 4.1, and Figure 4.3, the simulation starts with the creating the hauling truck entity. Upon creation, initial values of external factors' TTF and TTR are assigned randomly in addition to the input of block model data and operational parameters for the block under investigation (Figure 4.5). In addition, distinguishment among the material type is achieved after initial assignments.

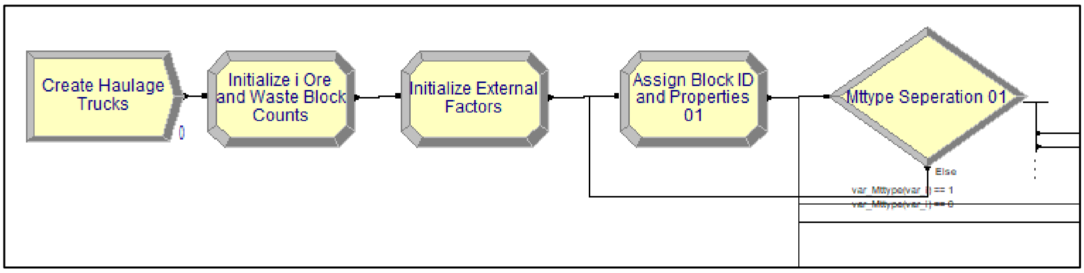


Figure 4.5: Entity Generation and Initial Assignments

According to the material separation, two paths are available: ore and waste (Figure 4.6). Although both paths have similar functionalities, ore haulage parameters are updated in the ore path, whereas waste parameters are updated if the waste path is activated. Both paths start with checking the remaining tonnage of the block. If the remaining block tonnage is more than zero, the operation proceeds; if not, it is understood that the total block is mined, and related information about the block is written to the output file. After the remaining load check, the last load check is performed to see if the cycle will be completed with an under-capacity truck. In this part, increments of the hauled block tonnage indicators (tonnage and metal amount) are achieved, and a delay of simulation time is reached. Upon delay, a minimum of five external factors TTF values are assigned to a variable. If an external event does not occur, then the hauling operation continues.

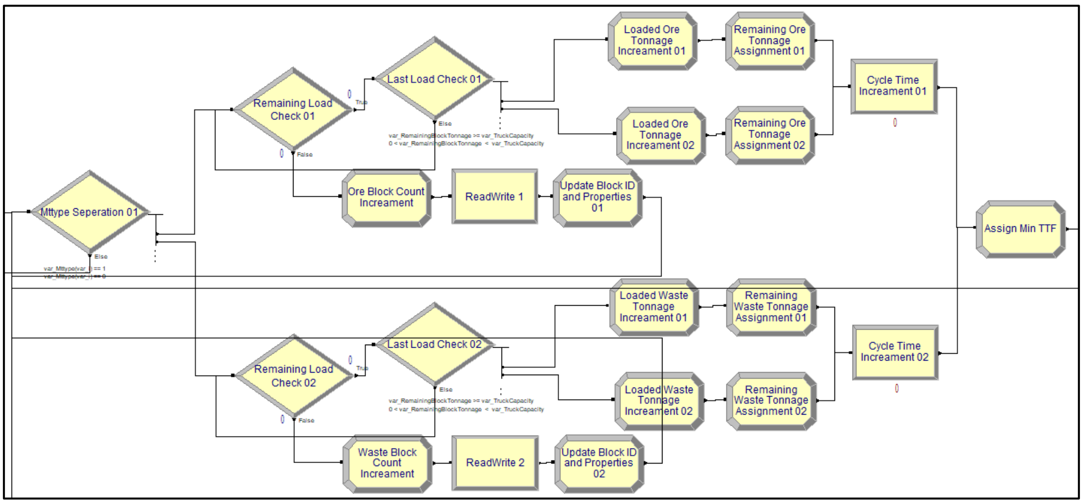


Figure 4.6: Material Type Separation in Arena

To activate the external factor module, min TTF must be last than or equal to the current simulation time. Details of the model are well defined in Figure 4.1, model steps (vii), (viii), (ix), an (x), and Figure 4.2. According to the given steps, the module is created in the Arena, as shown in Figure 4.7. This figure illustrates the Community relations sub-module alone. A similar process is also repeated for the remaining four external factors. At the end, downtime start and end times are determined, related external factors' TTF and TTR values are updated, and the simulation time is delayed with the difference between downtime start and end times.

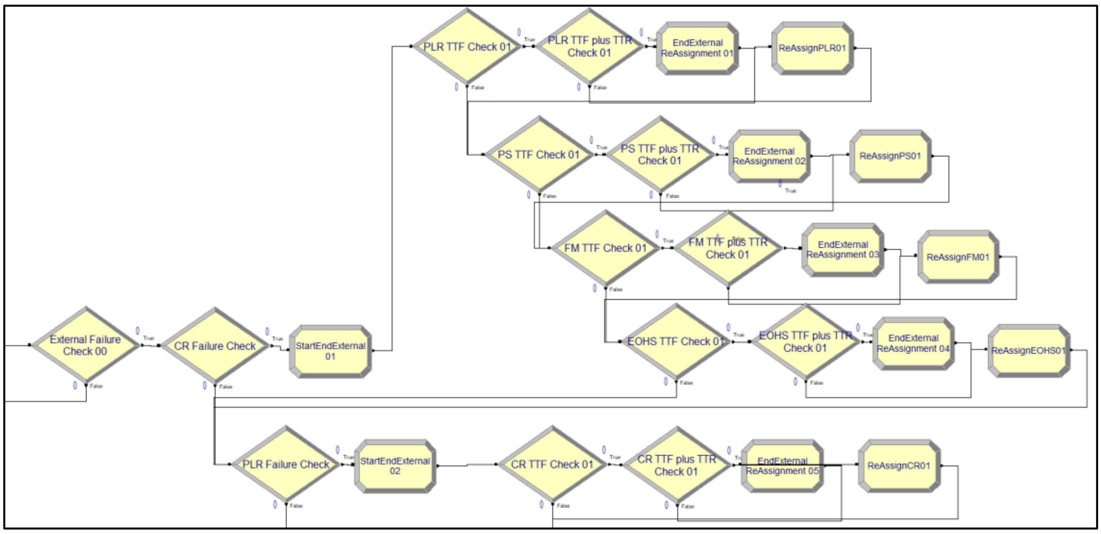


Figure 4.7: External Factors Initiation and Representation for Community Relations Failure

4.2 A Case Study of the Simulation Algorithm

Section 4.1 gives the parameters, sets, and variables of the algorithm, the system's boundary, stepwise DES algorithm logic, and algorithm construction in Arena. An implementation of the algorithm will be performed in the current section. First, the model input data will be discussed. Second, a case study will be presented to facilitate an understanding of the simulation model's use by computing two cases: The first case is deterministic representing long-term schedule while the second case is stochastic representing short-term production schedule.

In the design phase of the survey and DES model, the logic was to create a generic study that different parties can use in a wide variety of areas in mine planning. In the survey preparation process, the attendees who have experiences in different mining corporates and operations worldwide are selected to diversify results. In this way, obtained survey results can be used as input in a generic model in case of the absence of datasets particular to a mining site.

As mentioned in Section 3.2, three types of questions, one of them is linguistic (qualitative) and two are quantitative, are asked for each uncertainty item. The survey results of the quantitative questions (frequency and severity of the items) for 11 responders are presented for 21 basic events in Table 4-5. The values are calculated based on the weighting factors of 11 experts (Table 3-10) and their survey responses, as discussed in Section 3.4.1.

Table 4-5: Weighted Survey Responses of Basic Events Data

	Frequency (Days)			Severity (% Effect on Deviation)		
BEi	[Lowest]	[Most Expected]	[Highest]	[Lowest]	[Most Expected]	[Highest]
1	3	8	20	-10	10	35
2	5	14	37	-9	7	29
3	7	18	40	-8	8	25
4	12	30	72	0	8	22
5	20	39	82	2	13	28
6	29	80	174	0	11	31
7	38	74	144	2	11	27
8	46	93	150	2	6	9
9	7	21	70	-1	10	26
10	4	8	21	-11	4	13
11	3	7	24	-17	8	24
12	2	7	18	0	7	19
13	2	6	12	-17	2	22
14	10	41	53	-3	11	21
15	2	8	18	-6	8	18
16	20	68	122	-10	3	28
17	14	60	132	-16	8	19
18	40	101	256	-20	9	29
19	94	306	428	-15	8	21
20	64	248	322	-8	6	25
21	19	30	111	-18	9	24

Table 4-5 consists of two general groups of triangular distribution data. The first group consists of days passed for a failure to occur for a basic event (frequency, i.e. time to failure - TTF) (Figure 4.8). The second group of the obtained data is the percent deviations of long-term plans when the deviation in the short term is observed due to the determined 21 basic events. The purpose of this group is to quantify the severity of the plan deviation (time to repair - TTR) (Figure 4.9).

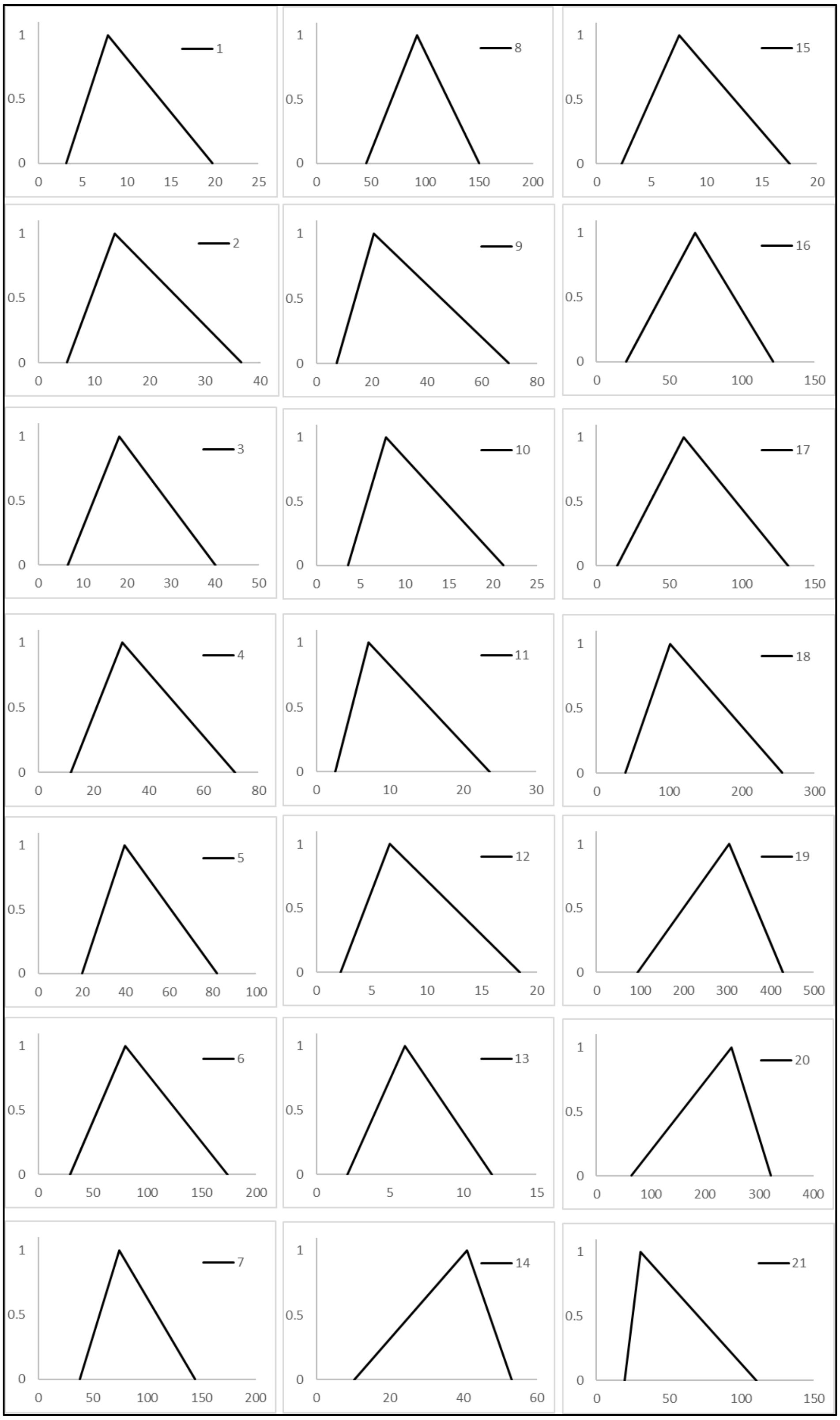


Figure 4.8: Survey Results of Days for a Failure (Frequency, TTF)

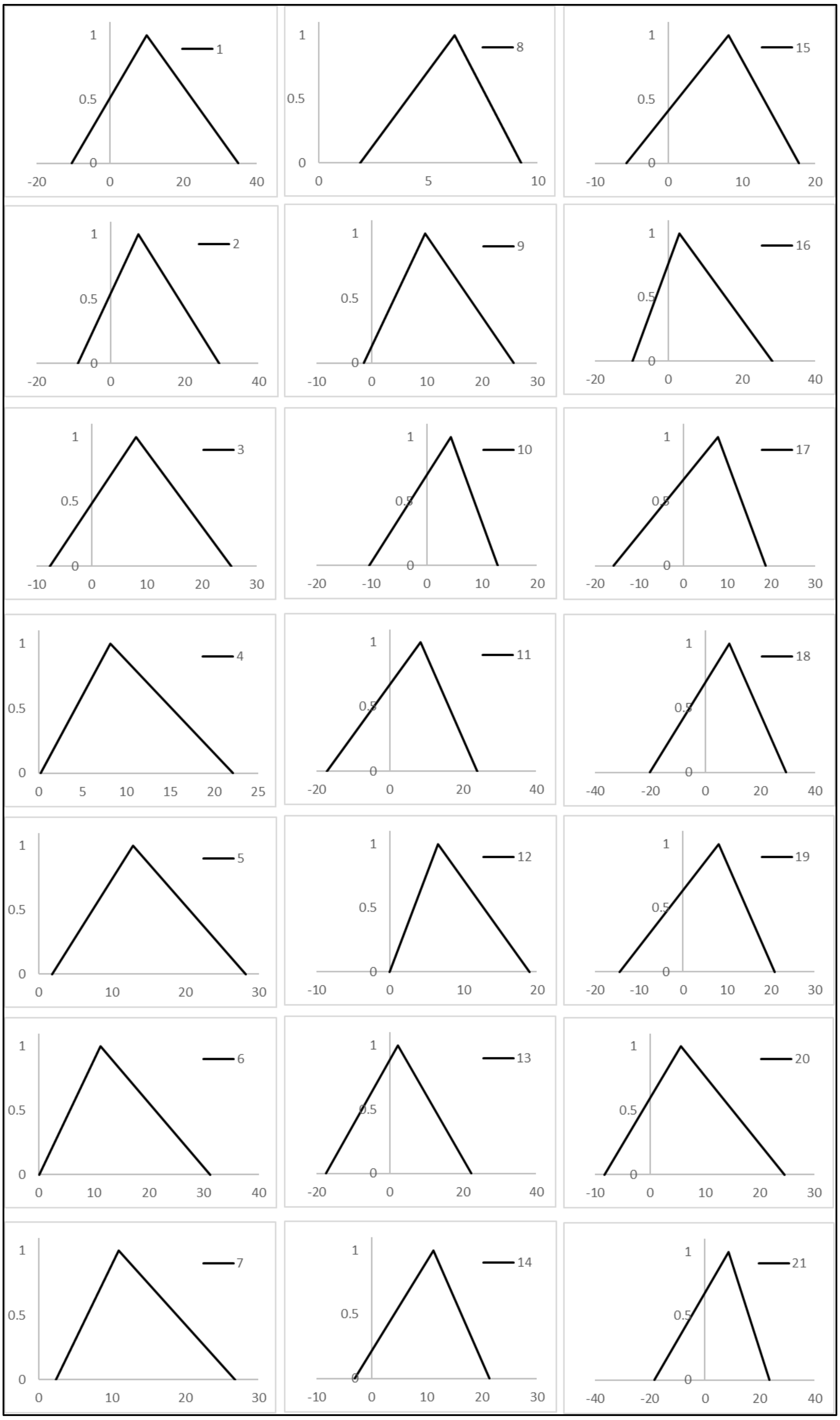


Figure 4.9: Survey Results of Percent Deviations in Plan Failure (Severity, TTR)

The ultimate goal of the simulation model was to include all factors that affect the plan failure to the model; however, due to the reasons detailed in Section 3.4.2, economic concerns are not included in the model. Additionally, some similar basic events are joined under single items for practicality. To group such items, FCI values of each basic event are recommended to be used. In this sense, DES_j items are formed out of basic events, BE_i, by using their FCI values as the weighting factor (Table 4-6). The data is given in triangular distribution form under two groups as frequency and severity in Figure 4.10 and Figure 4.11, respectively.

Table 4-6: Collected and Weighted Survey Results for the DES Input Data

	Frequency in Days			Severity as %		
DESi	**[Lowest]**	**[Most Expected]**	**[Highest]**	**[Lowest]**	**[Most Expected]**	**[Highest]**
1	3	8	20	-10	10	35
2	5	14	37	-9	7	29
3	8	27	45	-6	9	24
4	18	38	80	1	12	27
5	8	25	74	-2	9	26
6	3	7	19	-8	6	17
7	3	7	24	-17	8	24
8	14	60	132	-16	8	19
9	40	101	256	-20	9	29
10	94	306	428	-15	8	21
11	64	248	322	-8	6	25
12	19	30	111	-18	9	24

For the DES_j from 1 to 7, grade-based, tonnage-based, mineral processing, structural, workforce efficiency, mining equipment, efficiency and availability uncertainties, the day values (frequencies) are not used in the simulation model discretely,. Rather, these uncertainties are considered to occur continuously over the mining operation period. Therefore, their values are assigned to each block without considering their frequency values from the survey results presented in Table 4-6. The frequency values are also presented for future usage.

As mentioned earlier, the generic values of basic event frequencies and their percentile effects on production and final throughput, given in Table 4-5 and Table 4-6, can be used for any mine in case of the absence of site-specific data. The current case study from a gold mine located in Türkiye uses some of the survey outcomes and site-specific information jointly.

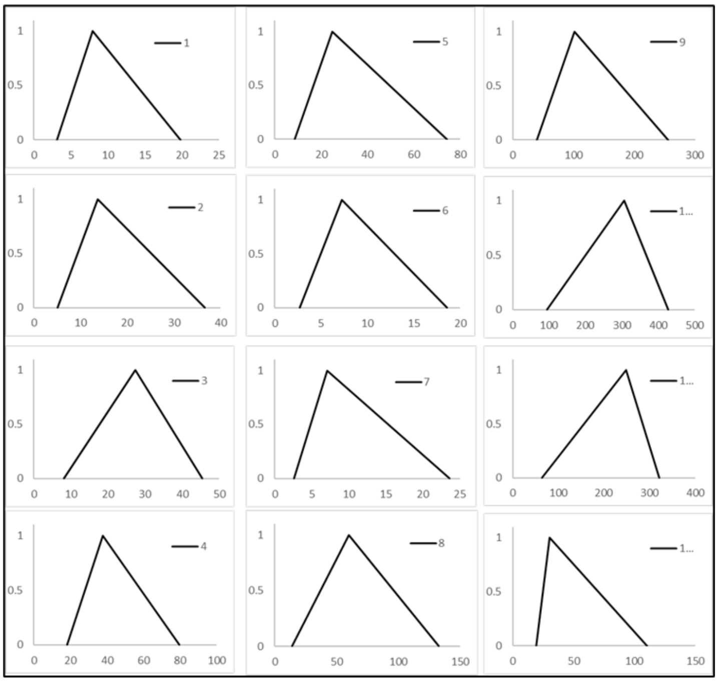


Figure 4.10: DES Days for a Failure (Frequency)

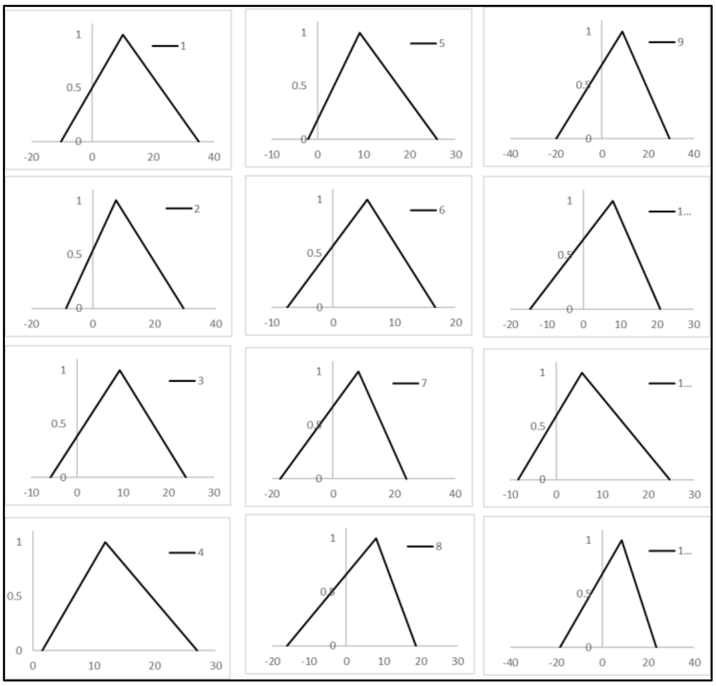


Figure 4.11: DES Percent Deviations in Plan Failure (Severity)

TTF and TTR values of the External Events between DES IDs of 8 and 12 are updated considering site-specific information, while the remaining DES IDs are taken from the survey results, as shown in Table 4-7. Additionally, frequency and severity distributions of the site-specific are also presented in Figure 4.12 and Figure 4.13, indicating with dashed lines.

Table 4-7: Survey Results Combined with Field Data for the DES Input Data

	Frequency in Days			Severity as %		
DESi	**[Lowest]**	**[Most Expected]**	**[Highest]**	**[Lowest]**	**[Most Expected]**	**[Highest]**
1	3	8	20	-10	10	35
2	5	14	37	-9	7	29
3	8	27	45	-6	9	24
4	18	38	80	1	12	27
5	8	25	74	-2	9	26
6	3	7	19	-8	6	17
7	3	7	24	-17	8	24
8	90	180	360	0	4	8
9	60	120	360	0	5	8
10	120	240	360	0	3	8
11	180	360	360	0	2	8
12	60	90	120	0	8	25

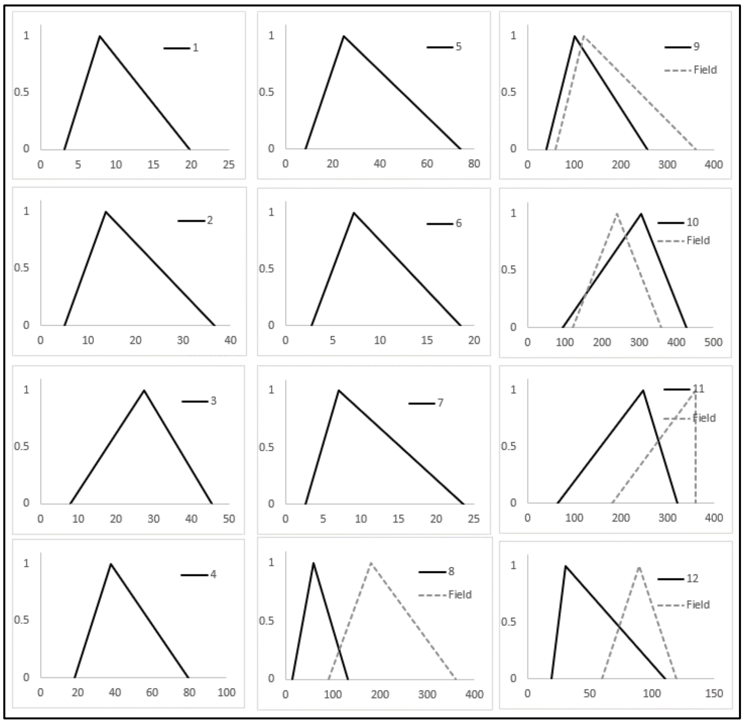


Figure 4.12: The Case Study DES Days for a Failure (Frequency)

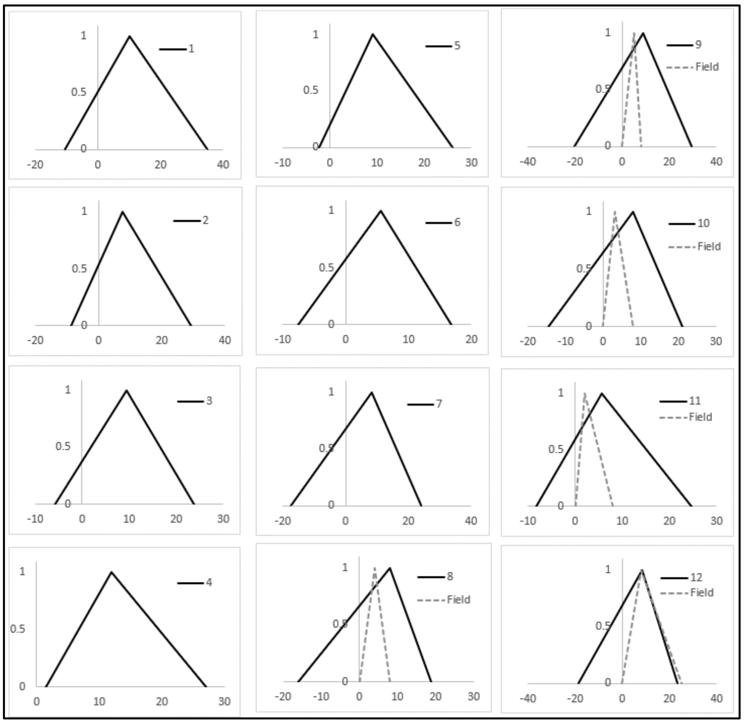


Figure 4.13: The Case Study DES Percent Deviations in Plan Failure (Severity)

Besides the survey results, the DES model's remaining inputs are taken from long-term schedule outputs. For the open pit gold mine block model, a representative case was assumed for a year of planned production, as given in Figure 4.14.

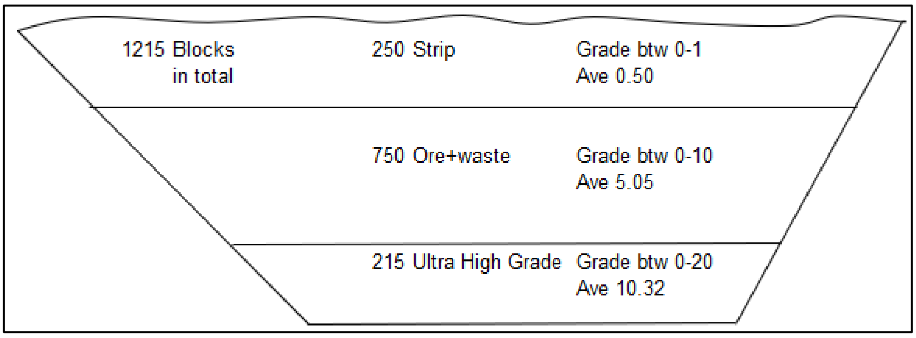


Figure 4.14: A representative Open Pit Gold Mine

Additional assumptions and inputs are presented in

Table 4-8 for the deterministic case that represents the prepared plan by the long-term planning department. The results are obtained at the end of the deterministic run of the simulation model.

Before running the model, the output was calculated manually from the scheduled 1,215 blocks for a year, as shown below. After calculations, the model is first computed with deterministic inputs for verification. Model outputs are compared with the manually calculated values. When two results are compared, it is seen that hauled tonnage, ore tonnage, grade, and metal content are identical. The long-term schedule is obtained at the end of the run, which will be compared with the stochastically produced schedule in the following parts. The model is assumed to be verified since the results align with manual calculations.

- # of cycles/year: 415,800/4.5 = 92,400
- Hauled tonnage per cycle: 45 tonnes
- Hauled tonnage per year: 45*92,400*0.9*0.9*0.9 = 3,031,182 tonnes
- Hauled ore tonnes and grade = 2,177,500 tonnes at 6.90 ppm
- Total metal with 90% plant recovery = 434,558 ounces

Second, a stochastic case was computed to validate and see the model's performance with the inputs presented in Table 4-9 with involved short-term uncertainties. The simulation is replicated by 40 runs with a computational time of nearly 48 hours. The results of the replication are shown in Table 4-10. Variations in the simulation results are evaluated to ensure that number of runs gives representative results. Normalized average values of the annual production amounts after the runs are expected to be flattened after a while. As observed from Figure 4.15, the normalized results are almost flattened after the 35th run. Therefore, it is decided that 40 replications of the case will offer representative results. The results reveal that 1,215 blocks are planned to be produced in the long-term plans; however, only an average of 1,041 blocks can be produced in the field. It means that production targets will deviate at short-range if the long-range plan is not updated with interim forecasts. However, it should be noted that such updates will also affect the life of mine (LOM) schedules. Therefore, for the related year, the results can be assumed to give the worst-case scenario where the deviations are not reduced by interim forecasts and the plan changes to satisfy the targeted total production and metal throughput at the end of the year.

Table 4-8: Deterministic Case Inputs

Deterministic (Long-term) Run Inputs		
Item, unit	**Value**	**Explanation**
Operating time in a year, min.	415,800	60*21*330
Cut-off grade, ppm	1	If grade>1 ore else waste
Assumed Plant Recovery	0.9	Assumed value in deterministic schedule
Assumed Equipment Efficiency	0.9	Assumed value in deterministic schedule
Assumed Workforce Efficiency	0.9	Assumed value in deterministic schedule
Assumed Equipment Availability	0.9	Assumed value in deterministic schedule
Shovel Loading Time, min.	4.5	5 swings, 50 seconds/swing, 10 seconds for each truck positioning and leaving
Truck Capacity, tonnes	45	Assumed capacity of the truck
Block ID	1 to 1215	Mining Sequence
Material Type	1 or 0	Either ore(1) or waste(0)
Block Model Dimensions, m	10x10x10	-
Density, t/cum	2.5	The density in the BM
Grade, ppm	0 to 100	BM grade of the block
Grade Uncertainty Factor	1	Constant Value
Tonnage Uncertainty Factor	1	Constant Value
Mineral Processing Uncertainty Factor	1	Constant Value
Structural Uncertainty Factor	1	Constant Value
Workforce Efficiency Uncertainty Factor	1	Constant Value
Mining Equipment Efficiency Uncertainty Factor	1	Constant Value
Mining Equipment Availability Uncertainty Factor	1	Constant Value
TTF, Community Relations, min	1,000,000	A Big Value
TTR, Community Relations, min	0	Constant Value
TTF, Permit, Legislation, and Regulation, min.	1,000,000	A Big Value
TTR, Permit, Legislation, and Regulation, min.	0	Constant Value
TTF, Political Stability, min.	1,000,000	A Big Value
TTR, Political Stability, min.	0	Constant Value
TTF, Force Majeure, min.	1,000,000	A Big Value
TTR, Force Majeure, min.	0	Constant Value
TTF, Environment and OHS, min	1,000,000	A Big Value
TTR, Environment and OHS, min	0	Constant Value

Table 4-9: Stochastic Case Inputs

Stochastic (Short-term) Run Inputs		
Item, unit	**Value**	**Explanation**
Operating time in a year, min.	415,800	60*21*330
Cut-off grade, ppm	1	Grade>1 ore else waste
Assumed Plant Recovery	0.9	Assumed value in deterministic schedule
Assumed Equipment Efficiency	0.9	Assumed value in deterministic schedule
Assumed Workforce Efficiency	0.9	Assumed value in deterministic schedule
Assumed Equipment Availability	0.9	Assumed value in deterministic schedule
Shovel Loading Time, sec.	TRD(4.08,4.5,4.92)	5 swings, 50+/-5 seconds/swing, 10 seconds for each truck positioning and leaving
Truck Capacity, tonnes	NORM(45,2.5)	Assumed capacity of the truck
Block ID	1 to 1215	Mining Sequence
Material Type	1 or 0	Either ore(1) or waste(0)
Block Model Dimensions, m	10x10x10	-
Density, t/cum	TRD(2.3,2.5,2.7)	The distribution of the density in the BM
Grade, ppm	0 to 100	BM grade of the block
Grade Uncertainty Factor	TRD(-0.1,0.1,0.35)	Comes from Survey Results
Tonnage Uncertainty Factor	TRD(-0.09,0.07,0.29)	Comes from Survey Results
Mineral Processing Uncertainty Factor	TRD(-0.06,0.09,0.24)	Comes from Survey Results
Structural Uncertainty Factor	TRD(0.01,0.12,0.27)	Comes from Survey Results
Workforce Efficiency Uncertainty Factor	TRD(0.882,0.981,1)	Comes from Survey Results*Assumptions
Mining Equipment Efficiency Uncertainty Factor	TRD(0.828,0.954,1)	Comes from Survey Results*Assumptions
Mining Equipment Availability Uncertainty Factor	TRD(0.747,0.972,1)	Comes from Survey Results*Assumptions
TTF, Community Relations, min	TRD(129600,259200,518400)	Comes from Field Data*24*60
TTR, Community Relations, min	TRD(0,10368,41472)	Comes from Field Data*24*61
TTF, Permit, Legislation, and Regulation, min.	TRD(86400,172800,518400)	Comes from Field Data*24*62
TTR, Permit, Legislation, and Regulation, min.	TRD(0,8640,41472)	Comes from Field Data*24*63
TTF, Political Stability, min.	TRD(172800,345600,518400)	Comes from Field Data*24*64
TTR, Political Stability, min.	TRD(0,10368,41472)	Comes from Field Data*24*65
TTF, Force Majeure, min.	TRD(259200,518400,518400)	Comes from Field Data*24*66
TTR, Force Majeure, min.	TRD(0,10368,41472)	Comes from Field Data*24*67
TTF, Environment and OHS, min	TRD(86400,129600,172800)	Comes from Field Data*24*68
TTR, Environment and OHS, min	TRD(0,10368,43200)	Comes from Field Data*24*68

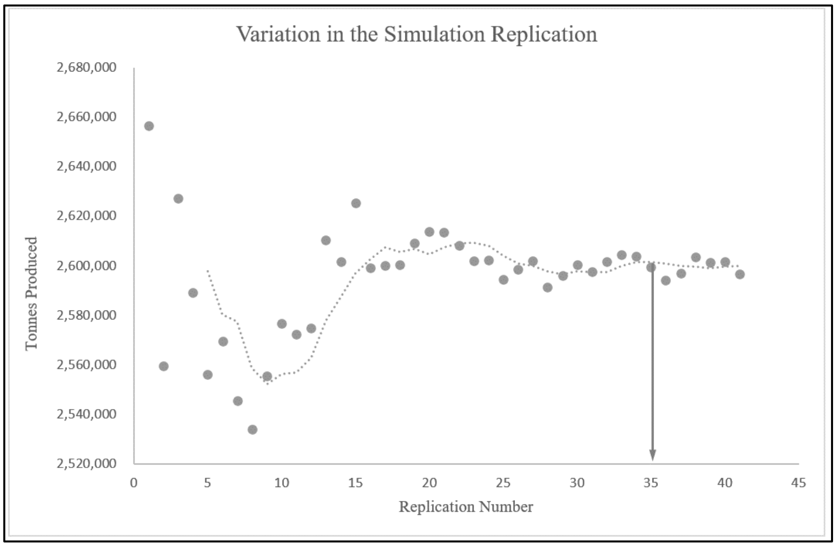


Figure 4.15: Variation in the Simulation Replications

Table 4-10: Results of Stochastic Simulation Run for Total Material

Replication Number	Sum of Hauled Tonnage	Count of Block No	Average of Block Tonnage	Weighted Average of Grade, ppm	Weighted Average of Grade Variance Factor	Weighted Average of Metallurgy Variance Factor	Weighted Average of Lithology/Rock Type Factor
1	2,656,453	1063	2,499	4.14	0.11	0.11	0.13
2	2,462,943	985	2,500	3.75	0.11	0.11	0.13
3	2,762,527	1104	2,502	4.35	0.11	0.11	0.13
4	2,474,681	990	2,500	3.75	0.11	0.11	0.13
5	2,424,586	970	2,500	3.73	0.11	0.11	0.13
6	2,636,344	1054	2,501	4.11	0.11	0.11	0.13
7	2,401,311	960	2,501	3.73	0.11	0.11	0.13
8	2,453,875	979	2,507	3.74	0.11	0.11	0.13
9	2,727,214	1093	2,495	4.29	0.11	0.11	0.13
10	2,767,727	1108	2,498	4.37	0.11	0.11	0.13
11	2,528,981	1011	2,501	3.85	0.12	0.12	0.13
12	2,601,990	1041	2,500	4.05	0.11	0.11	0.13
13	3,034,566	1215	2,498	4.89	0.11	0.11	0.13
14	2,492,057	998	2,497	3.77	0.12	0.12	0.13
15	2,956,716	1183	2,499	4.73	0.11	0.11	0.13
16	2,204,393	884	2,494	3.64	0.11	0.11	0.13
17	2,616,853	1048	2,497	4.09	0.11	0.11	0.13
18	2,606,868	1041	2,504	4.05	0.12	0.12	0.13
19	2,764,338	1105	2,502	4.35	0.11	0.11	0.13
20	2,703,874	1083	2,497	4.22	0.11	0.11	0.13
21	2,603,471	1042	2,499	4.05	0.11	0.11	0.13
22	2,495,835	998	2,501	3.76	0.12	0.12	0.13
23	2,464,856	986	2,500	3.75	0.12	0.12	0.13
24	2,614,832	1046	2,500	4.07	0.11	0.11	0.13
25	2,405,273	963	2,498	3.74	0.11	0.11	0.13
26	2,696,511	1079	2,499	4.20	0.12	0.12	0.13
27	2,691,879	1078	2,497	4.19	0.12	0.12	0.13
28	2,304,199	921	2,502	3.66	0.12	0.12	0.13
29	2,734,887	1095	2,498	4.30	0.11	0.11	0.13
30	2,724,609	1090	2,500	4.27	0.11	0.11	0.13
31	2,512,509	1005	2,500	3.80	0.11	0.11	0.13
32	2,722,945	1088	2,503	4.25	0.11	0.11	0.13
33	2,702,215	1081	2,500	4.20	0.11	0.11	0.13
34	2,583,833	1031	2,506	3.97	0.11	0.11	0.13
35	2,448,099	979	2,501	3.75	0.11	0.11	0.13
36	2,411,888	964	2,502	3.73	0.11	0.11	0.13
37	2,693,615	1078	2,499	4.18	0.11	0.11	0.13
38	2,839,413	1136	2,499	4.52	0.11	0.11	0.13
39	2,518,577	1008	2,499	3.83	0.11	0.11	0.13
40	2,622,666	1047	2,505	4.07	0.11	0.11	0.13
Grand Total	**2,601,760**	**1,041**	**2,500**	**4.07**	**0.11**	**0.11**	**0.13**

Since the short-term case is created with stochastic inputs, varied results are obtained in the simulation replication results. Therefore, instead of giving a single deterministic value, the results are fitten into distributions. Accordingly, the total annual production distribution is provided in Figure 4.16. It is observed that the data normally distributes nearly with a mean of 2.6M tonnes and a standard deviation of 0.2M tonnes.

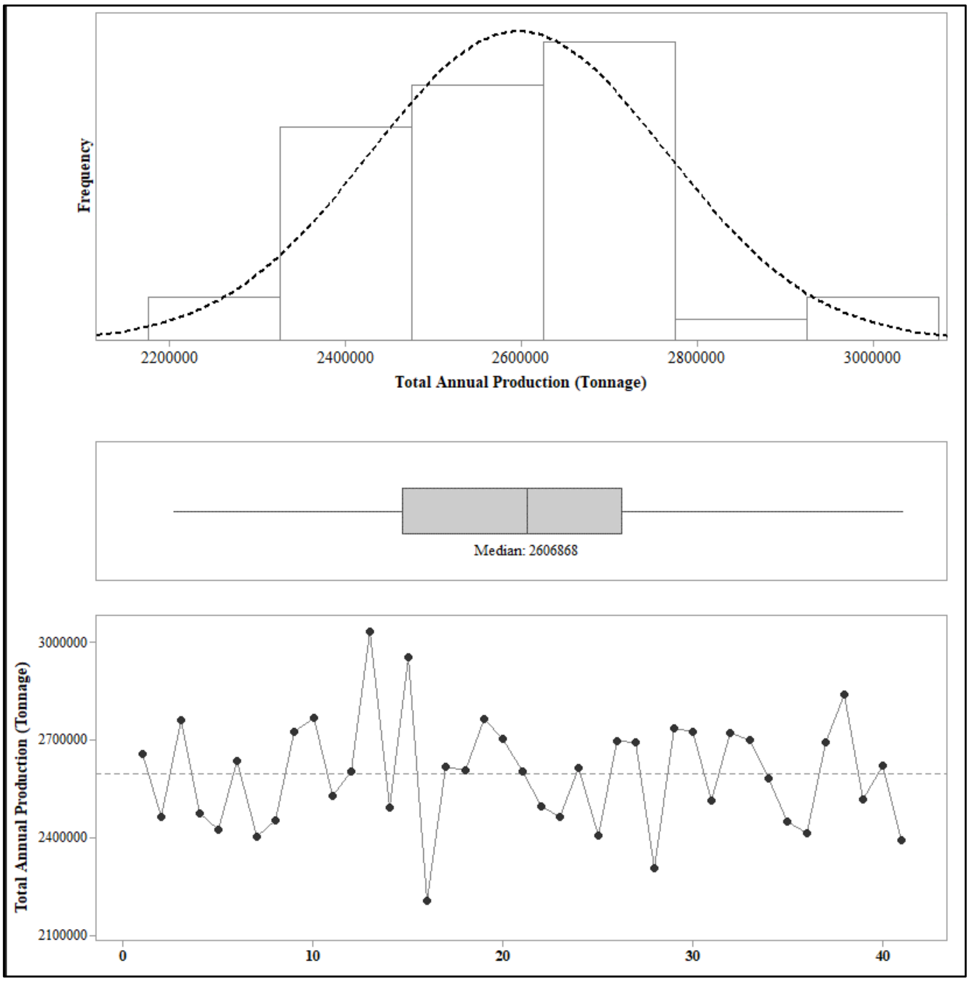


Figure 4.16: Total Annual Production Statistics of the Stochastic Case

In addition, the same examination was conducted for the total metal recovered, as given in Figure 4.17. The total amounts of metal recovered annually for 40 runs are also fitted into normal distribution.

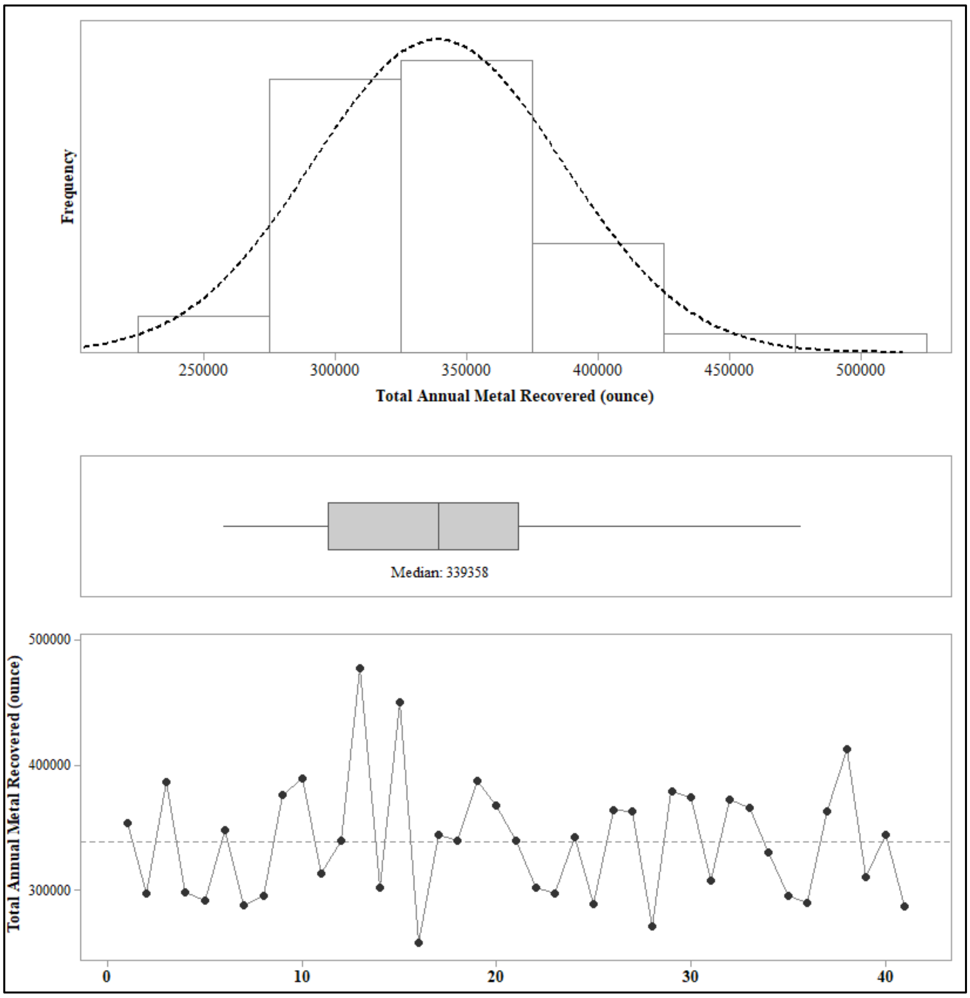


Figure 4.17: Total Annual Recovered Metal Statistics of the Stochastic Case

The average values of the total annual hauled material, total annual hauled ore material, metal recovered, and ore grade for the stochastic case are as follows:

- Hauled tonnage per year = 2,601,760 tonnes
- Hauled ore tonnes and grade = 1,761,338 tonnes 5.79 ppm
- Total metal with 90% plant recovery = 294,858 ounces

The expected ore production is also provided in Table 4-11. Based on the grade variance factor, it is expected to obtain an ore grade greater than the Block Model assumptions by 11%, so the expected ore grade is 6.43 ppm. Therefore, the metal content is expected to increase to 327,757 ounces with 90% plant recovery.

Table 4-11: Results of Stochastic Simulation Run for Ore Production

Replication Number	Sum of Hauled Tonnage	Count of Block No	Average of Block Tonnage	Weighted Average of Grade, ppm	Weighted Average of Grade Variance Factor	Weighted Average of Metallurgy Variance Factor	Weighted Average of Lithology/Rock Type Factor
1	1,811,632	725	2,499	5.86	0.11	0.11	0.13
2	1,629,978	652	2,500	5.43	0.11	0.11	0.13
3	1,909,461	763	2,503	6.09	0.11	0.11	0.13
4	1,641,548	657	2,499	5.42	0.11	0.11	0.13
5	1,595,607	638	2,501	5.43	0.11	0.11	0.13
6	1,795,218	717	2,504	5.81	0.11	0.11	0.13
7	1,574,543	630	2,499	5.44	0.11	0.11	0.13
8	1,621,501	647	2,506	5.42	0.11	0.11	0.13
9	1,875,367	752	2,494	6.03	0.11	0.11	0.13
10	1,915,974	767	2,498	6.11	0.11	0.11	0.13
11	1,694,381	677	2,503	5.51	0.11	0.11	0.13
12	1,762,062	705	2,499	5.76	0.11	0.11	0.13
13	2,175,314	871	2,497	6.63	0.11	0.11	0.13
14	1,656,947	664	2,495	5.43	0.12	0.12	0.13
15	2,094,900	839	2,497	6.49	0.11	0.11	0.13
16	1,405,414	564	2,492	5.44	0.12	0.12	0.13
17	1,778,096	712	2,497	5.81	0.11	0.11	0.13
18	1,765,971	705	2,505	5.75	0.11	0.11	0.13
19	1,910,622	764	2,501	6.09	0.11	0.11	0.13
20	1,853,024	742	2,497	5.95	0.11	0.11	0.13
21	1,763,565	706	2,498	5.76	0.11	0.11	0.13
22	1,657,564	664	2,496	5.43	0.11	0.11	0.13
23	1,636,353	653	2,506	5.42	0.12	0.12	0.13
24	1,775,229	710	2,500	5.78	0.10	0.10	0.13
25	1,581,790	633	2,499	5.44	0.11	0.11	0.13
26	1,845,913	739	2,498	5.92	0.12	0.12	0.13
27	1,842,116	738	2,496	5.90	0.12	0.12	0.13
28	1,489,312	595	2,503	5.40	0.12	0.12	0.13
29	1,884,211	754	2,499	6.04	0.12	0.12	0.13
30	1,873,203	749	2,501	6.00	0.11	0.11	0.13
31	1,675,904	671	2,498	5.47	0.11	0.11	0.13
32	1,869,351	747	2,502	5.98	0.11	0.11	0.13
33	1,852,334	740	2,503	5.92	0.11	0.11	0.13
34	1,744,804	696	2,507	5.66	0.11	0.11	0.13
35	1,617,993	647	2,501	5.43	0.11	0.11	0.13
36	1,583,235	633	2,501	5.44	0.11	0.11	0.13
37	1,843,091	738	2,497	5.90	0.11	0.11	0.13
38	1,984,018	794	2,499	6.27	0.11	0.11	0.13
39	1,684,859	674	2,500	5.50	0.11	0.11	0.13
40	1,781,099	711	2,505	5.78	0.11	0.11	0.13
Grand Total	**1,761,338**	**705**	**2,500**	**5.79**	**0.11**	**0.11**	**0.13**

One of the main reasons for the production loss is spotted as downtime due to external factors. In Table 4-12, the estimated total system downtimes are presented. On average, 79,231 minutes of downtime is expected to occur in a year for the case study, which is considerably high.

Table 4-12: Estimated Downtimes

Replication Number	Number of Downtimes	Sum of Estimated Downtime, min
1	35	78,815
2	29	104,845
3	27	62,670
4	27	102,293
5	32	79,028
6	27	81,525
7	30	111,273
8	30	65,590
9	31	48,573
10	30	65,171
11	30	97,321
12	29	76,204
13	20	34,947
14	33	101,292
15	32	39,346
16	27	118,908
17	26	86,081
18	37	65,502
19	33	65,967
20	27	44,106
21	24	77,042
22	27	69,637
23	33	104,631
24	29	86,837
25	24	94,391
26	33	62,042
27	29	74,302
28	18	120,331
29	37	61,526
30	25	71,390
31	24	75,972
32	31	72,167
33	24	75,253
34	27	88,212
35	27	90,839
36	26	112,730
37	36	73,670
38	31	56,927
39	23	89,701
40	33	82,190
Grand Total	29	79,231

As a result, the created model is verified and validated with the aid of the case study belonging to an open pit gold mine case. The planned production for a year is estimated to be 3M tonnes with 434,558 ounces poured. However, based on the available model input, the production is estimated to be 2.6M tonnes with 294,858 ounces poured for the worst-case scenario as illustrated in Table 4-13 and Figure 4.18.

Table 4-13: The Comparison Table of LTP and STP

Item		**Value**
Production, tonnes	*Long-term*	3,031,182
	Short-term	2,601,760
	Variation	17%
Grade, ppm	*Long-term*	6.9
	Short-term	5.79
	Variation	19%
Gold Poured, ounces	*Long-term*	434,558
	Short-term	294,858
	Variation	47%

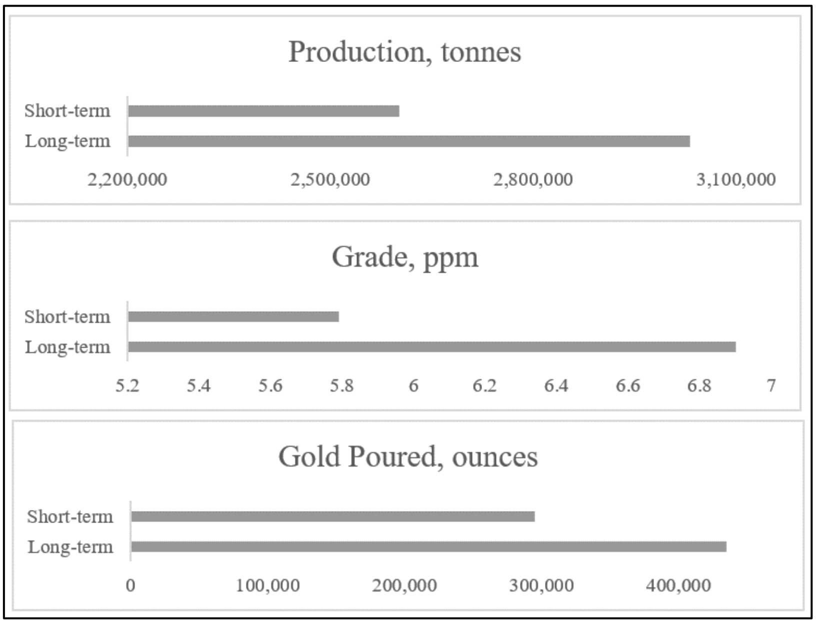


Figure 4.18: The Comparison Figure of LTP and STP

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

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) 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. As a result, the following conclusions are drawn:

- A comprehensive literature survey was conducted so that 21 main uncertainty factors (shown previously in Figure 3.1) are observed to be effective in deviations from long-term production plans in surface metal mines.
- 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.

- 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.
- A fuzzy logic analysis was conducted for linguistic survey results to determine the failure probabilities of basic events used in Fuzzy Fault Tree Analysis. 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.
- 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.

- The model is verified and validated with a case study. According to the deterministic simulation results of a long-term schedule, a 3M tonne of total production and 435 koz gold pour are obtained as the target. However, when the model is computed with stochastic inputs representing the short-term case, the total production is expected as 2.6M tonne and 295koz gold pour due to lost 79,231 minutes of downtime of geological, operational and external factors for the worst-case scenario where there is not any interim forecasts and plan revisions during the production year.
- Considering how uncertainty items can be effective in deviations from the annual production targets of mining companies, developing proactive actions in the long-term planning stage is seen to be vital for the plans' success. 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.

5.2 Recommendations

The following improvements are recommended for future studies:

- The DES model can be improved by detailing the interactions between the equipment. A complete production cycle can be simulated, but it is good to note that the simulation running time should be tolerable and manageable.
- The created model can be computed by including a complete site-specific dataset.
- The DES model observation time can be extended to simulate the whole life-of-mine period.
- The cost of failures not achieving targeted production can be considered in the model to see the economic consequences of such deviations and potential trade-offs.

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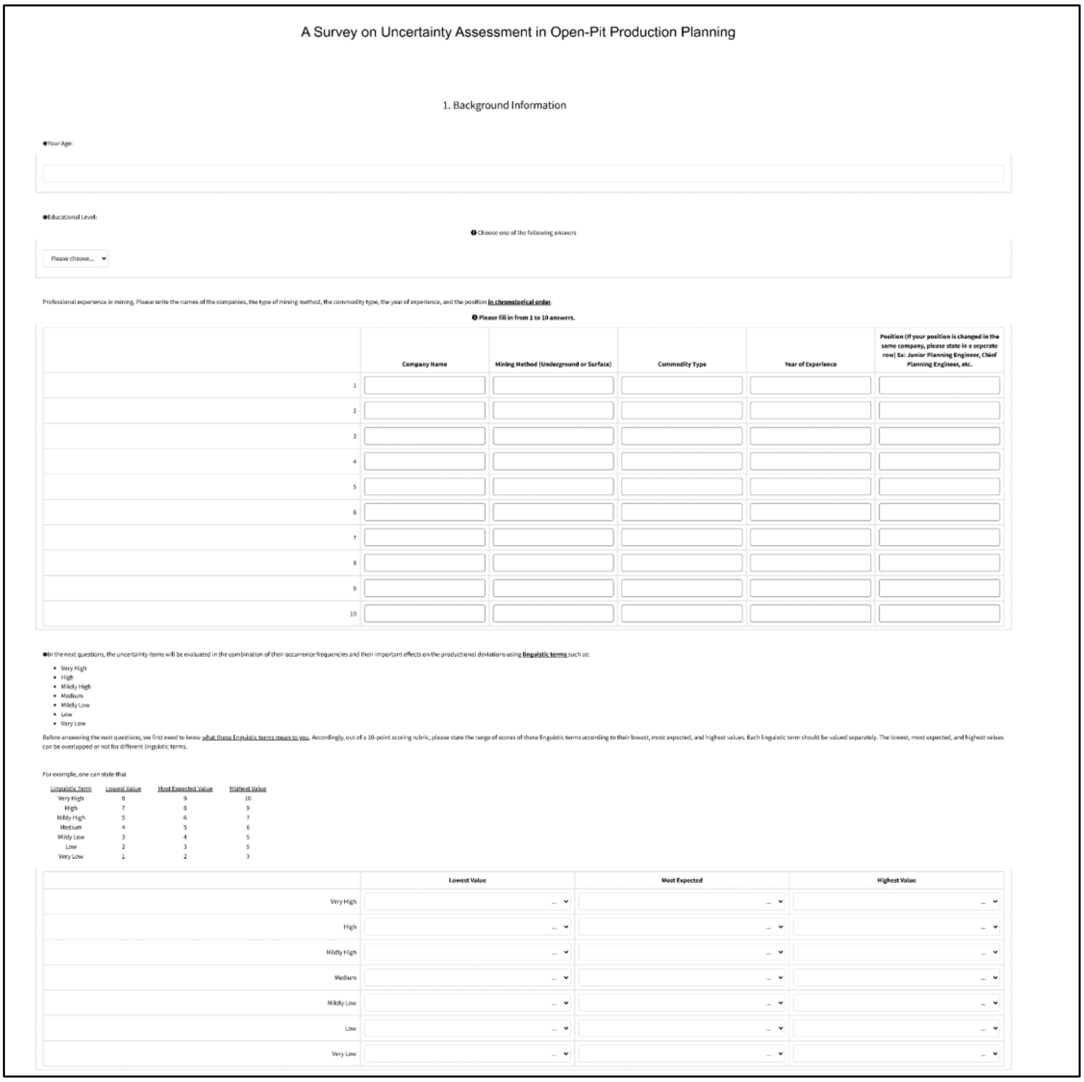
APPENDICES

A. Survey Window Presented to the Responders



A Survey on Uncertainty Assessment in Open-Pit Production Planning

1. Background Information

✱Your Age:

✱Educational Level:

Choose one of the following answers

Please choose...

Professional experience in mining. Please write the names of the companies, the type of mining method, the commodity type, the year of experience, and the position **in chronological order**.

Please fill in from 1 to 10 answers.

	Company Name	Mining Method (Underground or Surface)	Commodity Type	Year of Experience	Position (If your position is changed in the same company, please state in a seperate row) Ex: Junior Planning Engineer, Chief Planning Engineer, etc.
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					

✱In the next questions, the uncertainty items will be evaluated in the combination of their occurrence frequencies and their important effects on the productional deviations using **linguistic terms** such as:

- Very High
- High
- Mildly High
- Medium
- Mildly Low
- Low
- Very Low

Before answering the next questions, we first need to know what these linguistic terms mean to you. Accordingly, out of a 10-point scoring rubric, please state the range of scores of these linguistic terms according to their lowest, most expected, and highest values. Each linguistic term should be valued separately. The lowest, most expected, and highest values can be overlapped or not for different linguistic terms.

For example, one can state that

Linguistic Term	Lowest Value	Most Expected Value	Highest Value
Very High	8	9	10
High	7	8	9
Mildly High	5	6	7
Medium	4	5	6
Mildly Low	3	4	5
Low	2	3	5
Very Low	1	2	3

	Lowest Value	Most Expected	Highest Value
Very High	...	...	...
High	...	...	...
Mildly High	...	...	...
Medium	...	...	...
Mildly Low	...	...	...
Low	...	...	...
Very Low	...	...	...

Figure A.1: Opening Window of the Questionnaire

2. Geological Uncertainty Items

There are **five** main **geological uncertainty items** (i. grade, ii. tonnage, iii. metallurgical parameters, iv. lithology and/or rock type, and v. geotechnical and hydrogeological parameters) that are considered to be effective in deviations between long and short-range production plans. You will be asked **three different questions** in which the blank parts of the questions should be evaluated according to the related uncertainty item. Sample responses to these questions are given below.

->Answer Type01: Deviation in ......**item**..... causes a change in either the short-term production plan or the plant feed plan ......**.linguistic variable.**......

Note: While answering this question type, please consider the combined effect of the uncertainty item's frequency and severity.

Example: Deviation in ......**grade**..... causes a change in either the short-term production plan or the plant feed plan ....**very high**........

->Answer Type02: Deviation in ......**item**..... causes a change in either the short-term production plan or the plant feed plan, every .....**number of days to the below table.**.... day.

# of days	Lowest	Most Expected	Highest
Values in days:			

Note: While answering this question type, please consider only the effect of the uncertainty item's frequency.

Example: Deviation in ......**grade.**.... causes a change in either the short-term production plan or the plant feed plan, every .....**[Lowest:4], [Most Expected:10], [Highest:25].**.... day.

# of days	Lowest	Most Expected	Highest
Values in days:	**4**	**10**	**25**

->Answer Type03: In cases where the short-term production plan or the plant feed plan is affected by the deviation in ......**item**....., what is the amount of this deviation in percent you experienced before (can be positive or negative)?

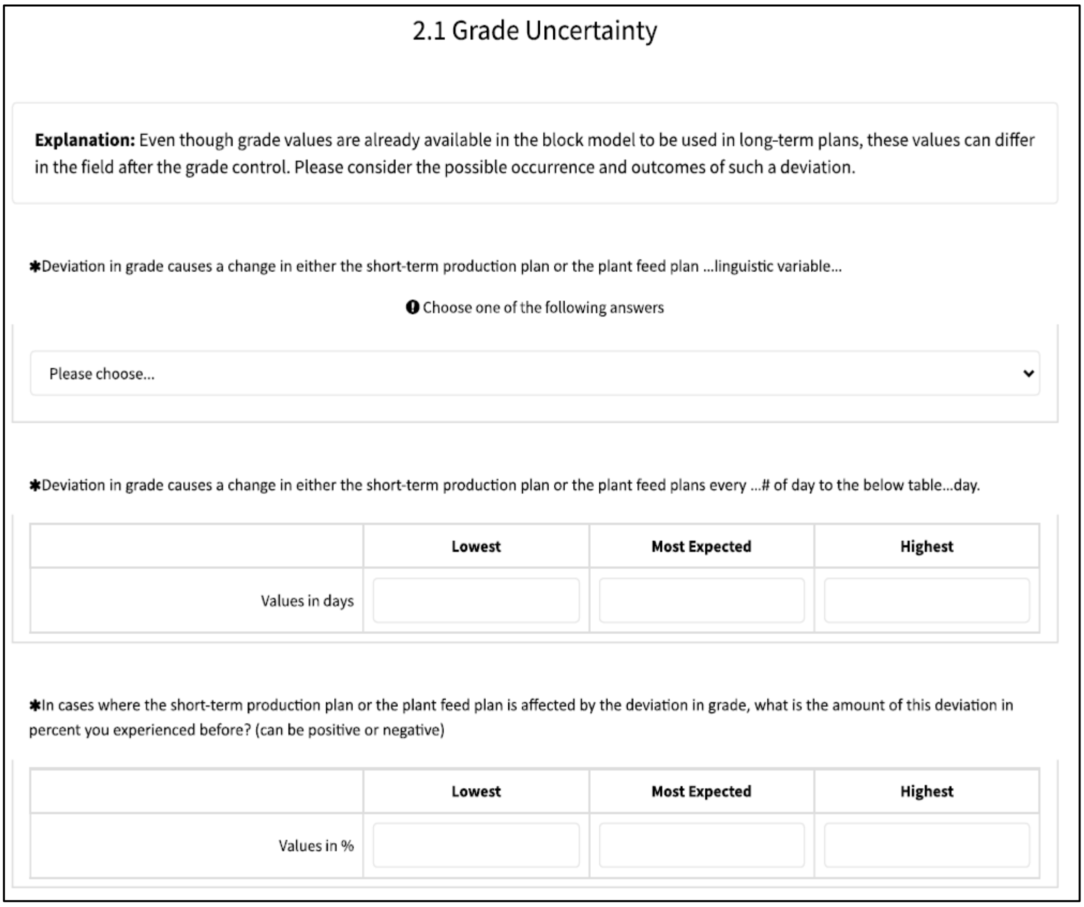
Amount of Deviation	Lowest	Most Expected	Highest
Values in %:			

Note: While answering this question type, please consider only the effect of the uncertainty item's severity.

Example: In cases where the short-term production plan or the plant feed plan is affected by the deviation in ......**grade**....., what is the amount of this deviation you experienced before in percent (can be positive or negative)?

Amount of Deviation	Lowest	Most Expected	Highest
Values in %:	**-15**	**-2**	**+5**

Figure A.2: General Information Window for Question Groups: A Representative Example of Geological Uncertainty Group



2.1 Grade Uncertainty

Explanation: Even though grade values are already available in the block model to be used in long-term plans, these values can differ in the field after the grade control. Please consider the possible occurrence and outcomes of such a deviation.

✱Deviation in grade causes a change in either the short-term production plan or the plant feed plan ...linguistic variable...

Choose one of the following answers

Please choose...

✱Deviation in grade causes a change in either the short-term production plan or the plant feed plans every ...# of day to the below table...day.

	Lowest	**Most Expected**	**Highest**
Values in days			

✱In cases where the short-term production plan or the plant feed plan is affected by the deviation in grade, what is the amount of this deviation in percent you experienced before? (can be positive or negative)

	Lowest	**Most Expected**	**Highest**
Values in %			

Figure A.3: Uncertainty Item Window: A Representative Example of Grade Uncertainty under Geological Uncertainty Group