Applied Machine Learning in Mine Safety and Short-Term Underground Mine Production Scheduling

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Abstract

Mining is a highly mechanized industry with inherent health and safety hazards. As operations have modernized, a safety-focused culture has been adopted and research-driven innovations have been implemented to reduce injuries and fatalities. A goal of the mining industry is to achieve zero injuries on all mine sites. To this end, researchers are developing ways of incorporating minimization of occupational hazards in the mine planning phase that maximizes net present value while managing safety and health risks.

This research explores the potential of machine learning in contributing to robust mine safety analysis of an accident and injury data set over a ten-year period from the Mine Safety and Health Administration through the use of multiclass logistic regression. The analysis provides a means to determine a miner's susceptibility to the following injury classes: non-fatal with no days lost or restricted activity, non-fatal with days lost and/or days of restricted work activity, and fatal and total permanent or partial permanent disability. The results reveal that a miner's experience on their current job is a significant factor in injury occurrence, even for those with decades of total mining experience. From this analysis, machine learning proves to be a tool that can be used beyond basic statistics in providing robust mine accident and injury analysis.

Furthermore, the research applies an artificial neural network (ANN), a machine learning tool, to other areas of mining, namely, mine ventilation, respirable dust, and underground mine production scheduling. The purpose of the neural network is to estimate, i.e., predict, the respirable dust emissions for a given mining activity. The ability to accurately estimate respirable dust concentrations can provide valuable information to the planning and ventilation engineers. Having information indicating the potential for higher concentrations of dust allows for appropriate actions to be taken prior to the initiation of the activity, thereby managing the situation proactively, instead of reactively.

A means of proactive management would be to incorporate the predicted concentrations and requisite ventilation into short-term production schedules. To this end, the research further explores short-term scheduling formulations in underground mining by applying the principles of rescheduling and deviation minimization. The author improves upon an existing formulation by incorporating more realistic penalty functions for activity and production goal deviations. Activity earliness and tardiness are penalized with exponentially increasing values as deviations increase, while goal penalties are only imposed if certain predetermined production target levels are not met. This culminates in a tool that is able to determine alternative schedules in response to unforeseen operational disruptions. The new penalty systems are evaluated using two different scenarios and the resulting schedules are compared. The comparative analysis shows how operational disruptions impact the schedule and how the new formulation makes up for the ensuing deviations. Future work will focus on developing mathematical constraints for incorporating the ANN predictions and ventilation requirements into the short-term formulation to provide an enhanced proactive approach towards the management of respirable dust exposure.

Acknowledgments

Exuding from within my heart are the words of Thomas Fuller, “Gratitude is the least of the virtues, but ingratitude is the worst of vices.” The completion of this work has been a synergy.

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AI	artificial intelligence
ANN	artificial neural network
BN	batch normalization
DLR	nonfatal injury with days lost and/or days of restricted work activity
DP	dropout
DPM	diesel particulate matter
FP	fatal and total permanent or partial permanent disability
IoT	internet-of-things
IP	integer programming
LP	linear programming
MIP	mixed integer programming
ML	machine learning
MSE	mean squared error
MSHA	Mine Safety and Health Administration
NDLR	nonfatal injury with no days lost or restricted activity
NIOSH	National Institute for Occupational Safety and Health
NPV	net present value
OT	operational technology
PEL	permissible exposure limit
RCPSP	resource-constrained project scheduling problem
SPSS	Statistical Package for Social Sciences
USA	United States of America
VIF	variance inflation factor
VoD	ventilation-on-demand

Chapter 1

Introduction

This chapter summarizes the work done in this dissertation. It begins with background information on the subject area concepts, and ends with a summary of work done in each chapter.

1.1 Background

Underground mining is the extraction of ore from deeply-buried mineral deposits in the earth crust that cannot be economically or safely mined from the surface (Haldar, 2018, Hartman and Mutmansky, 2002). Ore is that part of the deposit that contains economic quantities of metal or minerals. That part of the deposit that is uneconomic is referred to as waste. In situations where surface mining becomes uneconomic as a result of high stripping ratio (the amount of waste that must be mined to uncover a unit amount of ore), underground mining provides an alternative by offering greater selectivity, by means of which lesser amount of waste is mined to uncover ore. In other circumstances, safety factors, e.g., poor slope stability, may prohibit the use of surface mining methods (Hartman and Mutmansky, 2002).

In underground mining, the ore deposit may be accessed from the surface by shaft, decline or adit. Underground mines must have at least two entry-systems in combination for safe return route of miners that may be trapped in the event of an accident. This is also for the purpose of achieving adequate ventilation underground. A shaft is a vertical or near-vertical tunnel excavated downwards from the surface. Shafts are sunk as circular, square or rectangular openings, and are permanently lined with wood, concrete, or steel. A decline is an inclined road driven downwards from a natural slope or wall of an open pit. Declines usually connect to ramps, which are spiral roads that connect one level of the mine to the other. Declines and ramps enable driving of rubber-tired equipment such as light vehicles and mining machinery to the underground workings. An adit is a horizontal tunnel excavated from the side of a hill slope. It serves the purpose of development and production above the valley level (Haldar, 2018). Figure 1.1 shows the major components of an underground mine with a decline starting from the wall of an open pit. Figure 1.2 shows a decline entry system with a slope of about 10% to enable driving of mining machinery into the mine.

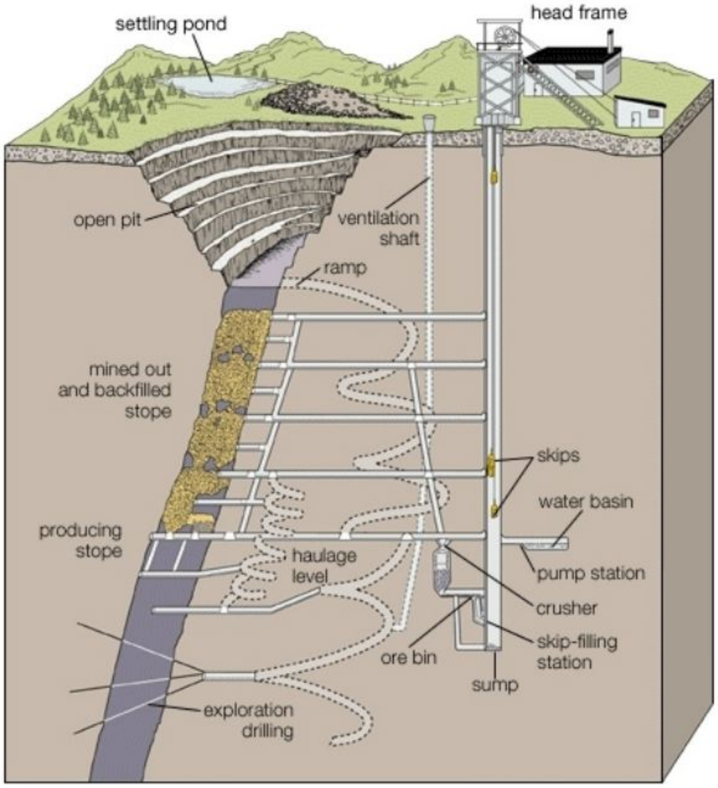

Figure 1.1: Diagram of Open Pit and Underground Mine (Source: Atlas Copco, 1997)

From the aforementioned entry points, drifts and haulage ways are constructed to provide further access to the ore deposit. The deposit may be mined by a variety of methods depending on the geometry and strength of the orebody, as well as the strength of the host rock. An orebody is a well-defined mass of material of sufficient ore content to make extraction economically feasible (USBM, 1996). The host rock refers to the rock in which the ore deposit occurs. Underground mining methods are broadly classified as naturally

Figure 1.2: A Decline Entry System (Source: Haldar, 2018)

supported, artificially supported, and caving. The naturally supported methods are used for extracting roughly tabular, flat or steeply dipping mineral deposits that are generally in contact with strong host rock (Hartman and Mutmansky, 2002). Examples of naturally supported mining methods include room and pillar, sublevel stoping, and shrinkage mining. In the first two examples, support is provided by natural pillars of ore that are left standing while mining advances. In the last example, support is provided by an accumulation of broken ore that is temporarily left in the stope to provide working platform for miners. A stope refers to an area where ore is removed from the surrounding rock (Hustrulid and Bullock, 2001).

Artificially supported mining methods are often applied in mines with weak rock structure (Hartman and Mutmansky, 2002). Examples include cut-and-fill, and stull stoping. In cut-and-fill stoping (which is applied to dipping, tabular deposits), the ore is mined in slices, and mined out stopes are backfilled with hydraulic sand tailings or waste rock (Hartman and Mutmansky, 2002, Hustrulid and Bullock, 2001). The fill serves both to support the stope walls and provide a working platform for equipment when the next slice of ore is mined. Stull stoping involves the use of timber or rock bolts for support in narrow, tabular orebodies. Caving mining methods utilize gravity and induced stresses in order to break rock *in situ* for subsequent transport and processing (Chitombo, 2017). They are employed when the orebody and host rock are of weak to medium strength, and are susceptible to caving. These methods cause the overlying waste rock mass to cave, eventually leading to subsidence of the surface. Examples include longwall mining and block caving. Longwall mining is applied to thin, flat lying seams, e.g., coal and trona. It consists of removing a panel of the coal or rock in a slice using a mechanical cutting device. During slicing, the panel roof is supported with hydraulic jacks. The removal of these jacks causes the overlying strata to cave, and this induces breakage of the coal or rock. Block caving is a bulk-production method that is applied to massive deposits (Hartman and Mutmansky, 2002). It involves undercutting a large block of ore, thereby inducing caving. As the block fragments and collapses, the ore is drawn off through loading points into haulage drifts.

In underground mining, the basic steps that contribute to mineral extraction are known as unit operations. The underground production cycle comprises unit operations which are normally grouped into rock breakage and materials handling functions (Hartman and Mutmansky, 2002). Rock breakage comprises drilling and blasting activities that ensure fragmentation of rock. Materials handling refers to loading and haulage activities. The haulage ways provide a means of transporting material to the shaft, decline, or adit using trucks, trains or conveyor belts, and then to the surface. In the case of shafts, hoisting is required to move the material to the surface.

Today, most underground mine designs are represented by a 3-D model, based on engineering, economic, and safety considerations, showing the detailed framework of an underground mine or part of it. An underground mine design shows the location and dimension of features such as the main access (i.e., shaft, decline, and adit), haulage ways, loading points, and ventilation network. Commercial software available for underground mine design include Deswik (Deswik, 2020), Vulcan (Maptek, 2020), Surpac (Dassault, 2020) and Datamine (Datamine, 2020). Figure 1.3 shows a 3-D design of an underground mine. Underground mine planning refers to the scientific process of making decisions involving the selection of actions to be taken to achieve set objectives. Objectives that may be set include achieving production targets, making maximum profit, providing social benefits, minimizing injury rates, and curtailing damage to the environment. The outcome of planning is a schedule of work showing the times to conduct mining activities, the tonnage of ore to produce in a given time, the material, human and financial resources to be used as well as the rules, regulations, and code of ethics that apply. Various factors are considered in the overall design and planning of an underground mine. These include geological, geotechnical, geomechanical, climatic, physiographic, and economic factors (Gertsch and Bullock, 1998, Suglo, 2013). Other factors include corporate policy, and environmental and mining laws of the host country.

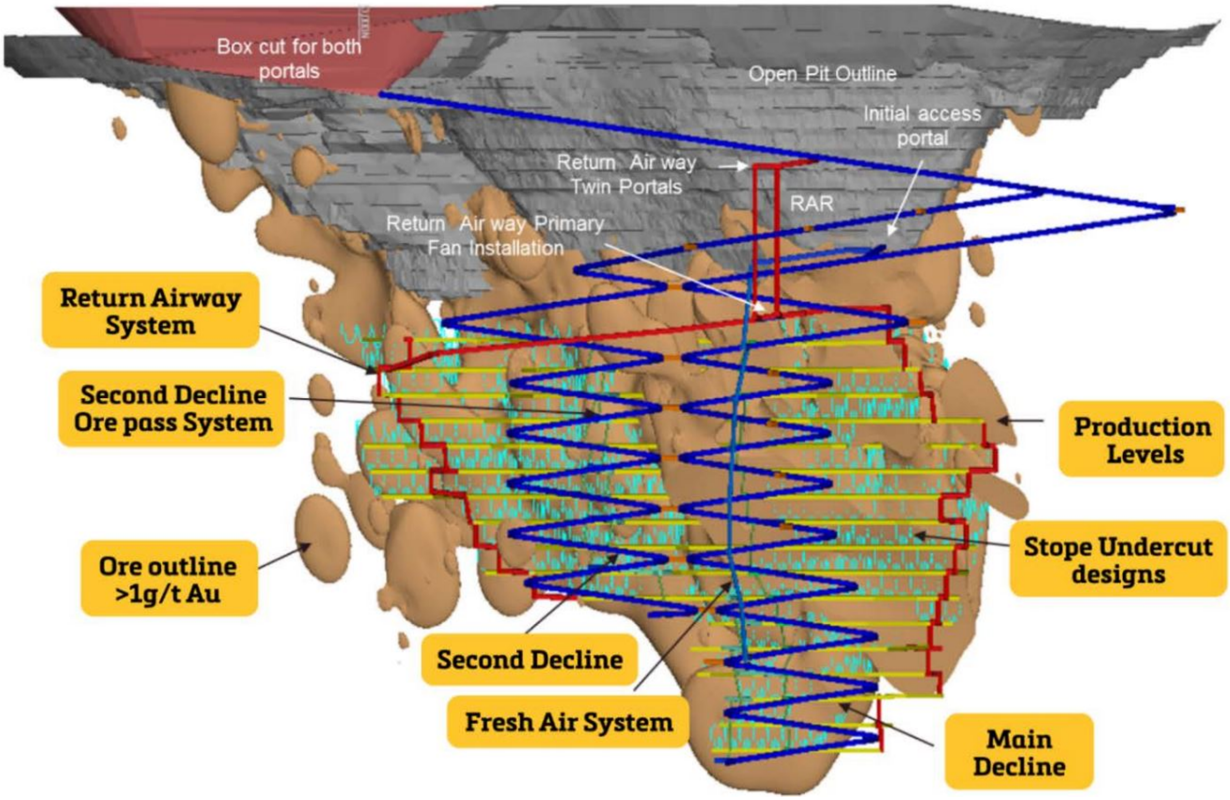

Figure 1.3: 3-D Underground Mine Design (Source: Resolute Mining Ltd, 2018)

In underground mine planning, production scheduling is the sequencing of mining activities to achieve clearly defined goals in order to generate revenue, while adhering to precedence and resource constraints (Chowdu, 2020). This results in the determination of activity start dates for the operation with a scheduling fidelity corresponding to the desired planning horizon, i.e., long-, medium-, or short-term planning (Chowdu et al., 2021, L'Heureux et al., 2013, Manríquez et al., 2020). Long-term production schedules establish the overarching goals, e.g., life-of-mine production and capital project goals, for the operation based on corporate policy. Medium-term production schedules focus on guiding operations to meet the overall long-term goals and seek to determine activity start dates for up to a five-year time horizon at monthly or quarterly fidelity. Short-term production schedules inform the day-to-day operations of the mine. They are developed based on the forecast from the medium-term schedule, and current operational conditions. Thus, they define an extraction sequence by specifying activity start dates at a finer fidelity, i.e., hourly, by shift, or daily over a time horizon spanning several weeks to months, and typically not exceeding two years (Blom et al., 2018). Short-term schedules focus on the effective utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets (Trout, 1997). Typical goals considered in short-term scheduling include minimizing deviation from medium-term production targets, and minimizing deviation from the medium-term activity start dates. Activities that can be scheduled in underground mining are varied, some of which include drilling, stoping, and backfilling mined out areas. Precedence constraints serve to impose an order in which activities can be carried out. The resource constraints represent production and processing limits, and include supply and demand limitations on tonnage of ore mined (Trout, 1997). The resource constraints ensure that activities that are active during a given time period do not exceed the resources available to accommodate them. Typical resources in an underground production scheduling problem include labor, mining equipment, and ventilation capacity (Nesbitt, 2020, Trout, 1997).

The underground production scheduling problem can be mathematically modelled as a resource-constrained project scheduling problem (RCPSP). The RCPSP can be classified as a non-deterministic polynomial-time optimization problem consisting of an objective function, resource constraints, and precedence constraints (Brickey et al., 2020, Hartmann and Briskorn, 2010, Terblanche and Bley, 2015, Lopes, 2017). The RCPSP can have binary decision variables that tell when to start a given activity. The solution set defines the optimal schedule of activities, and can be exported to a mine design software for implementation. Over the last few decades, underground production scheduling has evolved by solving for larger sets of decision variables, and including constraints which seek to provide more realistic solutions. This makes the problem complex and challenging to solve. Advancement in computational power and algorithms has made it possible to solve such problems in less time, but computational challenges remain as problems become increasingly complex.

Aside from integer programming (IP), production scheduling problems can be modeled using mixed integer programming (MIP), linear programming (LP), or simulation. The last two techniques represent early research endeavors in underground production scheduling. Simulation is a method for analyzing dynamic systems over time. A simulation model represents the operation of a real system in respect of individual events involving the model elements (Trout, 1997). A strength which makes simulation applicable to mine scheduling is its ability to characterise uncertainty in dynamic systems. Thus, researchers have used it to assess multiple scenarios of production scheduling in order to select the best performing ones. Simulation attempts to reproduce the results of a proposed schedule prior to implementation. The best solution is only available from the set of schedules being evaluated, and it is possible for the best schedule to lie outside this set (Gershon, 1986). Thus, it does not guarantee optimal results.

Linear programming (LP) is an optimization technique characterized by the expression of all mathematical functions, i.e., objective function and constraints, as linear functions. Its strength lies in solving problems that require allocation of resources to activities to achieve a specific objective. In mine production scheduling, LP has mainly been used for making decisions regarding ore extraction (Newman et al., 2010). For instance, it is efficient in determining the amount of material to extract, for a given mining method, in order to minimize deviation from prescribed production and/or cost targets. Though an optimization technique, LP does not account for discrete aspects such as activity sequencing, which is predominant in underground scheduling. Thus, it precludes use of integer decision variables required for determining optimal start dates of activities and enforcing activity precedence.

The use of IP and MIP provides a means of alleviating the aforementioned challenge with LP. IP and MIP have found wide application in underground scheduling problems, as they allow inclusion of integer decision variables in the model. Similar to LP, IP, and MIP are optimization techniques with an objective function, decision variables and constraints. The difference lies in the decision variables. The decision variables of LP can take continuous values, while those of IP can take only integer values. Those of MIP take both continuous and integer values. In most underground scheduling problems, the integer decision variables used are binary in nature, representing two alternative courses of action, i.e., either a “yes” or “no” response (Trout, 1997). This makes it possible to determine when to initiate a given activity or otherwise.

In underground mining, ventilation is required for clearing toxic gases, e.g., methane and radon, for removing fumes from blasts, and exhaust (particulate matter) from diesel equipment. Underground mine ventilation may thus be defined as the movement of air in underground mine openings in sufficient quantity and quality that it provides a safe and comfortable working environment for miners (Haldar, 2018, Mcpherson, 1993). Aside from providing fresh air, ventilation is the main mechanism for removing dust particles that might cause lung diseases such as silicosis. In deeper mines, ventilation is required for cooling the workplace for miners. Underground mine ventilation is usually characterized by air intake through an incline or main shaft, and air outlet through another incline or ventilation shaft fitted with a main fan (Haldar, 2018). An underground mine consists of multiple interconnected openings to and from the surface and working areas. This network of openings starts from the surface as a decline, shaft or adit (Figure 1.1). At various depths, drifts and haulage ways are constructed off the shaft, decline or ramp to provide access to the ore. Off the drift, crosscuts (small passageways) are constructed to connect other drifts or to gain direct access to the ore. The haulage ways provide a means of transporting material via trucks, trains or conveyor belts to the decline or shaft, and then to the surface. Figure 1.1 shows how the underground openings, i.e., decline, drift, haulage ways and crosscuts, are interconnected. In underground ventilation design, these interconnected openings can be represented mathematically as a network using nodes and arcs. Figure 1.4 shows a simplified ventilation network. In this network, the source node is represented by the intake, and the terminal node by the discharge. The underground workings (e.g. drifts, haulage ways and crosscuts), usually referred to as branches, can be converted to arcs in a network diagram. A junction is a common point where two or more branches are connected; this is represented in a network diagram as a node.

Mining operators employ various control mechanisms to distribute airflow in ventilation networks according to the mining activities in the workings. Figure 1.5 shows a ventilation system with control mechanisms. Regulators are control devices for adjusting airflow by partially or completely blocking a branch. This creates an artificial resistance that reduces airflow quantity to a desired level in a given branch. Regulators could be temporary such as plastic tarps (curtains) or more permanent such as wooden or metallic doors with adjustable openings. The artificial resistance created by regulators increases energy costs as a result of the additional pressures the main fan must overcome (Wu and Topuz, 1987). It is thus essential to consider effective placement of regulators during ventilation network analysis. Booster fans also help with airflow distribution by augmenting the air pressure from the main fan (Hartman et al., 1997, Mcpherson, 1993). These auxiliary fans help supply adequate quantities of air to workings that are far away from the main fan. Booster fans are

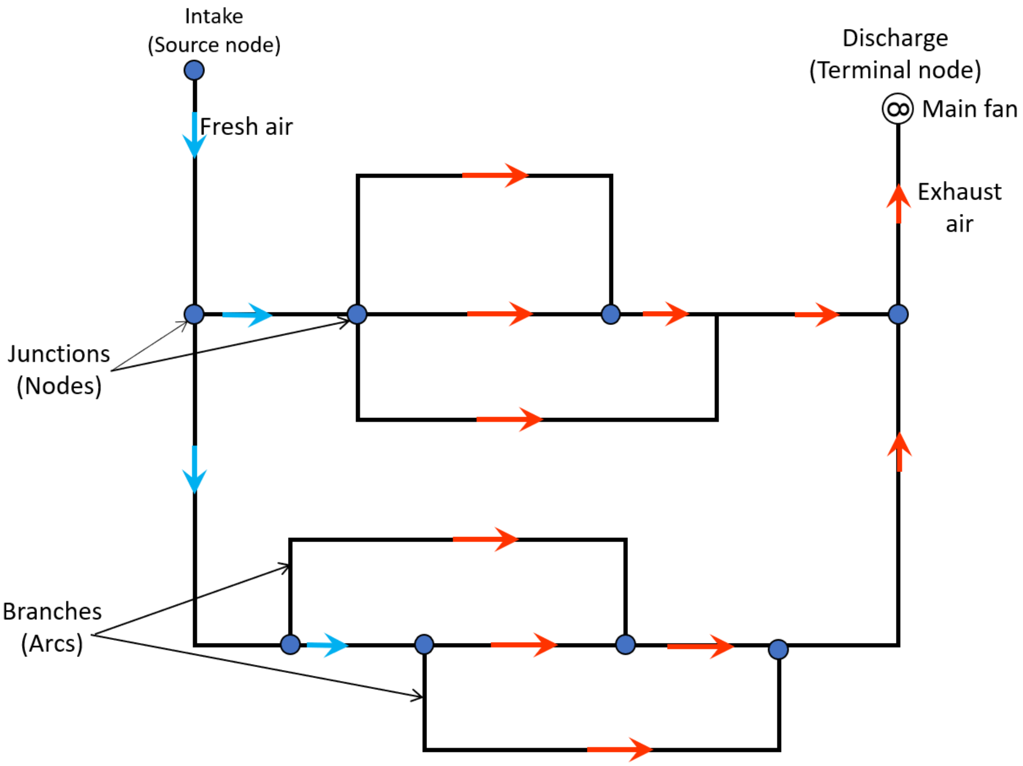

Figure 1.4: Ventilation Network Schematic (Adapted from Hartman et al, 1997)

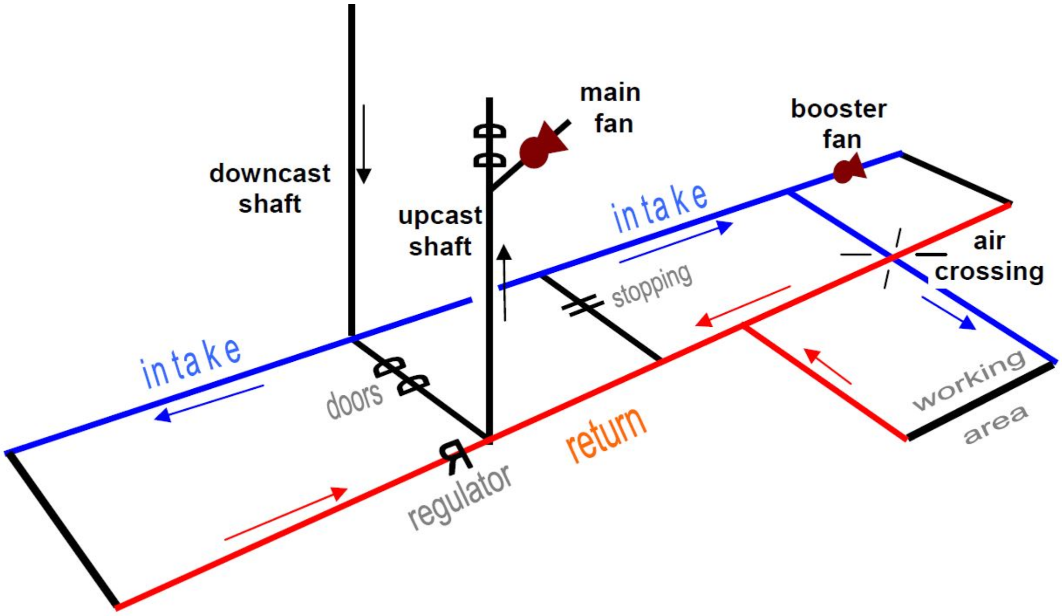

Figure 1.5: Underground Ventilation System (Source: Mcpherson, 1993)

smaller ventilation devices that are installed in series with the main fan in branches that are highly resistant to airflow. Other control devices are defined as follows (Hartman et al., 1997, Mcpherson, 1993):

- Stoppings: These are walls for blocking and redirecting airflow (Figure 1.5). They are constructed when connections between intake and return airways are no longer required for access or ventilation. Stoppings may be constructed from concrete blocks, fire-proofed timber blocks or prefabricated steel.

- Doors and air locks: Doors are steel or wooden structures mounted in stoppings to provide access for personnel and vehicles between intake and return airways (Figure 1.5). Doors are mounted such that they open towards the higher air pressure. This is to ensure they are self-closing. When doors are located between main intake and return airways, they are usually built as a set of two or more doors to form an air lock (i.e., one door is always closed while the other is opened). This is useful in preventing short-circuiting of air when one door is opened for passage of personnel or vehicles. The distance between doors is made long enough to allow the passage of the longest train of vehicles that would need to access the area. Also, building multiple doors in higher differential zones such as the main intake and return airways allows the pressure break to be shared between doors. This makes it easier to open doors during passage.

- Regulators: A regulator is a door fitted with one or more adjustable orifices for reducing airflow to a desired value in a given airway. In its basic form, a regulator may be a rectangular orifice cut in the door and partially closed by a sliding panel. Adjusting the position of the sliding panel causes a change in the flow of air. Regulators may also be in the form of louvres, the adjustment of which causes a change in airflow. Regulators may be adjusted manually or through automatic motor actuation. The latter is in response to airflow quantity and quality changes detected by sensors.

- Air crossings: These are air bridges which allow intake and return airflows to cross over each other without mixing, as Figure 1.5 shows. Air crossings can be made of metal or masonry construction. In masonry constructed air crossing, the horizon of one of the airways is elevated above the other during construction, leaving a sill of strata between the two airways. The elevated airway is known as the overcast, and the lower airway as the undercast. Metal air crossing takes the form of a stiffened metal tunnel, and may be purchased or manufactured locally.

- Line Brattice: Line brattice is a partition placed in the airway to divide it into intake and return airways for the purpose of ventilating idle working places. Fire-resistant brattice may be used as temporary stopping by tacking them to the roof, sides and floor in areas where pressure differentials are low.

- Vent tubing/auxiliary fans: Vent tubing is used in combination with auxiliary fans to supply air to development headings (dead-end workings). This is essential in helping advance drilling and blasting activities in these workings.

In underground mining, air is mostly supplied to the workings by means of a fan. A fan is a device that utilizes the mechanical energy of a rotating impeller to produce airflow. Various types of fans are used in an underground ventilation system. By location, fans may be classified as primary (main), booster, development-end or district (circuit) fans (de Villiers et al., 2019). Figure 1.6 is a schematic showing typical location of these fans in an underground mine. Primary fans are large fans that, either singly or in combination, handle all the air that circulates through the underground network (Mcpherson, 1993). They operate by either exhausting air through the upcast shaft, as Figures 1.5 and 1.6 show, or, forcing air into the ventilation system through the downcast shaft. Booster fans are smaller fans that are installed in series with the primary fan; they are usually installed in the return airway. Booster fans assist the primary fans in overcoming airflow resistances. Development-end fans are auxiliary fans used to ventilate a workplace with no air flowing through it (blind heading). The air is passed through ducts. District fans are auxiliary fan assemblages that are used for directing air into a specific district or area (de Villiers et al., 2019). A district can be one or more mining areas, raise boreholes, return airways, etc.

The main fan generates a pressure differential which causes fresh air to enter one or more downcast shafts (Mcpherson, 1993). As Figure 1.5 shows, the air flows along intake airways to the working areas. In the working areas, the air provides oxygen for breathing by miners, and for combustion in diesel equipment. As this is ongoing, the air gets contaminated by hazards such as dust, toxic or flammable gases, heat, and humidity. The contaminated air passes back through the system along return airways. It then gets back to the surface through one or more upcast shafts, or through inclined or level drifts.

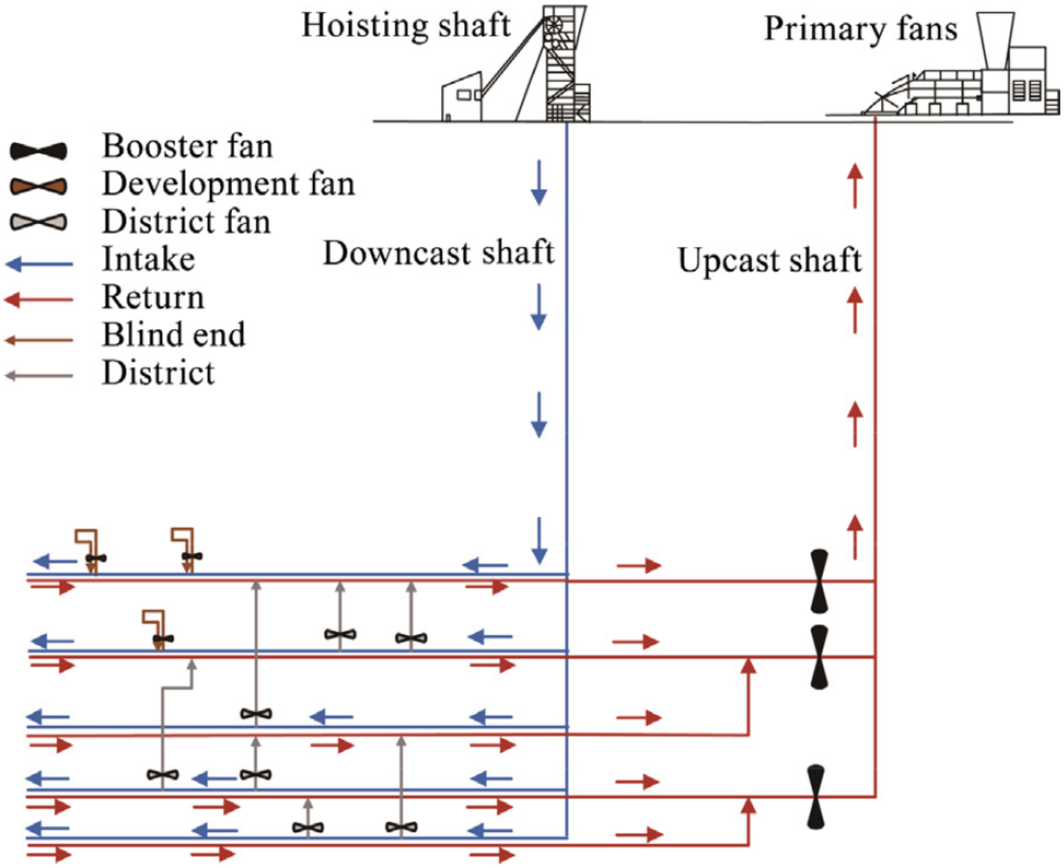

Figure 1.6: Location and Types of Mine Ventilation Fans (Source: de Villiers et al., 2019)

By design, underground fans fall into two broad categories: centrifugal and axial. A centrifugal fan consists of an impeller in a casing having a spirally shaped contour (Yu et al., 2011). It resembles a paddle wheel. Figure 1.7 shows the components of a centrifugal fan. The air enters near the centre of the impeller, turns through 90° and moves outward by centrifugal action between the blades of the rotating impeller (Mcpherson, 1993). As the speed of the impeller increases, so does the velocity, pressure and volume of the air delivered at the fan outlet. The casing collects the air as it is expelled from the wheel and directs it out in a single stream (Gingery, 1987). Axial fan derives its name from the direction of the airflow it creates. The impeller draws air in parallel to the axis of rotation, and forces the air out in the same direction (Pelonis, 2015). Figure 1.8 is a diagram showing the components of an axial fan.

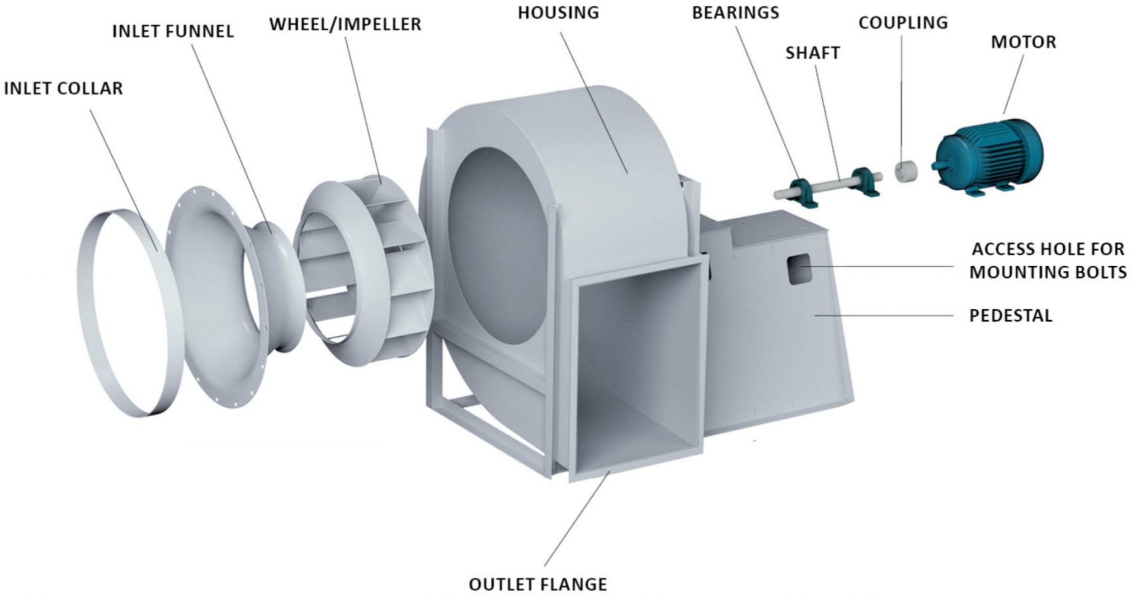

Figure 1.7: Components of a Centrifugal Fan (Source: TCF, 2018)

In deeper mines, mine ventilation may be supplemented by air conditioning. This is essential in meeting temperature-humidity standards aside from airflow quality and quantity requirements. Air conditioning consists of processes designed to regulate the sensible and/or latent heat of the mine air. It is necessary when fans alone are unable to provide airflow at acceptable atmospheric-heat standards. As depth increases in an underground mine, the heat content of the air also increases from a variety of sources. These include autocompression (of the air), wall rock, machinery, blasting, human metabolism, etc. At

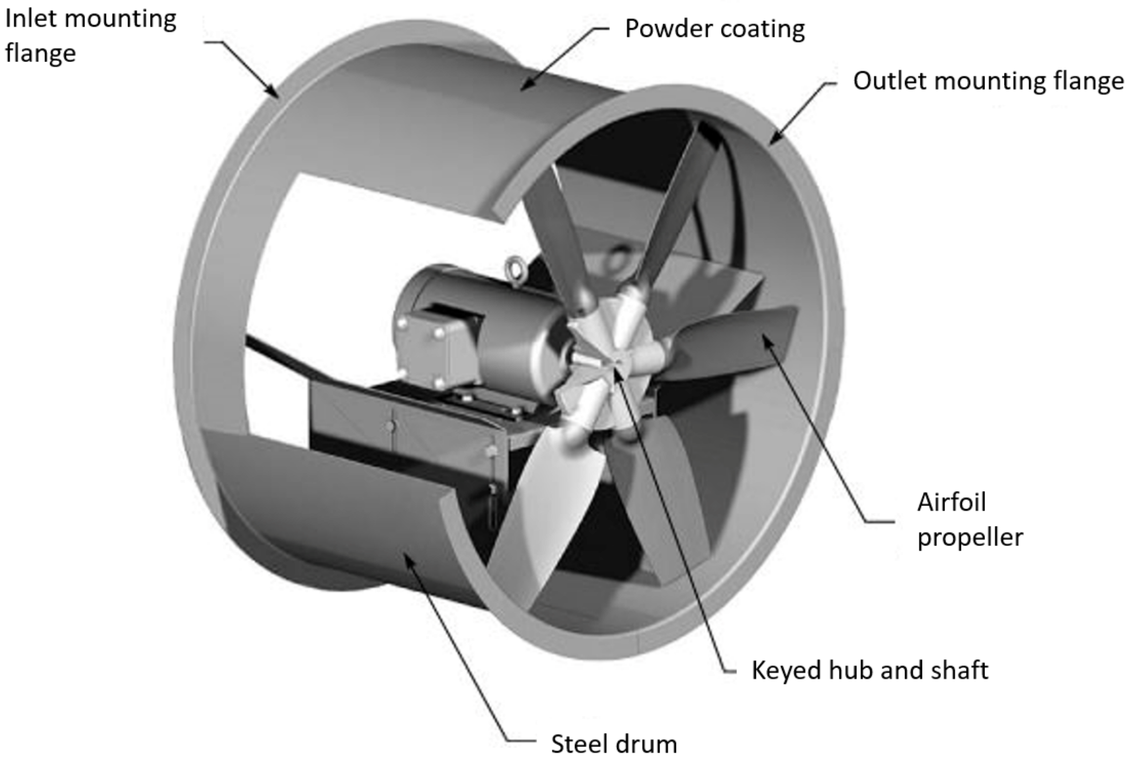

Figure 1.8: Components of Axial Fan (Source: Loren Cook, n.d.)

great depths, air conditioning makes it possible to maintain the heat content of mine air within acceptable limits to enhance workers' comfort, safety and efficiency. Similarly, in relatively shallow mines in cold climates, air conditioning may be required to supplement ventilation. The objective here is to heat the air being taken underground to acceptable temperature (Hartman et al., 1997). Aside from ensuring workers' comfort, the heating prevents freezing in the intake openings.

In an attempt to minimize fan operating cost, certain mines have adopted the ventilation-on-demand (VoD) system. VoD refers to the provision of airflow as needed during the mining cycle (Wallace et al., 2015). It is achieved by adjusting airflow, and supplying just the right amount of ventilation needed in the ventilation zones. This system reduces ventilation costs by allowing the use of airflow where and when needed. A VoD system consists of fan motors on variable speed drives, air quality sensors, airflow sensors, regulator and fan control systems, and equipment and personnel tagging systems (Bartsch et al., 2010, Wallace et al., 2015). The variable speed drives make it possible to adjust the speed of the fan blades to produce the required airflow. For a given machine in an active working zone, the tagging system identifies the location of the machinery to ensure constant supply of the required airflow throughout the duration of operation. The air quality sensors monitor the level of gases in the air. These gases include carbon monoxide, oxygen, and nitrogen oxides. After the machinery has left the working area, the sensors maintain the airflow until such a time when the air quality becomes acceptable. At this moment, the speed of the fan blade changes to decrease airflow in the area. Aside from cost savings, VoD improves health and safety, and productivity. The improved productivity results from the enhanced ability of the ventilation system to adapt to the needs of a production schedule, which is dynamic in nature.

With computers continuously advancing, ventilation engineers have become accustomed to better graphical interfaces and tools to support ventilation planning. Commercial ventilation software make it possible to develop underground ventilation networks with on-screen graphic construction and/or importation of mine networks from mine design software (Wallace et al., 2015). Commonly used commercial ventilation software include VentSim (Howden, 2020), VnetPC (Howden, 2020), and VUMA (VUMA, 2020). These software operate by conducting network simulation in order to predict airflows and pressure differentials throughout the network. Subsequently, ventilation engineers and mine management are able to obtain the information required to procure and install primary and booster fans, and to size raises and shafts. The information also helps evaluate the location of control devices such as regulators, doors and stoppings. In effect, the engineers are able to determine the cost of implementing the ventilation system (Wallace et al., 2015). Mostly, these commercial software implement network simulation using a technique known as the Hardy Cross method (McPherson and McPherson, 1993). The Hardy Cross method is an iterative method for solving for flow in network systems, where the inputs and outputs are known but flows inside network branches are unknown. It involves successive improvement of an initial solution until the error is acceptably small (Hartman et al., 1997). For an underground mine with a complex network, this can result in a computationally expensive process that would be impractical to handle without the use of modern computers. Aside from their primary purpose of determining airflows and pressure differentials, the software packages have tools that support calculations related to mine air quality. The quality of air with respect to gaseous or particulate pollutants, and mine environmental conditions (e.g., wet and dry bulb temperatures, and heat flow) is dependent upon the distribution of airflow (Mcpherson, 1993). Ventilation software packages thus have programs incorporated in them to predict individual aspects of air quality. These programs utilize branch airflows and/or other output data from the network simulation as input for air quality prediction.

The ventilation system in an underground mine can consume up to 70% of the power used by the operation, thus, contributing a significant proportion of the mine operating costs. As ventilation engineers seek out ways to reduce costs through optimization and VoD technology, depth becomes a natural challenge to contend with. As underground mines get deeper in response to production demands, provision of ventilation becomes an issue of concern, and a potential limiting factor. Depth can affect the economics of ventilation via increased pressure loss and temperature. Pressure loss through a ventilation system is what the fans must overcome to generate the required airflow. As the length of a ventilation system increases, the pressure loss increases, and this implies increased power supply in order to overcome the increased pressure loss. Consequently, operating cost increases since power is generally proportional to operating cost (Hardcastle and Kocsis, 2004). An increase in depth leads to increased air temperature in a mine. This results from autocompression of the air, and transfer of heat from the strata as a result of the earth's geothermal gradient. Removing the additional heat gain implies supplying extra airflow. Hardcastle and Kocsis (2004) report of a Canadian mine already operating at over 2000 m below surface. The airflow requirement at this mine increases by 20% for every 300 m increase in depth. This culminates in 73% additional cost of power supply. Increasingly, stringent standards are being set with regard to occupational health and safety, and this considerably impacts ventilation planning and cost. In the mining industry, maximum allowable pollutant levels are being reduced, and medical surveillance requirements are increasing (Bluhm et al., 2018). Underground mines are becoming more mechanized with more extensive networks of excavations, in response to increased production demands. It becomes challenging for mines to strictly adhere to reduced pollutant levels amidst increased mechanization and production. For instance, a highly mechanized mine that operates diesel equipment, faces the challenge of keeping the emission of diesel particulate matter and dust below regulatory standards. For large scale mines, this requires careful ventilation planning, and use of control strategies that tend to increase the cost of ventilation.

In recent years, machine learning (ML) has shown promising potential in mining and other industries including finance, agriculture, healthcare, security, communication, transportation, astronomy, industrial process control, computing, risk management, and marketing (Jo and Khan, 2018). ML is a branch of artificial intelligence (AI) that allows computer systems to improve their performance at a task through experience (learning) for the purpose of predicting future outcomes (Grosan and Abraham, 2011). It involves coding programs that automatically adjust their performance in accordance with their exposure to information in data. The learning comes about via a parameterized model with tunable parameters that are automatically adjusted according to different performance criteria (Igual and Seguí, 2017). ML is increasingly used in the aforementioned industries as a result of advancement in technology (Paturi and Cheruku, 2020). Specific tasks that ML algorithms handle in these industries include accident and injury analysis, pollutant prediction, handwriting recognition, face detection, email spam filtering, natural language processing, stock market prediction, weather forecast, fraud detection, sound recognition, fingerprint matching, and autonomous driving (Grosan and Abraham, 2011).

Machine learning is a multidisciplinary field that relies significantly on specialized subject areas such as probability and statistics, and control theory. ML techniques can be broadly classified as supervised and unsupervised learning. Supervised learning is concerned with the use of algorithms which learn from a training set of labeled examples to generalize to the set of all possible inputs. Examples of supervised learning techniques include logistic regression, linear regression, support vector machines, decision trees, random forest, and artificial neural network. Unsupervised learning is concerned with algorithms that learn from a training set of unlabeled examples. This type of ML is used to explore data according to some statistical, geometric, or similarity criterion (Igual and Seguí, 2017). It works by inferring patterns from the data without reference to known outcomes. It is thus useful for discovering underlying structure of a given data set. Examples of unsupervised learning techniques include k-means clustering and kernel density estimation.

Machine learning techniques implemented in this study include logistic regression and artificial neural network. Logistic regression is a type of supervised ML that is well suited for describing and testing hypotheses about relationships between a categorical outcome (i.e., response or dependent variable), and one or more categorical or continuous predictors (i.e., independent variables) (Peng et al., 2002). The purpose of logistic regression is to build a model that can predict a categorical response (e.g., the type of injury a miner is most susceptible to) given a set of independent variables (e.g., age, experience on the job, work location). Specifically, logistic regression is used in classification problems for analyzing the behavior of data (i.e., the relationship between the response and predictor variables), predicting data values, and for finding predictor values that have significant influence on the model (Igual and Seguí, 2017). The response from a logistic regression can be expressed as a combination of the predictor variables using the logit function, built on the concept of probability theory. A mathematical representation of the logistic regression model is as follows (Peng et al., 2002):

$$Logit(Y) = ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n \tag{1.1}$$

Where:

Y is the response variable,

p is the probability that Y occurs,

X_i is the ith predictor variable, where $i > 0$,

β_0 is the intercept of the regression line on the y-axis,

β_i is the regression coefficient (slope) for X_i where $i > 0$

In Equation 1.1, $Logit(Y)$ refers to the natural log (ln) of the odds of Y. The odds of Y is the ratio of the probability that Y occurs (p) to the probability that Y does not occur ($1 - p$). Taking the antilog of Equation 1.1 on both sides leads to a modified equation for predicting the probability of occurrence of Y, the outcome of interest. The value of B_i is used for determining the relationship between the response and the respective predictor variables. Logistic regression can be classified as binary (binomial), multiclass (multinomial) or ordinal, depending on the response variable (Peng et al., 2002). The binary logistic regression is suited for scenarios where the response variable can have only two categories (e.g., injury vs. no injury). If the response variable can have more than two categories which are not ordered, then multiclass logistic regression is preferred. The ordinal logistic regression is used for scenarios where there are more than two ordered categories. Such categories are usually characterized with adjectives (e.g., poor, fair, good, very good, excellent).

An artificial neural network (ANN) is a type of supervised ML that is inspired by the way biological neural system works, such as as how the brain processes information. Information processing in ANN involves a large number of highly interconnected processing elements known as neurons that work together to solve specific problems. The learning process involves adjustments to the synaptic connections existing between the neurons (Ertel, 2017, Grosan and Abraham, 2011). In the biological neural system, a neuron consists of a cell body known as soma, an axon, and dendrites (Figure 1.9).

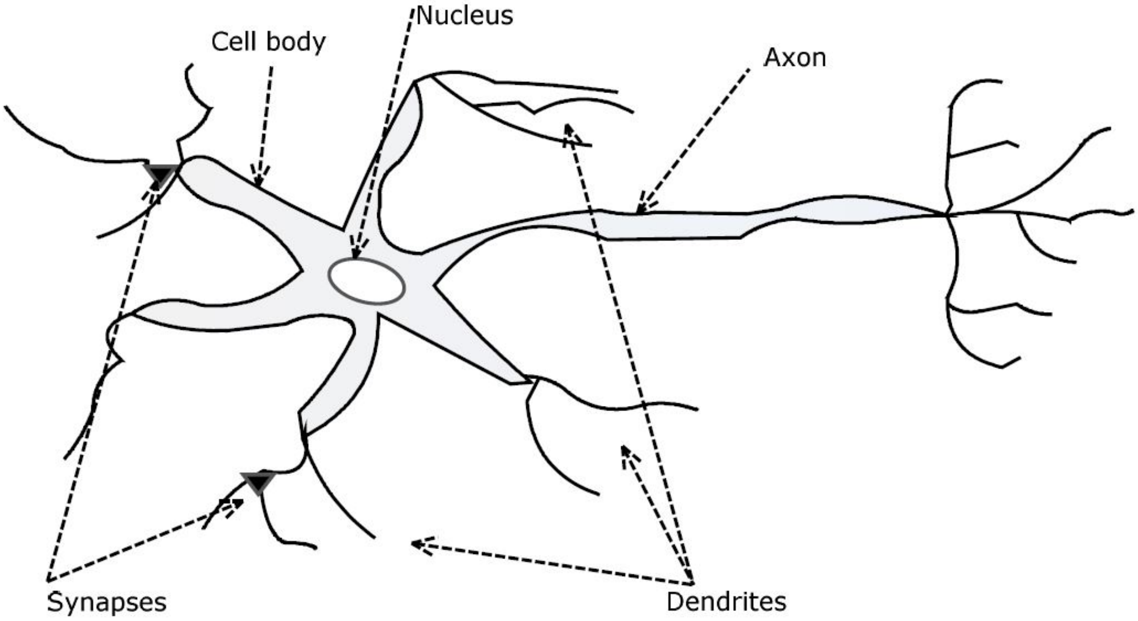

Figure 1.9: Structure of a Biological Neuron (Source: Grosan and Abraham, 2011)

The axon sends signals, and the dendrites receive these signals. A synapse connects an axon to a dendrite. Depending on the signal it receives, a synapse might increase or decrease electrical potential. An ANN consists of a number of neurons similar to the human biological neurons. These neurons are known as units, and are connected by weighted links that transmit signals from one neuron to the other (Dixon et al., 1995, Grosan and Abraham, 2011). The output signal is transmitted through the neuron's outgoing connection, which is analogous to the axon in the biological neuron. The outgoing connection splits into a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections (analogous to dendrites) of other neurons in the network (Grosan and Abraham, 2011). Figure 1.10 is a schematic representation of a neuron, which is the basic unit of an ANN. The activation function in Figure 1.10 is responsible for determining the output of the neuron based on the weighted inputs. In an ANN, the units are stacked in layers known as the input, hidden and output layers. Succeeding layers receive input from preceding layers. An output signal is then computed based on the input using the activation function. The output signal is then propagated to the next layer. While this is ongoing, the ANN adjusts its weights in order to record an acceptable minimal error between input variables and the final output variable(s) (Krose and van der Smagt, 1996). The complexity of the ANN architecture makes it well suited for solving both linear and nonlinear problems. These problems can be categorical (classification) or continuous (regression) in nature. Advancement in computational power has enhanced its use in the fields of engineering, industrial process control, medicine, risk management, marketing, finance, communication and transportation. In the mining industry, ANN has been a useful analytic tool for handling various tasks such as real-time control of mineral processing plants, air-quality prediction, and identifying combustibles present in the mine environment (Jo and Khan, 2018).

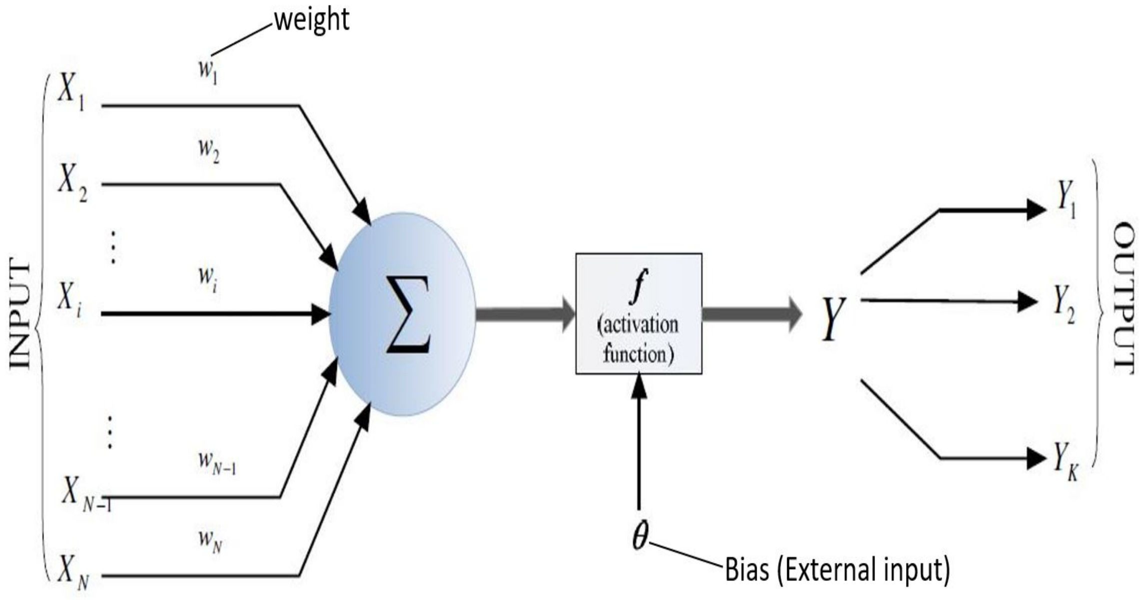

Figure 1.10: Schematic Representation of an Artificial Neuron (Source: Grosan and Abraham, 2011)

1.2 Chapter Summaries

Mining remains a relevant industry as it is essential to the production of goods, services, and infrastructure that improve our quality of life. The industry provides all materials that cannot be grown, or extracted as liquid or gas (Minerals Education Coalition, 2019). Aside from enhancing quality of life, mining is an economic driver that supports local businesses and contributes tax revenue to government entities. In most countries, the industry is heavily regulated, and adherence to stringent safety standards is paramount to sustained operation. For an industry that has a highly mechanized work environment with hazards such as rock falls, explosions, fires and harmful gases, strict safety regulations are to be expected. The drive towards zero injuries and occupational illnesses is an industry standard that has prompted increased research into ways to effectively reduce mine accidents. In the last decade, there have been novel research endeavors that have applied machine learning tools in mine safety analysis. Chapter 2 of this dissertation demonstrates the potential of machine learning in contributing to robust mine safety analysis by implementing a machine learning tool known as the multiclass logistic regression on a ten-year injury data set from the Mine Safety and Health Administration (MSHA). The tool provides a means to determine a miner's susceptibility to a given class of injury, and also identifies significant risk factors associated with different classes of injury. The injury classes considered in the study include non-fatal with no days lost or restricted activity, non-fatal with days lost and/or days of restricted work activity, and fatal and total permanent or partial permanent disability. Analysis reveals how the following risk factors interact to determine a mine worker's susceptibility to a particular type of injury: miner's age, mine type (coal vs. non-coal), experience on current job (years), shift start time, employment type (operator vs. contractor), mining district, and type of accident. Analysis also shows the difference and similarity between surface and underground mine incidents. The results reveal that a miner's experience on the job (the number of years worked in a current job) is a significant risk to injury occurrence, even for those with decades of total mining experience. The resulting paper from this work, *Identifying Risk Factors from MSHA Accidents and Injury Data using Logistic Regression*, has been published by the *Mining, Metallurgy and Exploration* journal of the Society for Mining, Metallurgy and Exploration.

Chapter 3 exploits further the potential of machine learning in other areas of mining, namely, mine ventilation and underground production scheduling. This phase of the dissertation involves building an artificial neural network (ANN) model for predicting respirable dust concentration based on production activities. Production activities in underground mines generate respirable dust which impacts worker's health and productivity. When inhaled, respirable dust evades the human natural defense mechanisms and gets deposited in the lungs. Prolonged exposure results in health problems including difficulty in breathing, fibrosis of the lungs, chronic bronchitis, and irregular heartbeat. Respirable dust concentration is associated with activity type and activity rate, both of which are prime to conventional short-term production scheduling in underground operations. This provides a linkage by means of which respirable dust pollution could be managed by being incorporated in production schedule optimization. Leveraging this, the author develops an ANN model that predicts respirable dust concentration in underground mines using input parameters derived from production activities. This study is a proof of concept that seeks to offer an extra layer of engineering control for dust exposure mitigation in underground mines. The goal here is to contribute to better decisions regarding ventilation and dust control resource management in a proactive manner. The ANN model developed in this study provides fairly good results, with the prospect of yielding better results with improved data collection. The model produces a correlation of 0.70 between the predicted and actual dust concentration. The work in this study constitutes the first phase of a larger framework that seeks to manage workers' exposure to respirable dust by incorporating ventilation in short-term production scheduling. Future work would seek to incorporate predictions from the ANN model and the impact of conventional dust controls into short-term production schedule optimization as mathematical constraints. This will aid in identifying high dust production activities proactively, and effectively managing available ventilation and dust control measures to enhance miners' safety. The resulting paper, *Activity-based respirable dust prediction in underground mines using artificial neural network*, has been presented at the *18th North American Ventilation Symposium*, a peer-reviewed symposium. The paper has subsequently been published in the ensuing proceedings titled, *Mine Ventilation*, by the CRC Press of the Taylor & Francis Group.

Chapter 4 builds on the resource-constrained project scheduling problem (RCPSP) modeling concept to develop a formulation for generating short-term schedules for underground mining operations. The focus has been to develop a tool that can help the mine planner generate short-term schedules that achieve forecast targets without significantly deviating from the sequence of activities in the medium-term plan. The formulation in this chapter is thus a rescheduling of the medium-term plan at a finer fidelity. Achieving this requires the ability to minimize deviations from the medium-term start dates and production goals. The author improves upon an existing formulation by incorporating more realistic penalty functions for minimizing activity and production goal deviations. Activity earliness and tardiness are penalized with exponentially increasing values as deviations increase, while goal penalties are only imposed if certain predetermined production target levels are not met. The resulting two-component objective function for the formulation offers mine planners the additional flexibility of prioritizing one type of deviation over the other. The chapter presents a case study that demonstrates the usefulness of this formulation as operational disruptions arise that cause deviation from the medium-term plan. By this formulation, mine planners have a tool with which they can quickly assess different scheduling options as deviations arise. Through the case study, this tool demonstrates how mine planners can assess the impact of operational disruptions on the schedule and how the new schedule makes up for the ensuing target deviations. The successful implementation of this short-term formulation for underground operations sets the stage to implement the final phase of work discussed in Chapter 3. That is, future work will focus on incorporating predictions from the ANN developed in the previous chapter along with ventilation requirements in the short-term formulation. Subsequently, this will be extended to include other health hazards in underground mining such as diesel particulate matter (DPM) and heat. The long-term goal is to be able to develop a short-term production scheduling framework that caters to miners' exposure to these hazards while optimizing the value of operations. The final chapter, 5, provides a summary of research documented in this dissertation. Additionally, the chapter provides a discussion on the direction of future work that would help realize the aforementioned long-term goals.

Chapter 2

Identifying Risk Factors from MSHA Accidents and Injury Data Using Logistic Regression

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Abstract

The global mining industry has recorded significant declines in accident and injury rates attributed to the advancement in technology, increased enforcement, and safety consciousness. A goal of the mining industry is to achieve zero injuries and occupational illnesses on all mine sites, prompting increased research into ways to further reduce mine accidents. A machine learning technique known as multiclass logistic regression is applied on a 10-year injury dataset from the Mine Safety and Health Administration (MSHA) to determine a miner's susceptibility to a class of injury and to help identify significant risk factors associated with different classes of injury. The data is aggregated based on injury classification to provide statistically relevant results. The analysis identifies specific risk factors that influence a mine worker's susceptibility to a given class of injury, i.e., non-fatal with no days lost or restricted activity, non-fatal with days lost and/or days of restricted work activity, and fatal and total permanent or partial permanent disability. These factors include miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and type of accident. The results of the analysis indicate that a miner's experience on the job, i.e., the number of years worked in a current job, is a significant risk to injury occurrence, even for those with decades of total mining experience. We further show the differences and similarities between the surface and underground mine incidents.

2.1 Introduction

Mine workers are exposed to a variety of hazards within the mining environment. These hazards include rock falls, equipment malfunctions, fires, explosions, and harmful gases, thereby increasing susceptibility to mine accidents; however, over the past three decades, the mining industry has recorded significant declines in injury occurrence (Onder et al., 2014, Karra, 2005). This is attributed to the increased enforcement, improved safety consciousness, and implementation of new technology (Friedman et al., 2019). The establishment of the mine safety legislation, the Federal Coal Mine Health and Safety Act of 1969, has resulted in a steady decline of mine accidents by institutionalizing an enforcement agency to implement codes and regulations. In the late 1800s and early 1900s, the mining industry recorded thousands of fatalities annually (Cullen et al., 2006). This led to the insistence of increased safety regulations by society and the government. In recent decades, mine safety has become an integral part of the mining industry culture through increased safety training and hazard recognition. At present, the United States Mine Safety and Health Administration (MSHA) enforces the health and safety rules outlined in the Federal Mine Safety and Health Act of 1977, as amended by the MINER Act of 2006. The National Institute for Occupational Safety and Health (NIOSH) works to develop innovative safety solutions through the provision of research grants with the focus of reducing safety and health-related accidents. Between research-focused NIOSH and regulation enforcement by MSHA, the USA has seen a steady decline in mine-related accidents. In 2019, 24 fatalities were reported for all mining sectors in the USA, one of the lowest numbers ever recorded (MSHA, 2020). Nieto and Duerksen (2008) summarize the effects of mine safety legislation on the US mining industry from 1872 to 2007.

MSHA requires mine operators under their jurisdiction to disclose all reportable accidents, occupational injuries, and illnesses that occur on their mine site. Information on the work location, accident classification, body part injured, degree of injury, and occupation are reported by the principal officer responsible for health and safety in the mine or the supervisor of the mine area where the injury occurred. Other information on the age and mining experience of the miner, work shift time, and other statistics are also reported. The injuries reported to MSHA are categorized into ten degrees (NIOSH, 2016) as shown in Table 2.1. This study examines injured miners involved in a single accident while working on a mine site. The first six degrees of injury, outlined in Table 2.1, fall within the scope of this study. To achieve statistical relevance, we aggregate the relevant six degrees of injury into three classes, listed in Table 2.2. Fatalities and permanent disability (total or partial) only make up 0.3% and 1.2% of the final dataset used in modeling, respectively. Aggregating them into a common injury class provides sufficient data to enable validation of the model at a 95% confidence level. Aside from statistical relevance, the aggregation also reflects injury severity among the three injury classes, with fatality and permanent disability (FP) representing the highest form of severity, followed by injuries with days lost and/or days of restricted work activity (DLR) and injuries with no days lost or restricted activity (NDLR). Setting NDLR as a reference provides reasonable grounds for comparison among the three classes of injury. This injury classification differs from MSHA 's injury classification, i.e., fatal, non-fatal with days lost and/or restricted activity, and non-fatal with no days lost. In this study, permanent disability is moved from nonfatal with days lost and/or restricted activity and aggregated with fatality to form a new injury class, fatality and total permanent or partial permanent disability (FP).

Many mining companies have set the goal of achieving zero harm. To this end, researchers have analyzed accidents and injury data with a goal of mitigating mine accident and injury occurrence using a variety of statistical, quantitative, and novel methods, among which includes machine learning (ML). In this era of “big data,” ML techniques have been employed to derive valuable information implicit in data. ML methods have been applied in various fields such as engineering, finance, transportation, and medicine. As a branch of artificial intelligence (AI), ML allows computer systems to improve their performance at a task through experience (learning) for the purpose of predicting future outcomes (Grosan

Table 2.1: Degrees of Injury

Degree	**Injury**	**Description**
1	Fatal	Injury occurrences resulting in the death of the miner
2	Permanent total or permanent partial disability	Injury occurrences resulting in loss or complete loss of use of any member or part of a member of the body
3	Nonfatal with days lost only	Injury occurrences not resulting in death or permanent disability but requires days away from work to recover from injury
4	Nonfatal with days lost and days of restricted work activity	Injury occurrences not resulting in death or permanent disability but requires days away from work to recover from injury and upon recovery might require the miner to be assigned to another job other than his primary job temporarily
5	Nonfatal with restricted work activity only	Injury occurrence not resulting in permanent disability or days lost but the miner is assigned to another job other than his primary job temporarily
6	Nonfatal with no days lost or restricted activity	Injury occurrences resulting only in loss of consciousness or medical treatment other than first aid
7	Occupational illness	Cases not caused by a single accident occurrence such as hearing loss, pneumoconiosis, silicosis, hepatitis and cancer
8	Fatal and nonfatal cases due to natural causes to employees on company business	Cases such as heart attacks and strokes
9	Fatal and nonfatal injuries involving non-employees on or off the mine property	Injury occurrence that falls under the jurisdiction of the Occupational Safety and Health Administration (OSHA)
10	All other cases including first aid	Injury occurrence resulting in death or permanent disability reported to MSHA which do not result in charges or citations to the company

Table 2.2: Injury Class

Degrees of Injury	**Definition**	**Abbreviation**
1 and 2	Fatal and total permanent or partial permanent disability	FP
3, 4, and 5	Nonfatal with days lost and/or days of restricted work activity	DLR
6	Nonfatal with no days lost or restricted activity	NDLR

and Abraham, 2011). It is a multidisciplinary field that includes probability and statistics, control theory, and computational complexity, among others. In general, ML is classified into two categories: supervised and unsupervised learning. In supervised learning, the relationship between the input and output data is known. Thus, there is foreknowledge (an estimation) of the output value. Here, the goal is to predict an outcome given a set of input data. Regression and classification methods fall under this category. Unsupervised learning, on the other hand, provides little or no information on the outcome. Its purpose is to discover patterns and trends that exist in a given input data. In mining, ML methods such as logistic regression have been applied to predict the presence or absence of gold mineralization in a deposit (Carranza and Hale, 2001) to predicting roof fall risks in underground coal mines (Palei and Das, 2009).

Logistic regression (LR), a supervised machine learning technique, is applied in this study. LR is well suited for describing and testing hypotheses about relationships between a categorical outcome, i.e., response or dependent variable, and one or more categorical or continuous predictors, i.e., independent variables (Peng et al., 2002). A set of independent variables (predictors) is needed to predict the dependent variable (outcome). The nature of the outcome variable dictates the type of logistic regression to use—binomial (binary), multinomial (multiclass), or ordinal. Binomial or binary logistic regression is used when the outcome variable can have only two categories, e.g., fatal vs. non-fatal. If the outcome variable has more than two categories in no order of priority, e.g., fatality, injury, and no injury, multinomial or multiclass logistic regression is used. If the outcome variable is ordered, e.g., severe, moderate, mild, and minimal, then ordinal logistic regression is used (Peng et al., 2002). This study applies multiclass logistic regression to a 10-year (2008 to 2017) injury dataset from MSHA to help identify potential risk factors associated with different classes of injury. The multiclass logistic regression model is expressed as (Peng et al., 2002) follows:

$$\text{logit }(Y) = \ln\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n \tag{2.1}$$

where

Y : the dependent or outcome variable., e.g., fatality and no days lost

p : the probability that Y occurs

$X_1 ... X_n$: the independent or predictor variables, e.g., age, work location, and mine type

β_0 : intercept of the regression line on the y-axis

$\beta_1 ... \beta_n$: corresponding regression coefficients for $X_1 \dots X_n$

The regression coefficient values $\beta_1 \dots \beta_n$ indicate the relationship between $X_1 \dots X_n$ and logit of Y. A coefficient value greater than 0 indicates an increase in logit of Y with an increase in X, and a coefficient value less than 0 indicates a decrease in logit of Y with an increase in X. A coefficient value of 0 indicates there is no linear relationship between logit of Y and X. The Wald test is used to measure the significance of the independent variables to the logistic regression model (Peng et al., 2002). Suppose we want to predict the mood (outcome) of a miner as happy or sad (outcome) given some independent variables (predictors) such as food, bad weather, and sleep. If the Wald test shows that the parameters for certain independent variables, such as food and sleep, are zero, it proves that there is no association between these predictors and the outcome; hence, they can be removed from the model. If the test shows the parameters are not zero, then the opposite holds true and those variables are included in the model.

2.2 Literature Review

Research investigating the factors associated with mine accidents using logistic regression has provided some insight into the occurrence of mine accidents. Bennett and Passmore (1985) use multinomial logit analysis to examine the relationship among the mine and injured miner characteristics, and the degrees of injury in underground bituminous coal mines in the USA from 1975 to 1982. Their study reveals that injury severity varies by the mining system used in the mine, the geographical region of the mine, circumstances surrounding the injury occurrence, the injured miner's age, the location in the mine where the injury occurred, and whether the injured miner used powered haulage in the year the injury occurred. They further reveal that for their period of study, injury severity is not associated with the injured miner's total mining experience, experience on the job, and experience in the mine. Friedman et al. (2019) study the injuries, i.e., fatal and non-fatal, associated with long working hours, i.e., more than 9h in a shift, among mine workers in the USA using binary logistic regression to analyze MSHA data from 1983 to 2015. They identify job change, lack of work routine, small mining operations, and being new at the mine as risk factors associated with injuries occurring during long working hours. Muzaffar et al. (2013) investigate the factors associated with fatal accidents among contractors and operators by applying binary logistic regression on MSHA data. The results show that a higher proportion of fatal injuries are associated with contractors, less mining experience at the current mine, and working more than 8h per day. A multinomial logistic regression model used by Maiti and Bhattacherjee (2001) examines the differences in accident susceptibility among various groups of underground coal mine workers, given their personal and workplace characteristics. The authors conclude that, among the occupation groups, face workers are more susceptible to injury than other groups, e.g., haulage. The analysis, however, considers only one type of mine—underground coal—and consists of data from five mines operating under the same company. Risk factors associated with injuries in artisanal and small-scale mining operations include gender, less working experience, long working hours, poor supervision, and job stress, among others (Ajith et al., 2020).

A 2004 study by Chau et al. (2004) examined the relationship between individual characteristics and occupational injuries for various jobs in the construction industry. Personal and work-related data from 880 male workers who have had at least one occupational injury during a 2-year period are analyzed using logistic regression. Results from this study show that young workers, workers with sleep disorders, and smokers are susceptible to occupational injuries. Zhang and Hassan (2019) and Robin (2014) analyze injury severity in work zone accidents using multinomial logistic regression in the construction industry. Both studies identify weather conditions (snow and rain), gender and age group of the driver as risk factors. Akboga Kale and Baradan (2020) identify factors contributing to the severity of construction injuries using a binary logistic regression model. Their findings show that work experience and accident type, among others, are significant factors affecting injury severity. In this study, we apply multiclass logistic regression on mine injury classifications, i.e., fatal and permanent disability, non-fatal with days lost and/or restricted activity, and non-fatal with no days lost and/or restricted activity, from the MSHA database to provide in-depth analysis on potential risk factors associated with different classes of injury in the mining industry. This study covers all mines required to report incidents to MSHA between the years 2008 to 2017.

2.3 Data and Methodology

Multiclass logistic regression is applied to accidents and injury data reported to MSHA from 2008 to 2017 to (i) determine a miner's susceptibility to a class of injury given characteristics such as age, mining experience, and work location and (ii) identify the various risk factors associated with each class of injury. We develop an analytics process by which safety managers can identify areas that require prioritized training or attention in helping advance the goal of zero injuries and fatalities in the mining industry.

The Federal Mine Safety and Health Act of 1977, Public Law 91-173, requires operators of mines in the USA to report occupational injuries and illnesses to MSHA (MSHA, 2018). The data is summarized by work location, mine type, accident classification, body part injured, nature of injury, and occupation of the miner. In this study, Part 50 accident, injury, and illness data files from 2008 to 2017 are downloaded from MSHA's website. The data format collected by MSHA is converted into the Statistical Package for Social Sciences (SPSS) (SPSS Software, 2020) file formats for data processing.

The study initially examines the following independent variables: (i) miner's age; (ii) gender; (iii) mine type (coal vs. non-coal); (iv) total mining experience (years); (v) experience at the current mine (years); (vi) experience on the current job (years); (vii) shift start time; (viii) hours at work prior to injury occurrence; (ix) employment type (operator vs. contractor); (x) employment status (permanent vs. trainee); (xi) work location (surface vs. underground); (xii) district; and (xiii) accident type. These variables have been categorized into subgroups. A description of the categories is presented in Table 2.3. We aggregate and categorize the degree of injury (dependent variable) into three classes (Table 2.3): fatal and total permanent or partial permanent disability (FP), non-fatal with days lost and/or days of restricted work activity (DLR), and non-fatal with no days lost or restricted activity (NDLR).

Table 2.3: Initially Examined (MSHA data) Dependent and Independent Variables

Variables	**Bins**
Dependent Variable	
Injury class	Fatal and total permanent or partial permanent disability (FP)
	Nonfatal with days lost and/or days of restricted work activity (DLR)
	Nonfatal with no days lost or restricted activity (NDLR)
Independent Variables	
Mine type	Coal; Non-coal
Work location	Surface; Underground
Employment status	Apprentice or trainee; Permanent
Employment type	Operator; Contractor
Gender	Male; Female
District	Multiple (6)
Accident type	Multiple (21)
Hours at work prior to injury occurrence	<9
	>= 9

Table 2.3 Initially Examined (MSHA data) Dependent and Independent Variables (cont’d.)

Age (years)	18 – 30
	31 – 40
	41 – 50
	51 – 70
Total mining experience (years)	0 – 1
	1 – 3
	3 – 6
	6 – 10
	10 – 20
	20 – 30
	>30
Experience at the current mine site (years)	0 – 1
	1 – 3
	3 – 6
	6 – 10
	10 – 20
	20 – 30
	>30
Experience on current job (years)	0 – 1
	1 – 3
	3 – 6
	6 – 10
	10 – 20
	20 – 30
	>30
Shift start time	7 am
	3 pm
	11 pm

2.3.1 Data Cleaning and Validation

This study looks at mine workers, aged 18 to 70 years, who suffered occupational injuries while working on a mine site. MSHA reported a total of 96,834 incidents during the period 2008 to 2017. We exclude 6707 records (6.93% of total incidents) due to incidents involving minors, non-employees, and occupational illness not caused by a single accident. These occupational illnesses include cancer, hepatitis, lung diseases, hearing loss, and heart attacks. We further exclude 16,170 incidents with missing records such as age, total mining experience, and experience on the current job. This represents 16.70% of the total data. We perform preliminary analysis, hereafter, on the remaining 73,957 records (processed data), representing 76.39% of the original data.

2.3.2 Statistical Analysis and Modeling

The authors perform descriptive statistical analyses on the dataset using IBM SPSS software (SPSS Software, 2020). The independent variables are divided into categories. Age is divided into four categories, i.e., 18–30, 31–40, 41–50, and 51–70 years, to approximately reflect the distribution of age in the dataset. Total mining experience, experience on the current job, and experience at the current mine have similar data distribution; therefore, they are divided into similar categories. The shift start time shows a large number of miners starting work at 7 am, 3 pm, and 11 pm, yielding three categories. Figures 2.1, 2.2a, and 2.2b show the distributions of the following variables: age, work location, and total mining experience (categorized). Figure 2.1 shows the age distribution of miners who were injured, ranging from 18 to 70 years. Figure 2.2a shows that over the past decade, more incidents occurred at surface work locations than underground. Tables 2.4 and 2.5 summarize statistics and distributions for the continuous and categorical independent variables, respectively. A preliminary step to justify the consideration of the independent variables involves conducting a two-tailed chi-squared contingency test. This test is performed on contingency tables to determine whether a significant relationship exists between the row and column variables of the table. A contingency table is a frequency table of two categorical variables where all the levels (categories) of one variable are listed as rows and the levels of the other variable as columns. The cells of the table are populated with the joint frequencies of the corresponding row and column levels of the two variables. The test verifies if the levels of the row variable are differentially distributed over the levels of the column variable. Obtaining a significant result means that a relationship exists between the two variables; i.e., one variable varies according to the other variable (Stockburger, 2016). In this study, we conduct the test between the dependent variable and each independent variable. The results confirm that a significant association exists between the dependent variable and each independent variable. That is, the degree of injury (dependent variable) varies according to variations in the predictors (independent variables). This warrants further analysis to characterize how variations in the predictors influence injury occurrence.

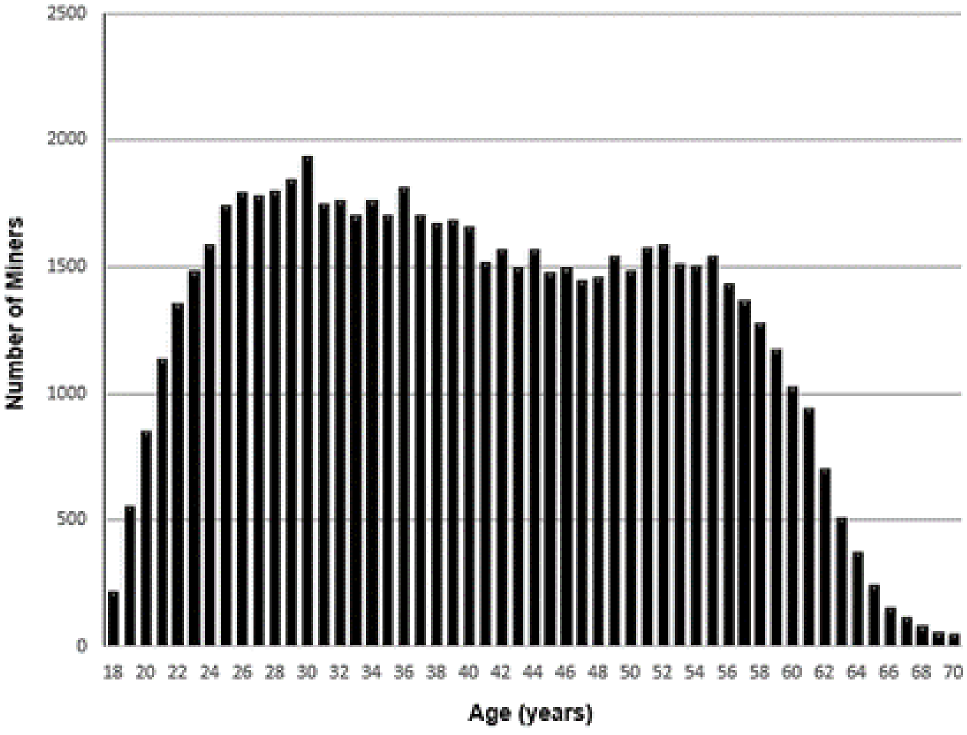
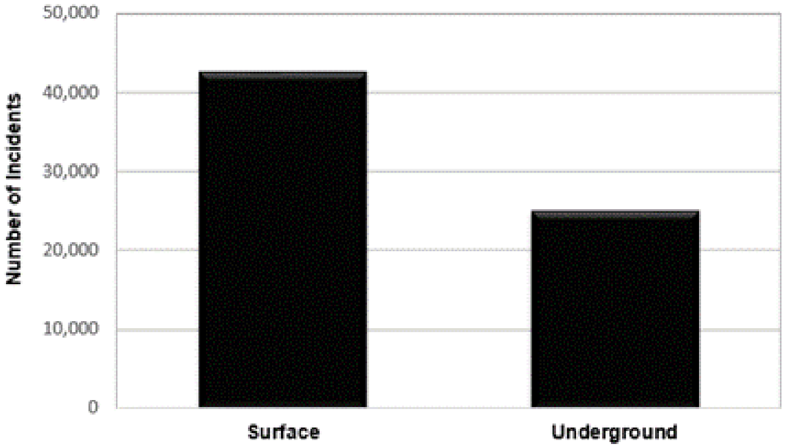
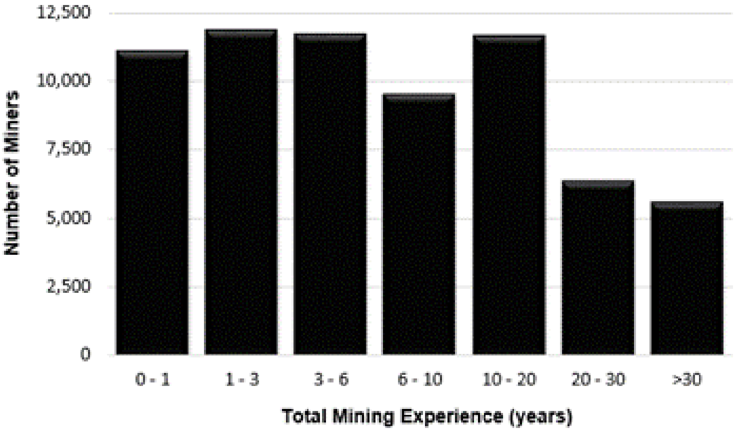


Figure 2.1: Age Distribution of Injured Miners (Processed Accident Data)

Preliminary analysis reveals the major accidents that have occurred over the 10-year period under study. Figure 2.3 presents the ten most common accidents. For the purpose of achieving statistical relevance, our study focuses on the first six common accidents, being



(a) Work Location



(b) Total Mining Experience

Figure 2.2: Distribution of Injured Miners for Processed Accident Data

Table 2.4: Summary Statistics for Continuous Variables (Processed Accident Data)

Variable	**Mean**	**Standard Deviation**
Age (years)	40.4	12.3
Hours at work prior to injury occurrence	4.7	2.9
Total mining experience (years)	10.2	10.8
Experience at current mine (years)	6.0	8.3
Experience at current job (years)	6.6	8.4

Table 2.5: Data Distribution for Categorical Variables (Processed Accident Data)

Variable	Subgroup	Number of Incidents	Percent (%)
Mine type	Coal	31,215	46.2
	Non-coal	36,365	53.8
Work location	Surface	42,581	63.0
	Underground	24,999	37.0
Employment type	Operator	59,570	88.1
	Contractor	8,010	11.9
Employment status	Permanent	67,410	99.7
	Trainee	170	0.3
District	Multiple (6)	67,580	100.0
Accident type	Multiple (21)	67,580	100.0

the ones with the most occurrences over the decade (each with at least 3000 cases). These include handling material, slip or fall, hand tools, machinery, powered haulage, and fall of roof, back, or brow. To this end, we exclude cases involving all other accidents, leaving a total of 67,580 cases for modeling. This represents 91.38% of the processed data.

We subject the independent variables to Pearson correlation analysis. The Pearson correlation measures the strength of the linear relationship between two continuous variables. It results in values ranging from $+1$ to -1; these are known as correlation coefficients. Obtaining a value of zero implies that there is no linear association between the two variables. A value greater than zero implies that the association between the two variables is positive, i.e., an increase in one variable is associated with an increase in the other variable. A value less than zero signifies a negative association between the two variables, i.e., an increase in one variable is associated with a decrease in the other variable. Values closer to $+1$ indicate a strong positive relationship while values closer to -1 indicate a strong negative relationship (Heumann et al., 2016). Results of the analysis show a strong positive relationship between pairs of the following variables: total mining experience, experience at the current mine, and experience on the current job. For each pair, we obtain a corre-

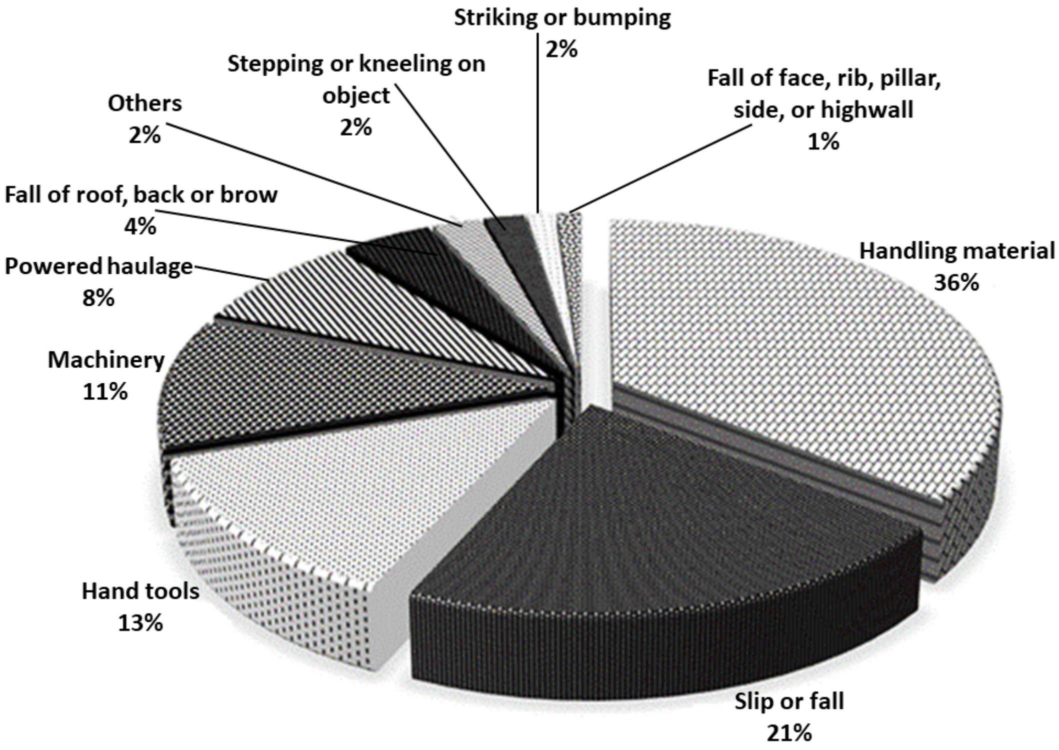


Figure 2.3: Most Frequent Accidents (2008 - 2017)

lation coefficient in the range 0.59 to 0.71. In all cases, the correlation proves significant at a 1% level of significance. The condition where correlation exists between independent variables is termed multicollinearity. This condition could render the output of the logistic regression inaccurate. In order to avoid the potential effect of high multicollinearity, only one of these variables is considered for modeling, i.e., experience on the current job.

We further perform a multicollinearity test on experience on the current job and the remaining independent variables. Multicollinearity is measured by examining the variance inflation factor (VIF). This is the increase in the variance of an estimated regression coefficient if the independent variables are correlated. According to Minitab (2020), if all the VIFs are equal to one, no multicollinearity exists; however, if some of the VIFs are > 1, the independent variables are correlated. Multicollinearity is of significant concern when the VIF of any of the independent variables is above ($>$) five. When this happens, the estimated regression coefficient may not be accurate. For this study, the VIFs for all the independent variables considered are less than 5 (between 1.01 and 2.05). This implies that there is no significant multicollinearity in the dataset.

2.4 Results

We develop the multiclass logistic regression model using IBM SPSS software (SPSS Software, 2020). The dataset used for modeling comprises a total of 67,580 incidents, representing valid records on the six major accidents. Gender and employment status variables are excluded from the model since they are highly skewed. Gender data consists of 97.4% males, and employment status comprises 99.7% permanent employees. The independent variables that are finally considered for modeling include (Table 2.6) miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, hours at work prior to injury occurrence, employment type (operator vs. contractor), work location (surface vs. underground), district, and type of accident. Degree of injury is the dependent variable in the final model, and it comprises the following categories (Table 2.6): fatal and total permanent or partial permanent disability (FP), non-fatal with days lost and/or days of restricted work activity (DLR), and non-fatal with no days lost or restricted activity (NDLR).

We validate results from the model and proceed with analysis to determine which independent variables have had a significant impact on injury occurrence over the decade under study. These variables are identified as risk factors and include miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and accident type. Using the odds ratio output of the model, we determine injury susceptibility among different groups of miners. We also conduct a comparative study between the surface and underground incidents; this is informed by the significant differences that exist between the surface and underground operations.

Table 2.6: Dependent and Independent Variables in Logistic Regression Model

Variables	**Bins**
	Dependent Variable
Injury class	Fatal and total permanent or partial permanent disability (FP)
	Nonfatal with days lost and/or days of restricted work activity (DLR)
	Nonfatal with no days lost or restricted activity (NDLR)
	Independent Variables
Mine type	Coal; Non-coal
Work location	Surface; Underground
Employment type	Operator; Contractor
District	Multiple (6)
Accident type	Multiple (6)
Hours at work prior to injury occurrence	<9
	>= 9
Age (years)	18 – 30
	31 – 40
	41 – 50
	51 – 70
Experience on current job (years)	0 – 1
	1 – 3
	3 – 6
	6 – 10
	10 – 20
	20 – 30
	>30
Shift start time	7 am
	3 pm
	11 pm

For the surface incidents, we identify the following risk factors: miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and accident type. For underground incidents, we identify the following risk factors: miner's age, shift start time, mining district, and accident type.

2.4.1 Model Validation and Risk Factors

We validate the fitted model at a 5% level of significance using the likelihood-ratio chi-squared test. The purpose of the test is to determine if the model is a good fit for the data. Significance of the test statistic implies that the model fits the data well and that one or more of the predictors (independent variables) have a significant influence on the model. From the validation results, a value of $p = 0.00$ is obtained signifying that the model is a good fit for the data. We identify the specific predictors that have a significant impact on the model by conducting a series of the likelihood-ratio chi-squared test, focusing on each predictor at a time. At a 5% level of significance, all predictors prove significant apart from time until injury occurrence and work location. This means that these two variables have not had a significant impact on the three classes of injury over the study period. Table 2.7 summarizes the significant and insignificant predictors. The significant predictors are termed risk factors. We subsequently assess whether there is a significant difference in injury susceptibility between the different categories of each risk factor. The output of the model also presents interactions among the three injury classes as follows: non-fatal with days lost and/or days of restricted work activity (DLR) vs. non-fatal with no days lost or restricted activity (NDLR), and fatal and total permanent or partial permanent disability (FP) vs. non-fatal with no days lost or restricted activity (NDLR). Thus, we set NDLR as a reference response variable to enable assessment of the relative impact the various predictors have on the injury classes. For DLR vs. NDLR, the results in Table 2.8 show how the established risk factors influence one's susceptibility to DLR, relative to NDLR (the reference injury class). The results in Table 2.9 show how the risk factors determine one's susceptibility to FP, relative to NDLR. A detailed discussion of these results follows in section 2.4.2.

Table 2.7: Significance of Predictors

Significant (p <0.025)	**Not Significant (p>= 0.025)**
District	Time until injury occurrence
Experience on the job (years)	Work location
Shift start time	
Age (years)	
Employment type	
Mine type	
Accident type	

2.4.2 Injury Susceptibility

A means of assessing injury susceptibility among different groups of miners lies in understanding the odds and odds ratio. The odds is the ratio of the probability that an event will occur to the probability that the event will not occur. Suppose the numerical values of 0 and 1 are the outcomes of a binary event, where 1 represents event occurrence (success) and 0 represents event non-occurrence (failure). If p is the proportion of observations with an outcome of 1 (probability of success), then $1-p$ is the probability of an outcome of 0 (probability of failure). The ratio $\frac{p}{1-p}$ is called the odds (Hosmer and Lemeshow, 2000). It provides a sense of how many times an event is likely to succeed than it is to fail.

Suppose this binary event can be observed among two groups of miners, A and B, with the former being a reference (control group) and the latter being a target (treatment group). If O_A is the odds of the event in the reference group, and O_B is the odds of the event in the target group, then the ratio of O_B to O_A is called the odds ratio (see equation 2.2). The odds ratio provides a sense of how many times the event is likely to occur in the target group, relative to the reference group (Hosmer and Lemeshow, 2000).

$$\text{Odds ratio} = \frac{O_B}{O_A} \tag{2.2}$$

Table 2.8: DLR vs NDLR

Predictor	**Category**	**Wald Statistic**	**Significance (p value)**	**Odds Ratio**
District	**Northeast**	**62.64**	**0.00**	**1.32**
	Southeast	**5.68**	**0.02**	**1.09**
	North Central	4.57	0.03	0.92
	South central	**20.57**	**0.00**	**1.19**
	Rocky Mountain	**24.75**	**0.00**	**0.84**
	Western (Reference)			
Experience on the current job (years)	**0 - 1**	**42.95**	**0.00**	**1.45**
	1 - 3	**31.87**	**0.00**	**1.37**
	3 - 6	**30.18**	**0.00**	**1.37**
	6 - 10	**25.63**	**0.00**	**1.34**
	10 - 20	**12.48**	**0.00**	**1.22**
	20 - 30	1.68	0.20	1.08
	>30 (Reference)			
Shift	7 am	1.21	0.27	0.97
	3 pm	**8.27**	**0.00**	**1.10**
	11 pm (Reference)			
Age (years)	**18 - 30**	**84.19**	**0.00**	**0.77**
	31 - 40	**14.22**	**0.00**	**0.90**
	41 - 50	2.58	0.11	0.96
	51 – 70 (Reference)			
Accidents	**Handling material**	**6.84**	**0.01**	**1.12**
	Hand tools	**264.64**	**0.00**	**0.48**
	Powered haulage	**253.39**	**0.00**	**2.26**
	Machinery	**9.12**	**0.00**	**0.87**
	Slip/fall of a person	**530.58**	**0.00**	**2.83**
	Fall of roof, back, brow (Reference)			
Employment type	**Operator**	**53.58**	**0.00**	**1.21**
	Contractor (Reference)			
Mine type	**Non-coal**	**15.32**	**0.00**	**1.09**
	Coal (Reference)			

Categories with significant odds ratios are in bold[1]

Table 2.9: FP vs NDLR

Predictor	**Category**	**Wald Statistic**	**Significance (p value)**	**Odds Ratio**
District	Northeast	0.01	0.92	0.99
	Southeast	1.61	0.20	0.84
	North Central	4.00	0.05	0.75
	South Central	0.01	0.93	1.01
	Rocky Mountain	1.04	0.31	0.88
	Western (Reference)			
Experience on the current job (years)	0 - 1	0.01	0.93	0.98
	1 - 3	0.10	0.75	1.06
	3 - 6	0.09	0.77	0.95
	6 - 10	0.39	0.53	0.89
	10 - 20	0.10	0.75	0.94
	20 - 30	1.04	0.31	0.81
	>30 (Reference)			
Shift	7 am	0.03	0.86	0.98
	3 pm	0.27	0.60	1.07
	11 pm (Reference)			
Age (years)	**18 - 30**	**42.83**	**0.00**	**0.51**
	31 - 40	**28.37**	**0.00**	**0.59**
	41 - 50	**5.50**	**0.02**	**0.80**
	51 – 70 (Reference)			
Accident type	Handling material	1.59	0.21	0.82
	Hand tools	**59.99**	**0.00**	**0.21**
	Powered haulage	**58.07**	**0.00**	**3.50**
	Machinery	**10.42**	**0.00**	**1.68**
	Slip/fall of a person	**27.96**	**0.00**	**0.33**
	Fall of roof, back, brow (Reference)			
Employment type	**Operator**	**10.04**	**0.00**	**0.75**
	Contractor (Reference)			
Mine type	Non-coal	0.48	0.49	0.94
	Coal (Reference)			

Categories with significant odds ratios are in bold[2]

Applying this concept to the results in Table 2.8, odds will be the ratio of the probability that a miner suffers DLR to the probability that they do not. The age variable in the table shows four groups of miners, with the last group (miners aged 51–70) being the reference. For each age group, the odds is determined as the ratio of the probability that a miner in that group suffers DLR to the probability that they do not. Thereafter, we can determine the odds ratio using the reference group and any other group in the age variable. With the first group (miners aged 18–30) as a target, we initially determine the odds as the ratio of the probability that a miner aged 18–30 suffers DLR to the probability of not suffering DLR. Having done the same for miners in the reference group, we proceed to determine the odds ratio for the target group. We determine this as the ratio of the odds that a miner aged 18–30 suffers DLR to the odds that a miner aged 51–70 suffers DLR. The odds ratio provides a measure of how more or less susceptible the first group is to DLR, relative to the reference group. We subject the remaining groups to a similar process to obtain the corresponding odds ratios. A group with an odds ratio greater than one denotes higher susceptibility to DLR injuries, relative to the reference group. An odds ratio less than one denotes lesser susceptibility, while an odds ratio of one means there is no significant difference in susceptibility between the reference and target groups. Reference groups always have an odds ratio of one, since they serve as their own target groups.

From the age variable in Table 2.8, we note that miners aged 51–70 (reference category) are the most susceptible to DLR; all the other categories have odds ratios that are less than one. In determining injury susceptibility via the odds ratios, one thing to consider is the significance (p values) of the odds ratios. The susceptibility of a target group is not significantly different than that of the reference group if the corresponding p value for the target group is greater than 0.025. For instance, we observe that though the odds ratio for miners aged 41–50 in Table 2.8 is lower than one, their susceptibility is not significantly different than that of the reference category, since $p = 0.11 > 0.025$. Thus, miners aged 41–50 have about the same susceptibility to DLR as do miners in the reference category.

We obtain the p values for the odds ratios from a two-tailed Wald test at a 5% level of significance.

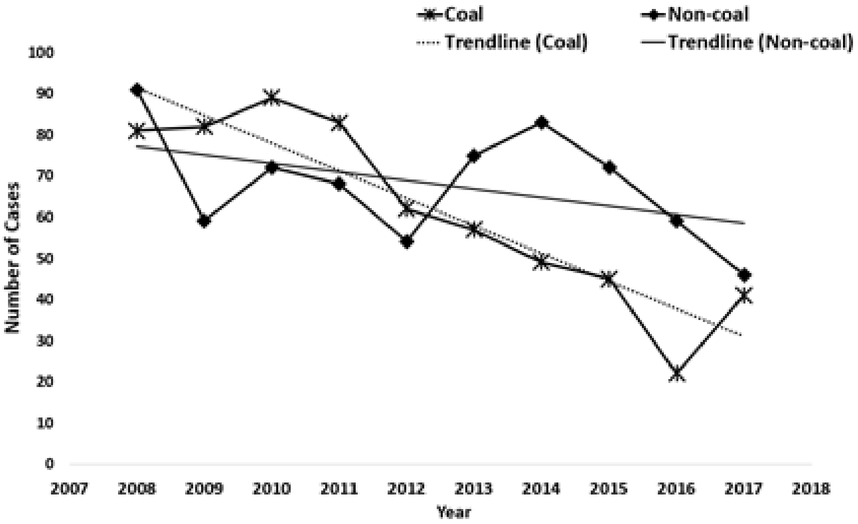
All categories of the accident type variable show a significant difference in susceptibility when compared to the reference category (fall of roof, back, or brow). A worker who suffers a hand tools incident has the least susceptibility to DLR. Among the remaining accidents, slip or fall presents the highest susceptibility to DLR. The northeastern district has the highest susceptibility to DLR among all mining districts, with the Rocky Mountain district showing the least susceptibility. An operator starting work in the swing shift (2nd shift) in a non-coal mine is highly susceptible to DLR.

From the results in Table 2.9 (FP vs. NDLR), an increase in age is associated with increased susceptibility to FP. With a change in shift, there is no significant change in susceptibility to FP. Though shifts 1 and 2 have different odds ratios than shift 3 (the reference category), they do not present a significant change in susceptibility to FP (since $p > 0.025$). Likewise, there is no significant difference in susceptibility to FP among the various districts and experience on the current job. Among the six accident categories, powered haulage incidents make a worker most susceptible to FP. The category with the least susceptibility is hand tools. Operators are less likely to sustain FP injuries than contractors (0.75 times as likely as contractors). This result has some similarity with the study by Muzaffar et al. (2013), which reports that contractors are more susceptible to fatalities than operators. Though workers in non-coal mines have lesser odds ratios than those in coal mines, the difference is not significant ($p = 0.49 > 0.025$). This implies that the susceptibility to FP for the coal and non-coal miners, over the study period, has been about the same. This again has some similarity with the work by Muzaffar et al. (2013), where results show there is no significant difference in susceptibility to fatality between the coal and non-coal miners ($p = 0.68$). Further analysis reveals that fatality and permanent disability records gathered over the study period by MSHA , i.e., original data, have been about the same for the coal and non-coal mines (Figure 2.4a). From Figure

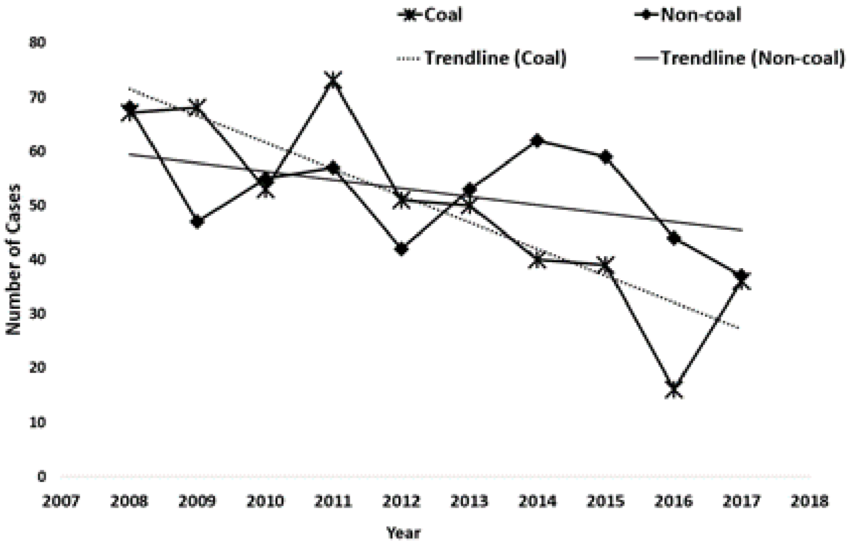
2.4a, the number of cases for coal mines is relatively higher during the first half of the period. This is reversed in the second half of the period, with non-coal mines recording a relatively higher number of cases. Figure 2.4b, which summarizes fatality and permanent disability records for the final dataset used in modeling, corroborates the observation we make in Figure 2.4a). Both figures show similar trends for the coal and non-coal mines over the 10-year period. While logistic regression can identify this trend, the analysis does not take into consideration the population size, e.g., employee hours worked. This limitation, which has the potential to yield biased results for the mine type variable, is further discussed in section 2.5.

2.4.3 Risk Profile

At a 5% level of significance, the odds ratios provide a means to assess how the independent variables interact to influence a miner's susceptibility to a class of injury under consideration. Specifically, the categories of a given risk factor (independent variable with significant influence on the model) are compared to one another using the odds ratios to assess relative susceptibility to the class of injury being considered. Figures 2.5, 2.6, 2.7, and 2.8 summarize these interactions and show how categories of a given risk factor vary in susceptibility to DLR and FP. The odds ratios in these figures have been adjusted to account for the 5% level of significance; i.e., odds ratios that are not significant at the 5% level are recomputed to one. Figure 2.5 shows a decreasing trend of susceptibility to DLR with an increase in experience on the job, i.e., experience working in a specific job title, not experience as a miner. An increase in a miner's experience on the job does not cause a significant change in their susceptibility to FP. An increase in age generally comes with increased susceptibility to both DLR and FP (Figure 2.6). From Figures 2.5 and 2.6, the susceptibility to DLR decreases with increasing experience on the job but increases with an increase in age. A general convention would be for DLR susceptibility to decrease with an increase in age, just as we observe for experience on the job, since we expect experience



(a) Unprocessed Data



(b) Final Data Used in Modeling

Figure 2.4: MSHA Data Summary for Fatality and Permanent Disability (FP) for Coal and Non-coal Mines

on the job and age to be generally proportional. This is, however, not always the case, considering that the experience we refer to here is the experience on a miner's current job, prior to the incident. Thus, a miner might be relatively older but with less experience on a particular job. Figure 2.7 shows that the accident type one encounters comes with significant variation in susceptibility to either DLR or FP. In both cases of injuries, hand tools presents the lowest susceptibility among the six major accidents under study. Powered haulage has the highest susceptibility to FP, while slip or fall has the highest susceptibility to DLR. While there is no significant change in susceptibility to FP from one district to the other, susceptibility to DLR varies from one district to the other (Figure 2.8). Miners in the swing shift (with a peak start time of 3 pm) are the most susceptible to DLR. This is not so with FP; none of the shifts shows higher susceptibility to FP. While operators are more susceptible to DLR than contractors, the converse is true for FP. Though non-coal miners are more susceptible to DLR than coal miners, they have about the same susceptibility to FP. Table 2.10 summarizes the most susceptible categories for each class of injury under consideration.

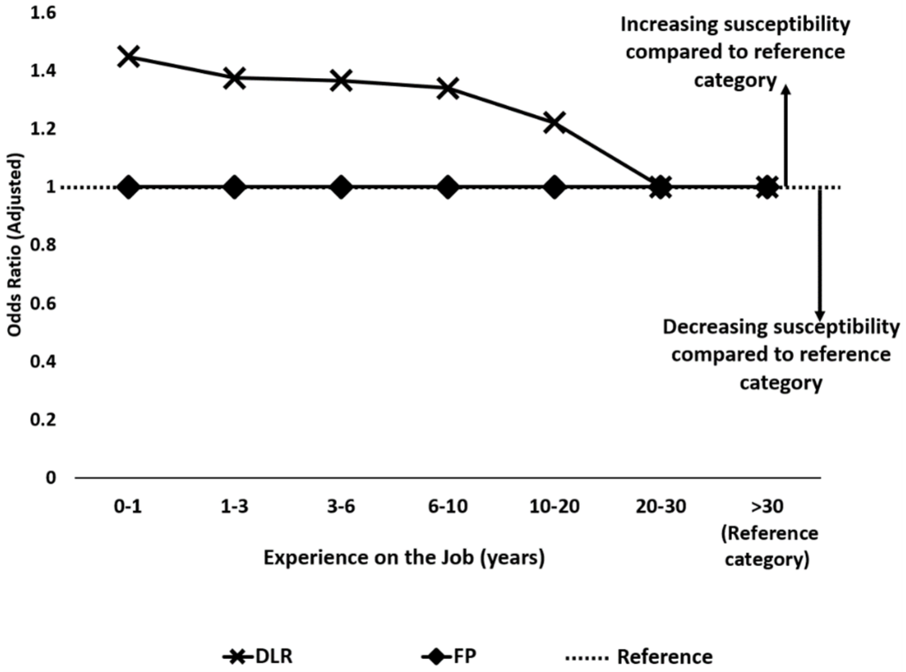


Figure 2.5: Risk Profile for Experience on the Job

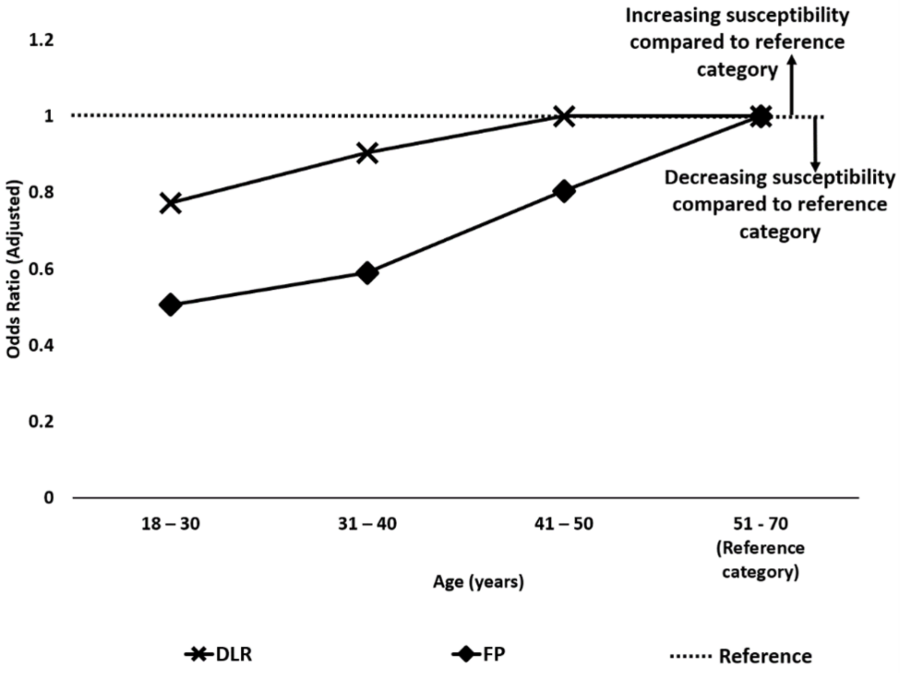


Figure 2.6: Risk Profile for Age

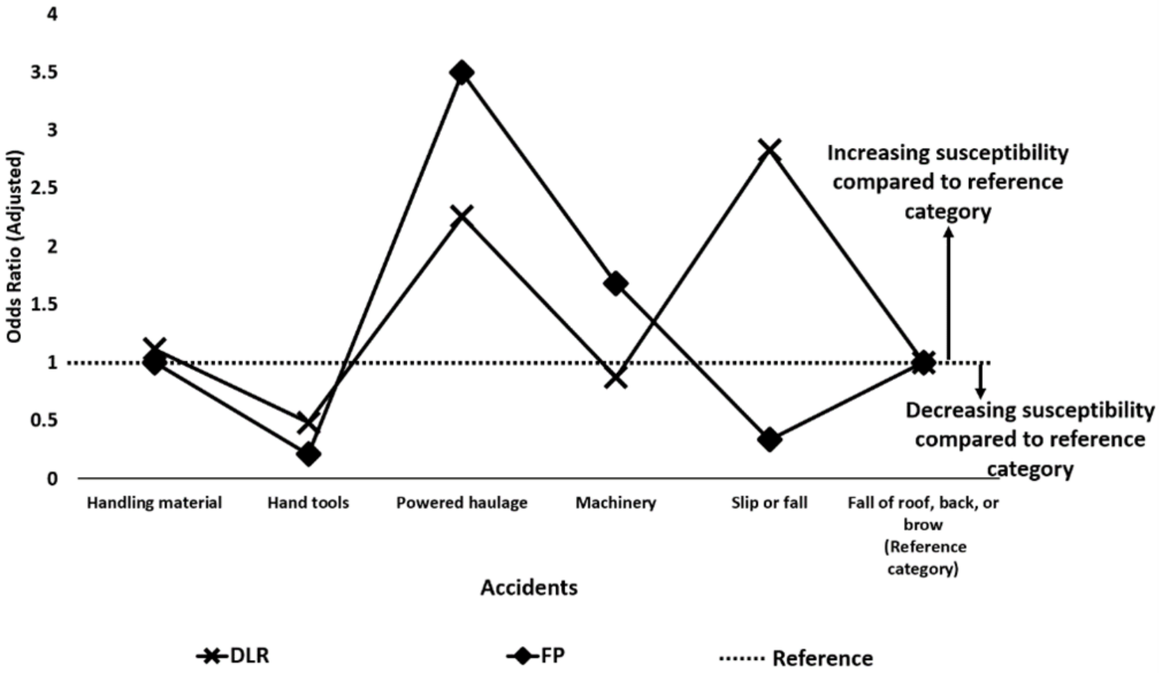


Figure 2.7: Risk Profile for Accidents

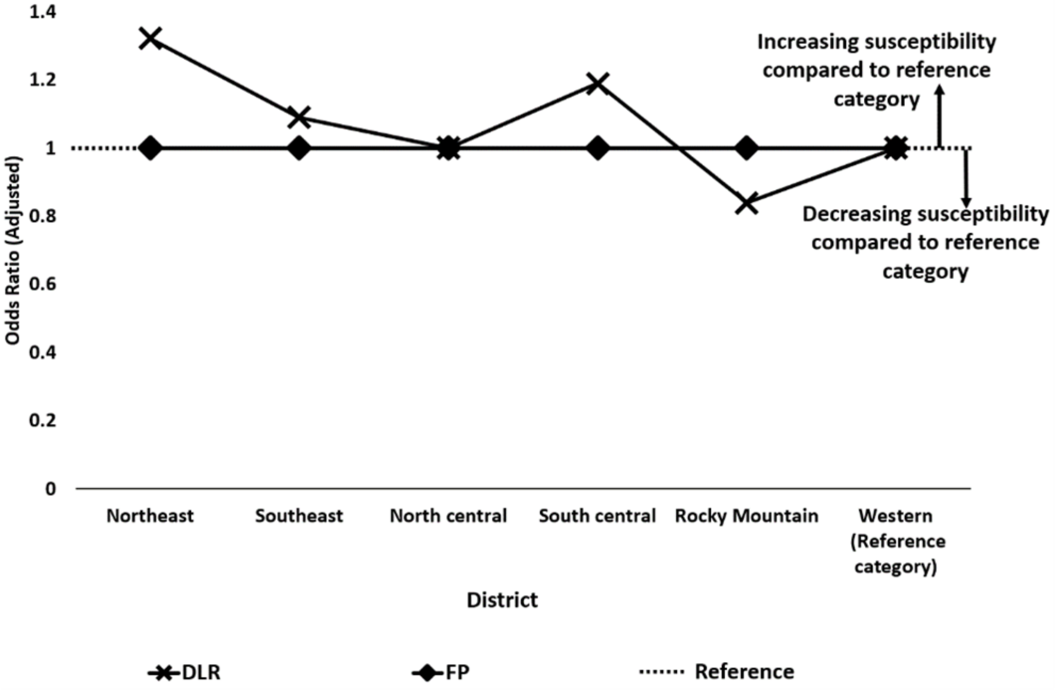


Figure 2.8: Risk Profile for Districts

Table 2.10: Most Susceptible Categories

Predictor	DLR	FP
District	Northeast	*
Experience on the job (years)	0 - 1	*
Shift start time	Shift 2 (Peak start time: 3 pm)	*
Age (years)	51 - 70	51 - 70
Employment type	Operator	Contractor
Mine type	Non-coal	*
Accident type	Slip or fall	Powered haulage

*Implies all categories of the predictor have equivalent injury susceptibility[3]

Though handling material is the most reported accident, as shown in Figure 2.3, it does not prove to be the most susceptible incident to either DLR or FP, as Figure 2.7 shows. Such detail is provided by logistic regression, which presents a more robust form of analysis. From the logistic regression analysis, we identify powered haulage and slip or fall as incidents that make a worker most susceptible to FP and DLR, respectively. This shows the applicability of logistic regression over basic statistics for injury analysis.

2.4.4 Surface vs. Underground

Considerable differences exist between the surface and underground operations regarding equipment type and design, schedule of operations, ambient conditions, and layout of the working environment. To this end, we split the dataset into the surface and underground incidents and conduct comparative analysis to assess the differences between them. Apart from work location (redundant for this purpose), all variables that have been considered in the final model of the general case are also considered for both the surface and underground scenarios.

From the analysis of the surface incidents, we realize that hours at work prior to injury occurrence do not have a significant impact on the model. For the underground incidents, the following variables do not significantly impact the model:

1. Experience on the job
2. Employment type (operator vs. contractor)
3. Mine type (coal vs. non-coal)
4. Hours at work prior to injury occurrence

Table 2.11 summarizes the respective variables that have had a significant impact on the surface and underground injury occurrences over the period under study. Figures 2.9 and 2.10 show the risk profiles for experience on the job and age variables, respectively, for the surface scenario. There is a decreasing trend in susceptibility to DLR as experience on the job increases, while a change in experience on the job does not cause a change in susceptibility to FP (Figure 2.9). This is similar to the results for the general case (Figure 2.5). Figure 2.10 shows an increase in susceptibility to FP as age increases. DLR susceptibility increases with age until 40 years and levels off thereafter. Figure 2.11 shows the risk profile for age in the underground scenario. An increase in age generally comes with an increase in susceptibility to both DLR and FP.

Table 2.11: Significant Predictors (Surface vs Underground)

Significant Predictors	Surface	Underground
District	✓	✓
Experience on the job (years)	✓	
Shift start time	✓	✓
Age (years)	✓	✓
Employment type	✓	
Mine type	✓	
Accident type	✓	✓
Hours at work prior to injury occurrence		

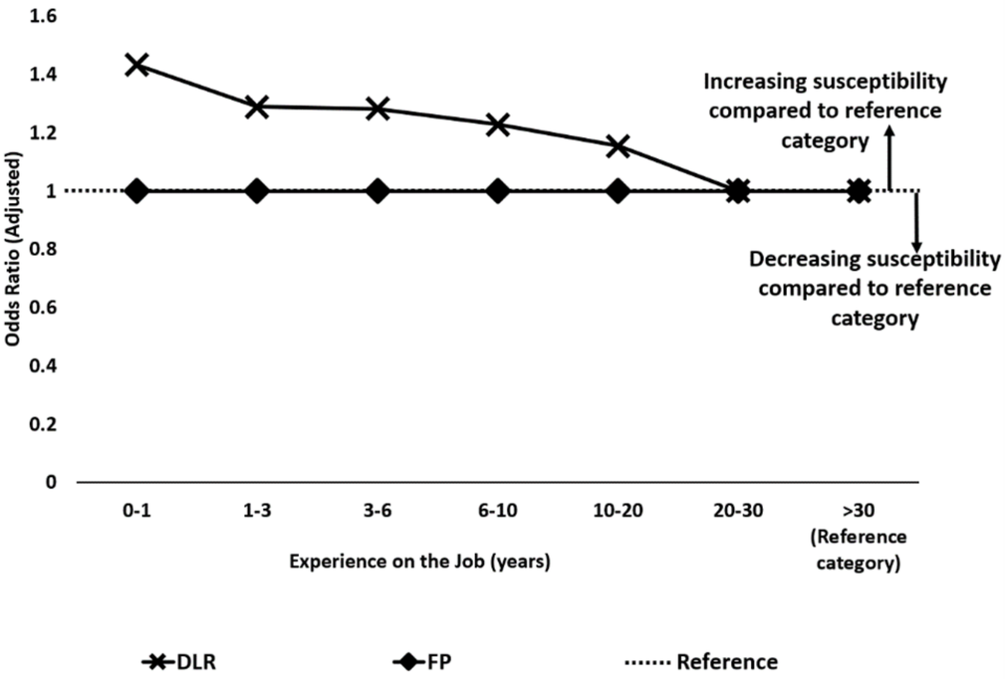


Figure 2.9: Risk Profile for Experience on the Job (Surface)

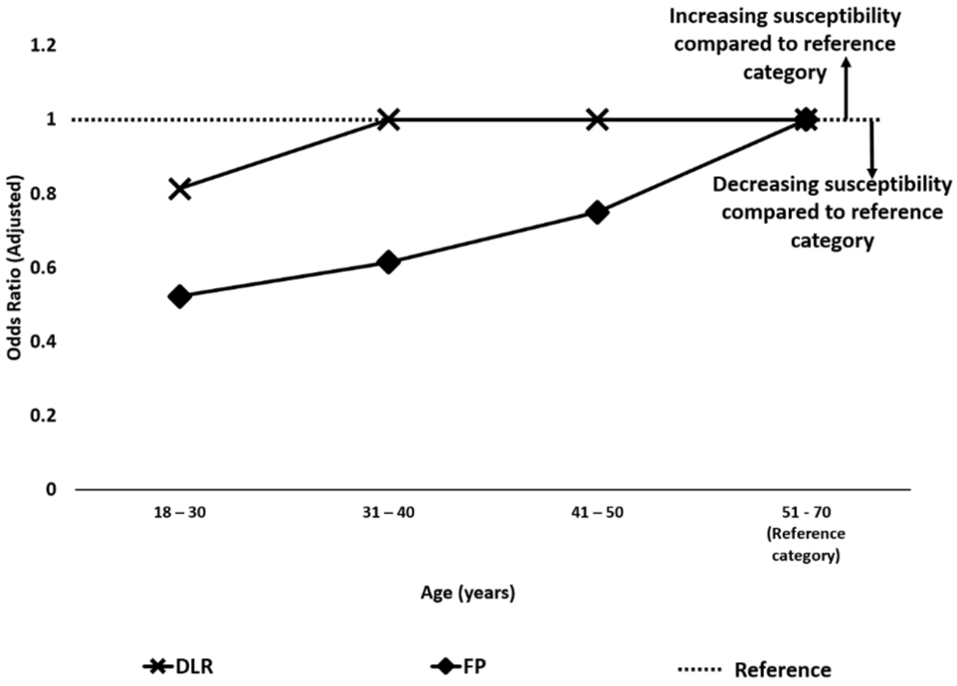


Figure 2.10: Risk Profile for Age (Surface)

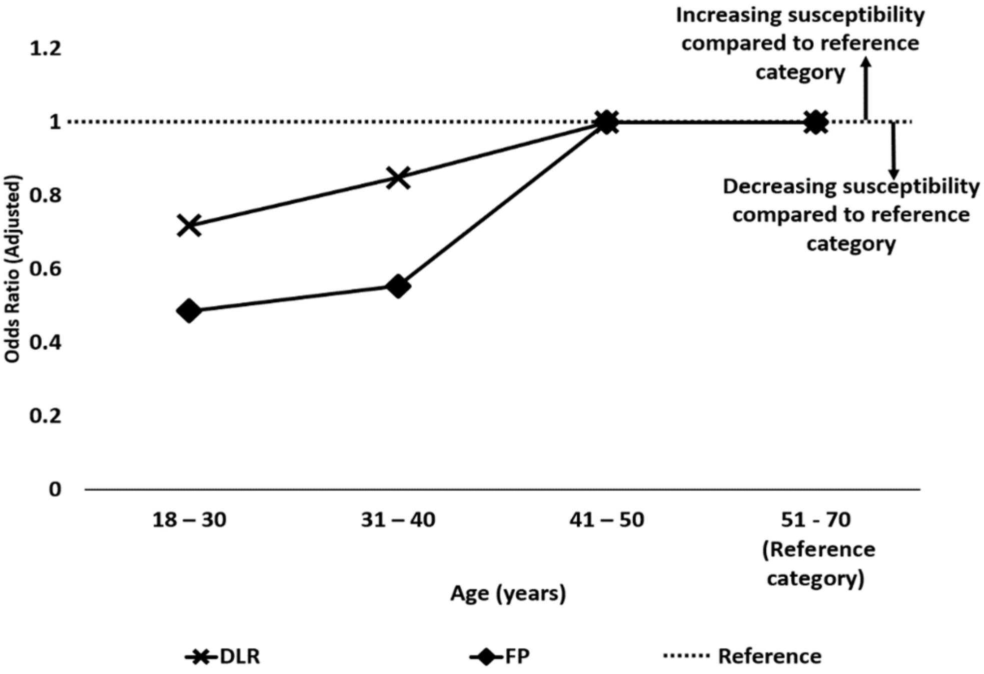


Figure 2.11: Risk Profile for Age (Underground)

Table 2.12 summarizes the differences between the surface and underground incidents in respect of the most susceptible groups of miners. There are a few instances where the results for the surface and underground are similar. For DLR injuries, both the surface and underground have miners aged 41–50 and 51–70 as the most susceptible categories. Likewise, they share slip or fall as the most susceptible accident to DLR. Aside from these two variables (i.e., age and accident type), they have varying results for DLR. For FP, both the surface and underground incidents have miners aged 51–70 as the most susceptible category. Another similarity is that no district or shift stands out as the most susceptible category for either surface or underground incidents.

Table 2.12: Most Susceptible Categories (Surface vs Underground)

Predictor	**DLR**		**FP**	
	Surface	**Underground**	**Surface**	**Underground**
District	Southeast	Northeast	*	*
Experience on the job (years)	0 - 1	N/A	*	N/A
Shift start time	*	Shift 2 (Peak start time: 3 pm)	*	*
Age (years)	31–40, 41–50, 51-70	41–50, 51-70	51-70	41–50, 51-70
Employment type	Operator	N/A	Contractor	N/A
Mine type	Non-coal	N/A	*	N/A
Accident type	Slip or fall	Slip or fall	Machinery	Powered haulage

N/A refers to predictors that have no significant impact on underground incidents; they are subsequently dropped from the model[4]

*Implies all categories of the predictor have equivalent injury susceptibility[5]

2.5 Discussion

The results of this study identify the risk factors associated with three injury classes, namely, fatal and total permanent or partial permanent disability (FP), non-fatal with days lost and/or days of restricted work activity (DLR), and non-fatal with no days lost or restricted activity (NDLR). The age variable for both DLR vs. NDLR (Table 2.8) and FP vs. NDLR (Table 2.9) identifies the older miners, i.e., 51–70 years of age (reference category), as the most susceptible group. This may be as a result of an increase in the population of older workers in the workforce in recent years (Smith and Pegula, 2020). Slip or fall accidents have the highest susceptibility to DLR injuries. This aligns with a study by Nowrouzi-Kia et al. (2017) who identify slip and fall accidents as a major contributor to lost-time injuries (defined in this study as DLR) in the mining industry. Contractors are more likely to sustain FP injuries than operators, and this has some corroboration with the study by Muzaffar et al. (2013) on MSHA data, where the authors observe that contractors are more susceptible to fatalities than operators. In consequence, the results of our study and that of Muzaffar et al. (2013) suggest that contractors have been more susceptible to the severest form of injury over the past two decades.

The foregoing analysis culminates in a useful tool for identifying areas of risk in mining operations. This can be applied to historic data from a single mine to enable safety officers to obtain detailed information about aspects of operations that require immediate risk or hazard mitigation measures. Corporations and government institutions with stakes in mine health and safety can apply this tool to historic data from a cluster of mines, with the aim of identifying common areas of risk. This will, subsequently, enhance the ability of such institutions to provide the necessary support and guidance towards targeted risk mitigation on the concerned mine sites. This information can benefit the industry by identifying specific training areas based on the operation's demographics, for example. The usefulness of this analytic tool can be further enhanced if the data quality is improved. Issues with data quality include missing records, inconsistency, and subjectiveness. For instance, apprentices and trainees are used interchangeably when referencing the over 200 job titles found in the database. Aggregation of these titles into related job roles will enhance data analysis that incorporates the effect of job roles. To this end, MSHA can introduce a new variable in the database that represents an aggregated form of the existing job titles. Furthermore, safety supervisors can review accident and injury reports for missing data before onward submission to MSHA . This will contribute to a more comprehensive and robust data analysis.

It must be noted that logistic regression does not provide all of the necessary analysis to have a complete understanding of safety accidents. It can be used to identify trends and to look beyond industry standard safety statistics, e.g., incident rates. We use logistic regression in this study to identify trends that are not easy, if even possible, to distinguish using standard safety statistics. We, however, note that there is a limitation to the results of the analysis, and that is, the study does not consider the impact of case rate (number of incidents over a given population, e.g., hours worked or number of mines per type). Thus, results developed for the mine type variable may be biased since the analysis only considers the number of incidents. For instance, we realize from the results that workers in non-coal mines have about the same susceptibility to FP as workers in coal mines. This conflicts with the conventional knowledge that there are more non-coal miners in the USA than coal miners and that both categories of miners recorded about the same number of incidents during the period under study (Figures 2.4a and 2.4b), which suggests that coal miners are rather more susceptible than non-coal miners. Interestingly, this convention is also in contrast with the study by Muzaffar et al. (2013), where results show there is no significant difference in susceptibility to fatality between the coal and non-coal miners ($p = 0.68$) over the period 1998–2007. Further analysis by the authors, based on work location (surface vs. underground), shows that non-coal miners are more susceptible to fatality in either work location.

2.6 Conclusions

We analyze injury data collected by the Mine Safety and Health Administration for the period 2008 to 2017 using multiclass logistic regression. As a result, miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and accident type have been identified as safety risk factors. We show how interactions between these variables contribute to a miner's susceptibility to the following injury classes: non-fatal with no days lost or restricted activity (NDLR), non-fatal with days lost and/or days of restricted work activity (DLR), and fatal and total permanent or partial permanent disability (FP). Powered haulage and slip or fall are the incidents that make miners most susceptible to FP and DLR, respectively. Contractors are more susceptible to FP than operators, while operators are more susceptible to DLR than contractors. Miners in shift two (with a peak start time of 3 pm) are the most susceptible to DLR, compared to miners in other shifts. Miners aged 51–70 are the most susceptible age group to both DLR and FP. The researchers identify miners with up to a year's experience on the job as the most susceptible to DLR, which is perhaps the most actionable takeaway from this analysis. Regardless of the overall mining experience of the individual, the initial year in a new position incurs the highest DLR risk.

This method does have a limitation, as seen when comparing the FP susceptibility of the coal and non-coal miners. The results show that both injury classes have about the same susceptibility, yet we know that there are more non-coal mines in the USA than coal mines and that both mine types recorded about the same number of incidents over the period. Therefore, the analysis is not correctly weighted for mine type (coal vs. non-coal).

We further show the differences and similarities between the surface and underground mine incidents. Miner's age, mine type (coal vs. non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and accident type are the risk factors associated with susceptibility to surface injuries. Those associated with susceptibility to underground injuries are miner's age, shift start time, mining district, and accident type. Both the surface and underground cases have slip or fall as the accident type that makes miners most susceptible to DLR. Regarding FP, machinery and powered haulage are the accident types that make miners most susceptible in the surface and underground, respectively.

To this end, multiclass logistic regression proves to be a tool that can be used beyond basic statistics in providing robust mine accident and injury analysis. Using this tool, safety managers can identify areas that need prioritized training or attention. Periodic analysis with this tool and taking pragmatic measures, thereafter, will promote a strong safety culture and risk mitigation in the mine environment.

It must be acknowledged that a significant proportion of the original data has incomplete records. A total of 16.70% of the records are missing one or more of the variables considered in this study; therefore, that data was not included in this analysis. We recommend that safety supervisors review accident and injury reports for missing data before onward submission to MSHA . Having a more complete dataset will contribute to a more robust analysis by researchers and safety personnel. Additionally, incorporating the distribution of coal to non-coal mine operations and surface to underground operations would provide more realistic results by taking into account the number of operations and incidents in each category.

Plans for future work include evaluating different dependent variables, e.g., accident type, and aggregation strategies to provide more insight into injury and accident occurrence on mine sites. With the aggregation of the degrees of injury, variations of aggregation methods should be evaluated in addition to varying the dependent variable. Different supervised machine learning techniques could be evaluated to compare results. While this study identifies risk factors, it does not provide the why. Identifying the root cause of increased susceptibility to a given injury class would require additional data and analysis.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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Chapter 3

Activity-based Respirable Dust Prediction in Underground Mines Using Artificial Neural Network

Amoako, R. and Brickey, A. (2021). Activity-based respirable dust prediction in underground mines using artificial neural network. In Tukkaraja, P. (Ed.), *Mine Ventilation (*1st *ed.)* (pp. 410 – 418). CRC Press. https://doi.org/10.1201/9781003188476

Abstract

Production activities in underground mines generate respirable dust which impacts workers' health and productivity. This underscores the importance of accurately predicting dust concentration towards effecting proactive and timely measures of mitigation. We develop an artificial neural network (ANN) model for an underground metal mine that predicts dust concentration using input parameters that are derived from production activities. The model provides fairly good results, with the prospect of yielding better results with improved data collection. The model produces a correlation of 0.70 between the predicted and actual dust concentration. The work in this paper constitutes the first phase of a larger framework that seeks to manage workers' exposure to respirable dust by incorporating ventilation in short-term production scheduling. In a future work, we seek to incorporate predictions from the ANN model and the impact of conventional dust controls into short-term production schedule optimization as mathematical constraints. This will aid in identifying high dust production activities proactively, and effectively managing available ventilation and dust control measures to enhance miners' safety.

3.1 Introduction

Mining operations generate respirable dust which can result in the development of lung diseases, collectively known as pneumoconiosis, in mine workers. Dust may be defined as a solid aerosol particle formed by the mechanical disintegration of a parent material by various processes such as blasting, mucking, crushing, and grinding (Belle, 2004). Dust particles have a size (diameter) range of 1 to 100 μm, and they settle slowly under the influence of gravity (Sellara and Sarver, 2014, WHO, 1999). Dust particles that are 4.0 μm or less in size are known as respirable dust (NIOSH, 2005). When inhaled, respirable dust particles evade the human natural defense mechanisms. Eventually, they get deposited in the lungs where they penetrate past the bronchioles into the gas-exchange region of the lungs. Over the long term, this causes lung diseases with varied health impact ranging from swelling in the lungs to shortness of breath, fatigue, slight fever and chills, scarring of the lung tissues (fibrosis), and death (American Lung Association, 2020, Mayo Foundation for Medical Education and Research, 2017, NIOSH, 2005). The lung diseases may also increase the risk of other health problems. For instance, silicosis increases the risk of tuberculosis and lung cancer (American Lung Association, 2020).

In underground metal mining, dust may be generated from production activities such as drilling, blasting, cutting, loading, hauling, and crushing. Underground mine workers can be exposed to dust particles that differ in composition such as crystalline silica, and metals such as lead, cadmium, and arsenic. These constituents make dust a health hazard in underground mines. High levels of dust can reduce visibility and become a safety hazard. The rock geology and production activities determine the type and quantity of dust particles generated. In-place ventilation and dust control systems influence the amount of dust generated and the fraction that becomes airborne (WHO, 1999).

The concentration of respirable dust generated in underground mining operations is associated with activity type and activity rate, both of which are prime to conventional short-term production scheduling in underground mining. In underground metal mine planning, production scheduling can be defined as the sequencing of mining activities to achieve clearly defined goals in order to generate revenue (Chowdu, 2020). This results in the determination of activity start dates for the operation with a scheduling fidelity corresponding to the desired planning horizon, i.e., long-, medium-, or short-term planning. Long-term production schedules establish the overarching goals, e.g., life-of-mine production and capital project goals, for the operation based on corporate policy (Chowdu, 2020, Chowdu et al., 2021). Medium-term production schedules focus on guiding operations to meet the overall long-term goals and seek to determine activity start dates for a three-to five-year time horizon at monthly or quarterly fidelity. Short-term production schedules inform the day-to-day operations of the mine. They are developed based on the forecast from the medium-term schedule and current operational conditions. Thus, they define an extraction sequence by specifying activity start dates at a finer fidelity, i.e., shift, daily or weekly over a time horizon of one to three months. They focus on the effective utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets (Trout, 1997).

We develop an artificial neural network (ANN) model for predicting respirable dust concentration for an underground metal mine with input parameters that are derived from production activities, specifically activity types and activity rates. The work in this paper constitutes the first phase of a larger framework that seeks to manage workers' exposure to respirable dust by incorporating ventilation in short-term production scheduling. In a future work, we seek to incorporate predictions from the model into short-term production schedule optimization as mathematical constraints, along with the resultant dust reduction offered by conventional dust mitigation measures such as ventilation and water sprays. This will help identify high dust production activities proactively and determine how to manage available ventilation and dust control measures to enhance miners' safety while optimizing production.

3.1.1 Artificial Neural Network

Artificial neural network (ANN) is a machine learning technique that is inspired by the way biological neural system works, such as how the brain processes information. Information processing in ANN involves many highly interconnected processing elements known as neurons that work together to solve specific problems. The learning process involves adjustments to the synaptic connections existing between the neurons (Ertel, 2017, Grosan and Abraham, 2011). In the biological neural system, a neuron consists of a cell body, known as soma, an axon, and dendrites. The axon sends signals, and the dendrites receive these signals. A synapse connects an axon to a dendrite. Depending on the signal it receives, a synapse might increase or decrease electrical potential. An ANN consists of a number of neurons similar to the human biological neurons. These neurons are known as units, and are connected by weighted links that transmit signals from one neuron to the other (Dixon et al., 1995, Grosan and Abraham, 2011). The output signal is transmitted through the neuron's outgoing connection, which is analogous to the axon in the biological neuron. The outgoing connection splits into a number of branches that transmit the same signal. The outgoing branches terminate at the incoming connections (analogous to dendrites) of other neurons in the network (Grosan and Abraham, 2011).

An ANN has three types of neurons, and these are known as input, hidden, and output neurons. They are stacked in layers, and receive input from preceding neurons or external sources, and use this to compute an output signal using an activation function. The activation function is a mathematical formula for determining the output of a neuron based on the neuron's weighted inputs. The output signal is then propagated to succeeding neurons. While this is ongoing, the ANN adjusts its weights in order to record an acceptable minimal error between input variables and the final output variable(s) (Krose and van der Smagt, 1996). The complexity of the ANN architecture makes it well suited for solving both linear and nonlinear problems. Advancement in computational power has enhanced its use in the fields of engineering, industrial process control, medicine, risk management, marketing, finance, communication, and transportation.

3.2 Literature Review

Early epidemiological and pathogenic research has established cumulative exposure to respirable dust as a critical factor in the development of pneumoconiosis, i.e., lung diseases caused by respirable dust (Belle, 2004, Cohen et al., 2016). Duration of exposure and the amount of respirable dust in the mine environment also have significant influence on workers' susceptibility to pneumoconiosis. Belle (2004) reports that the risk of progression to a higher category of pneumoconiosis grows with increasing intensity of exposure (mean dust concentration) and increasing cumulative exposure (intensity x duration). Rossiter (1972) studies the relation between radiological category of pneumoconiosis and dust content of the lung among a mixed group of 221 miners, of whom 76 have progressive massive fibrosis. The author's findings show that the average radiological scores for pneumoconiosis are related, by multiple regression, to the quartz and iron contents of the lungs.

In an experimental study, King et al. (1953) inject different forms of silica, i.e., fused silica, quartz, cristobalite, and tridymite of high purity and equal size distribution, into the lungs of rats. The objective is to study any differences in the rate and severity of pathogenic reactions. Results from the study suggests that the crystal structure of pure silica influences lung tissue reaction. Tridymite produces the most rapid pulmonary fibrosis, followed by cristobalite, quartz, and fused silica in a decreasing order of rate of reaction. In a similar study, the injected silica dust produces pathological changes that are more closely related to the mass of the dust than to the total number of particles (Belle, 2004). Meldrum and Howden (2002) establish that the toxicity, i.e., fibrogenic potency, of crystalline silica is variable. The authors cite the following as factors responsible for the variability: polymorphic type of crystalline silica; presence of other minerals; particle number, size, and surface area; and age of rock fragment surface, i.e., freshly fractured surface vs aged surface. The authors assert that the presence of aluminium-containing minerals and the absence of significant exposure to freshly cut surfaces of crystalline silica contribute to low risk estimates for silicosis, a form of pneumoconiosis caused by exposure to silica.

Characterizing the dispersion of dust is an important exercise in mining since it helps to estimate the amount of dust a facility will emit. Conventionally, dust dispersion models for underground mines have been built around one or more of the fundamental equations used in air dispersion modeling, i.e., the Box, Gaussian, Eulerian and the Lagrangian models Collett and Oduyemi (1997). In recent years, dust dispersion research has focused on the use of computational fluid dynamics (CFD) to characterize dust emission, deposition and suppression. CFD is a numerical analysis method used to solve fluid-flow problems with the aid of a computer, based on the laws of conservation of mass, momentum, and energy. The method generally follows the Eulerian approach, and can also incorporate the Lagrangian algorithm (NIOSH, 2005).

In more recent times, however, researchers have made attempts to utilize historical data accumulated over the years through dust sampling for machine-learning based prediction. Machine learning offers established algorithms that are able to learn dust dispersion patterns without the need to develop complex dust-specific equations. The objective has been to improve accuracy in the prediction of dust concentration. Grivas and Chaloulakou (2006) and Park et al. (2018) successfully demonstrate the potential of artificial neural network (ANN) as a suitable machine learning technique for evaluating the exposure level of dust. The former focuses on predicting particulate matter concentration in the atmosphere while the latter focuses on particulate matter prediction in subway stations. The authors model the ANN using historical data of variables such as wind speed, ambient temperature, relative humidity, number of subway trains running and ventilation supply.

3.3 Data and Methodology

We obtain dust sample data from Mine Y, an underground metal mining operation in South America. The data set comprises a total of 214 dust monitoring data points collected from 2017 to 2019 on personnel who are employed in the following jobs: development drilling, production drilling, blasting, loading and haulage. We settle for samples from these personnel since they are directly involved in the underground production activities by virtue of their jobs. Since this number is insufficient for training a machine learning model, we generate artificial data based on the statistical distribution of the samples, and the types of production activities undertaken at the mine. The data set is lognormally distributed with the following parameters: location = -1.327 and scale = 0.957. The minimum and maximum values are 0.02 and 3.8 mg/m^3, respectively, with an eight-hour average permissible exposure limit (PEL) of 3 mg/m^3. For each of the aforementioned job types, we generate a thousand samples, yielding a total of five thousand samples.

Based on the mine planning data from Mine Y, we categorize the production activities into production drilling, development drilling, ore extraction and backfilling activities. Since we are considering activity-based prediction, it is essential to obtain dust samples that are specific to these activities. However, at present, dust sampling in underground mines is generally sampled using a personal dust collection system worn by a miner rather than sampled at the working face of a given activity. To this end, we develop a weighting method that maps the personnel, job-type, samples to production activities in order to obtain representative sample values for each activity type. This involves weighted (fractional) combinations of job-type samples for each activity, based on the fraction of time a given job type lasts during a given activity. This yields a total of four thousand activity-based data points—a thousand for each activity type. Using this new data set, we develop a variety of multi-layer artificial neural network models, and test for the one that most satisfactorily predicts the expected dust concentration for a given production activity. It should be noted that this model is developed with available data with the intent of validating the proposed predictive model to help support and justify the collection of activity-based dust measurements.

3.3.1 Feature Selection and Preprocessing

With the scope of the study being activity-based dust prediction, we consider features (predictors) that are directly associated with production activities and have direct influence on dust generation. To this end, we consider the four production activity types mentioned in the previous section, i.e., production drilling, development drilling, ore extraction, and backfilling, as features. We also consider activity rate in meters per day (m/day) and activity rate in tonnes per day (t/day) as features, yielding a total of six features. Since a data point (training example) can be associated with only one of the four production activity types, each of these is treated as a binary variable, i.e., they are represented in the model as zeros or ones, while the last two features, i.e., activity rates, are represented as continuous variables. The binary representation enables the model to identify which of the four production activities is associated with a given data point. So, for each data point, only one binary variable will have a value of 1 (turned on) while the others are assigned a zero (turned off). Based on the mine planning data, the activity rates are determined as follows: meters/day is used for development and production drilling, while tons/day is used for development, ore extraction and backfilling activities. We split the data into training, validation, and test sets comprising 2800, 600 and 600 samples, respectively. The data is scaled within the range 0 – 1 since the variables have different orders of magnitude. We employ the MinMaxScaler function of the scikit-learn python library for scaling (Pedregosa et al., 2011).

3.3.2 ANN Modeling

Using the Keras python library developed by Chollet (2015), we build a variety of multi-layer ANNs with up to four hidden layers for prediction. In each instance, we conduct hyperparameter tuning to obtain optimal number of neurons (units) for the hidden layers under consideration. In all cases, the input and output layers have fixed neurons, being six and one, respectively. These represent the six input variables (features) and the output parameter (dust concentration), which we seek to predict. Figure 3.1 is a schematic representation of the ANN architecture we use in this study.

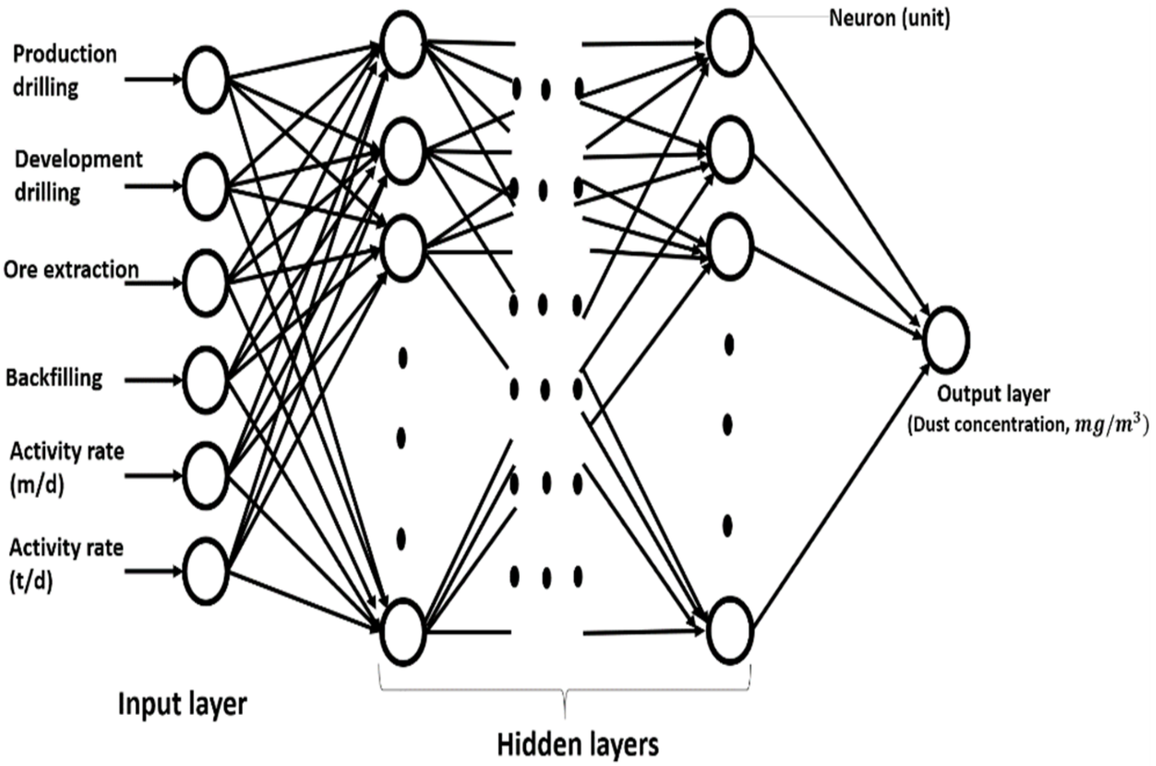

Figure 3.1: ANN Architecture for Dust Concentration Prediction

3.3.2.1 Hyperparameter tuning

Hyperparameter tuning is the process of searching for a set of optimal parameters which define the architecture of a machine learning model. These parameters are known as hyperparameters. In this study, we implement hyperparameter tuning to determine the optimal number of neurons for each of the four ANN instances. We do this using the Bayesian optimization object in Keras (Chollet, 2015) on a DELL latitude E6430 computer with a processing speed of 2.6 GHz, and 8 Gb of memory. The process involves iterating over several combinations of neurons for a given instance of hidden layers and returning the combination that yields the best performance. In this study, the iteration occurs over the range of four to two hundred neurons for each hidden layer in each instance. This process can be cumbersome and time consuming when done manually. The use of the Bayesian optimization saves time by automating the search process for the best combination of neurons for a given number of hidden layers. Table 3.1 shows the results of

Table 3.1: Optimal Neurons for Hidden Layers

Number of Hidden Layers	Optimal Neurons for Hidden Layers
1	120
2	184-66
3	168-BN-DP-60-67
4	101-BN-DP-137-34-121

the hyperparameter tuning. For each instance, we show the optimal number of neurons for the hidden layers. In the last two configurations of hidden layers, the batch normalization (BN) and dropout (DP) techniques serve to control model overfitting, so as to improve model generalization in respect of unseen, real-world data. The batch normalization technique applies a transformation that maintains the mean output close to zero and the output standard deviation close to one, thereby standardizing the inputs to a given layer (Chollet, 2015). The dropout technique randomly selects neurons that are ignored during training; their contribution to the activation of succeeding neurons is temporarily removed. This is achieved by setting those neurons to zero. The results in Table 3.1 become the candidate model configurations for subsequent training, validation, and testing.

3.4 Results and Discussion

Each of the four models is trained on a total of 2600 dust samples. The training involves running 350 epochs to yield an acceptable reduction in prediction error. To assess model generalization, we proceed with model validation and testing. The validation and testing data sets comprise 600 samples each; these are not used for training. The performance of the model on validation data after training determines if the model requires further tweaking to improve performance. The test set represents unseen, real-world data. Table 3.2 shows the performance of the models on the training, validation and test sets using the mean squared error (MSE) as a metric. The MSE is a statistical metric that provides a means of assessing performance between two or more models. For each model, the MSE measures the average squared difference between the actual and predicted values. A perfect model would yield a MSE of zero, signifying that the actual values are perfectly predicted by the model, i.e., there is no error in prediction. In machine learning, the best performing model among alternatives will be the one with MSE closest to zero. The selection of the final model is based on the MSE values for the test data, i.e., test scores. These scores represent the ability of the models to generalize to unseen, real-world data, i.e., data not included in the modeling process. Subsequently, we choose the four-hidden-layer architecture as the final model since it has the lowest test score (closest to zero).

Table 3.2: Model Performance Based on Mean Squared Error

Model	**mean squared error (MSE)**			**Selected model**
	Training	**Validation**	**Test**	
120	0.00271	0.0034	0.00292	
184-66	0.00266	0.00333	0.00291	
168-BN-DP-60-67	0.00274	0.00349	0.00302	
101-BN-DP-137-34-121	0.00265	0.00342	0.00287	✓

Figure 3.2 is a scatter plot for the test data with the threshold limit value superimposed on it. The plot shows how well the predicted dust concentration correlates with the actual concentration. It shows fairly good performance with a correlation (r) of 0.70. The plot also gives a sense of how well the model classifies respirable dust as being above or below threshold. We observe significant underestimation in the lower right quadrant of the plot, and this reflects the imperfection in the data used for modeling, i.e., limited features, insufficient original samples, and lack of direct activity-based data. To this end, we are in continued correspondence with industry partners regarding collection of additional data that corresponds with the different activity types. We expect to have better results with an improved data collection regime. We are also looking at determining additional variables to include as features to help improve model complexity and performance.

This study has shown the potential of using ANN to sufficiently predict respirable dust concentration based on attributes of production activities in underground mines. In the next phase of this project, we will develop mathematical constraints for the predictions from the

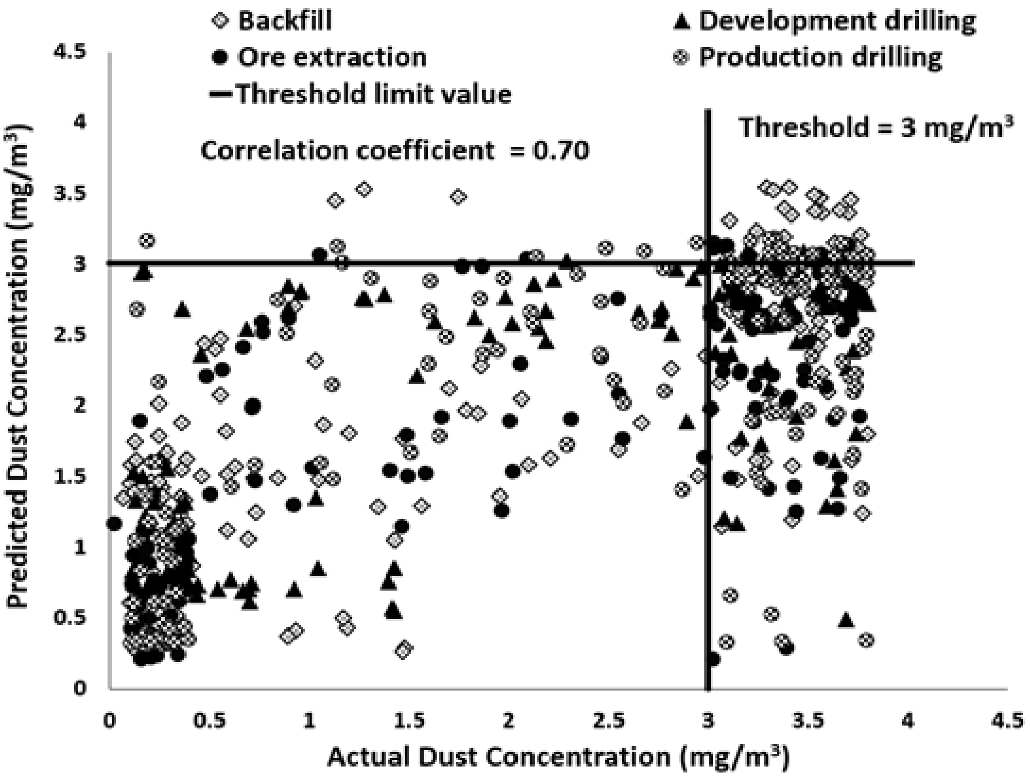

Figure 3.2: Actual vs Predicted Values for Test Data

ANN for all production activities. The constraints will also consider the resultant reduction in concentration offered by existing dust control measures such as ventilation and water sprays. These constraints will then be included in the short-term production schedule optimization. In effect, this will aid planning engineers in proactively determining where further dust mitigation measures are needed, and how to manage dust by effectively utilizing available mitigation resources, e.g., ventilation and water sprays. This will help enhance miners' safety while optimizing production.

3.5 Conclusions and Future Work

We develop, for an underground metal mine, an artificial neural network model that predicts dust concentration with input parameters that are derived from production activities, specifically activity types and activity rates. Despite the imperfection with the current data set, the model provides fairly good results, with the prospect of yielding better results with improved data collection. The model yields a correlation of 0.70 between the predicted and actual dust concentration. In the future, we seek to improve model performance by determining additional relevant features to include in the model and maintaining correspondence with the case study mine to obtain additional data that corresponds with the different activity types. We also seek to develop appropriate mathematical constraints that will make it possible to include predictions from the artificial neural network, and the resultant reduction in concentration offered by existing dust control measures, e.g., ventilation and water sprays, in the short-term production scheduling process. This will help identify high dust production activities in a proactive manner, and aid planning engineers in managing available ventilation and dust control measures to enhance miners' safety while optimizing production.

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Chapter 4

Scenario Analysis for Short-Term Underground Production Scheduling with Activity Start Time Penalties and Variable Target Deviations

This paper is in preparation and is planned to be submitted to the journal *Optimization and Engineering*.

4.1 Introduction

In underground mine planning, production scheduling is the sequencing of mining activities, i.e., development, production, and remediation, needed to achieve clearly defined goals in order to generate revenue, while adhering to precedence and resource constraints. Scheduling results in the determination of activity start dates for the operation with a scheduling fidelity corresponding to the desired planning horizon, i.e., long-, medium-, or short-term planning (Manríquez et al., 2020, L'Heureux et al., 2013). Long-term production schedules establish the overarching goals, e.g., portions of the orebody that can be economically extracted, life-of-mine production, annual production targets, and capital project goals, for the operation based on corporate policy. Utilizing this information, the medium-term schedule determines the sequence of activities at a finer fidelity, e.g., monthly or quarterly, for up to a period of 5 years while adhering to production constraints (Chowdu et al., 2021, Manríquez et al., 2020). The prescribed sequence of activities from the medium-term schedule helps mine planners determine a production forecast for the operation. Short-term production schedules inform the day-to-day operations of the mine. They are developed based on the forecast from the medium-term schedule, and current operational conditions. Thus, they define an extraction sequence by specifying activity start dates at a very fine fidelity, i.e., hourly, by shift, or daily over a time horizon spanning several weeks to months, and typically not exceeding two years (Blom et al., 2018). They focus on the effective utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets (Trout, 1997).

Considering that the production forecast from the medium-term schedule represents the best path forward for the operation to achieve the corporate or operational goals, e.g., contract requirements, market demand, and corporate objectives, mine planners strive to develop short-term schedules that closely match the forecast (Chowdu et al., 2021). Notwithstanding, unforeseen circumstances, such as equipment breakdown and the downstream impact of geological and commodity price uncertainty, can cause significant deviations from established production forecasts in the short term. Situations as these require timely mitigation of the effects of the deviations in an attempt to stay as close as possible to the medium-term plan.

Many mining operations work continuously, e.g., 365 days per year, 24 hours per day. This never-ending schedule requires rapid adjustments to accommodate the changing conditions associated with equipment breakdowns, labor shortages, and extreme weather, for example. The ability to efficiently integrate new information into a model and produce a revised, high-quality schedule would help to minimize the negative impacts of these operational challenges and better achieve the desired operational performance. To accomplish this, mines have added technology that allows for the collection of data reflecting operational conditions. Advances in operational technology (OT) systems enable real-time or near real-time tracking and monitoring of a myriad of operational data points using fleet management systems, GPS equipment tracking, and real-time production rates (Mitchell and van Dinter, 2018). Improved integration of such data into the mine planning processes can significantly help to mitigate production uncertainty and risks by maintaining flexibility in the overall mine plan (Kloppers et al., 2015). The improved coupling between operations and planning departments has been possible with the implementation of Short-Interval Control (SIC) systems at operations. The SIC process, traditionally applied at manufacturing facilities, can provide mine engineering and management personnel with real-time data to guide decision-making (Global Mining Guidelines Group, 2019).

To this end, we develop a deterministic mathematical formulation for short-term scheduling that could be incorporated into existing workflows at operations to help assess different options as deviations arise. The considerations we make in this formulation include minimizing deviation from medium-term production goals, and minimizing deviation from the medium-term activity start dates. We achieve this by introducing penalties for the respective deviations. Aside from incorporating scaling factors by which mine planning engineers can assign priorities to the aforementioned deviations, this formulation makes it possible to prioritize one production goal over the other, depending on operational conditions and considerations at the mine. This is to contribute to a more flexible and realistic short-term scheduling of underground mining operations. We also simulate realistic operational scenarios by modifying production goals in the short-term, and assessing solutions to determine impact and viable options while minimizing deviations from the medium-term plan.

4.2 Literature Review

The unique characteristics of underground mining makes it more challenging to optimize underground production schedules, relative to optimizing production schedules in open pit mining (Musingwini, 2016, O'Sullivan et al., 2015). Underground mining operations are more heterogeneous, and contingent on geotechnical considerations and the selected mining method, require decisions to be made as to which section of the orebody to extract next (Chowdu et al., 2021). These decisions come with greater degrees of freedom when compared to the case of open pit mining. In open pit mining, the direction of extraction is more predictable because the pit keeps expanding laterally and getting deeper as mining progresses. Furthermore, the stopes extracted in an underground mine may vary significantly in shape, unlike blocks in an open pit mine which are more homogeneous. The underground extraction sequence is pronouncedly characterized by activity precedence, where certain types of activities must precede others.

Over the last five decades, operations research (OR) principles have been developed and applied to underground production scheduling in ways that have progressively honored the aforementioned characteristics. Early application of OR tools involved evaluating alternative schedules and making decisions regarding extracted ore (Newman et al., 2010). For instance, Williams et al. (1973) develop a model that minimizes production fluctuations among multiple production faces of a copper mine. Most of the early implementation utilized simulation and linear programming techniques for underground production scheduling until the mid 90s, when mixed-integer programming (MIP) techniques were introduced. While simulation fails to guarantee optimality, linear programming precludes use of integer decision variables. These variables are required for determining optimal start dates of activities, facility siting, and enforcing activity precedence. Thus, the use of MIP models and subsequently, integer programming (IP) models, improved the representation of operational procedures in underground mining. In an early implementation of MIP, Trout (1997) determines the time periods for the extraction and backfilling of stopes in a cluster of base metal mines. Carlyle and Eaves (2001) build upon Trout's work by incorporating additional activities, i.e., development drilling and stope preparation, in their model for a platinum and palladium underground mine. The model is used by mine planners for routine economic analysis and tactical planning. These and subsequent models have focused on solving long- and medium-term scheduling problems with improved solution time amid increasing complexity over the years. For instance, Smith et al. (2003) improve solution time by using aggregation techniques to reduce the number of variables in the model. A common objective has been to maximize the net present value or minimize the overall cost of operations over the long or medium term (Trout, 1997, Carlyle and Eaves, 2001, Smith et al., 2003, Nezhadshahmohammad et al., 2018, Huang et al., 2019).

Advances made over the last few decades in operations research techniques and computational power have enhanced solution of large-scale and complex underground production scheduling problems. Notable is the casting of underground production scheduling as a Resource-Constrained Project Scheduling Problem (RCPSP). The RCPSP is an OR framework that schedules activities subject to precedence and resource constraints while minimizing the makespan, i.e., the time difference between the start of the first activity and finish of the last activity (Artigues et al., 2013, Hartmann and Briskorn, 2021). The RCPSP belongs to the class of non-deterministic polynomial-time (NP)-hard problems. The standard RCPSP model cannot cover all real-world scenarios; thus researchers have proposed variants and extensions of the RCPSP in the literature. One group of the extensions considers alternative objectives and the majority of the RCPSP-based underground schedules fall under this group. Variants considered for this group in the literature include objectives based on net present value (NPV), cost, resource leveling, time-based requirements, and limitations on rescheduling (Hartmann and Briskorn, 2021, Tirkolaee et al., 2019, Zoraghi et al., 2017, Chakrabortty et al., 2021). The first two variants are common in underground production scheduling and have mainly been used in solving long- and medium-term scheduling problems. For instance, Maybee and Fava (2011), Fava et al. (2012), and Sharma (2015) generate schedules that improve NPV over the medium and long term. They solve their models using the Schedule Optimization Tool (SOT) (RPMGlobal, 2020) that makes use of genetic algorithms and heuristics. O'Sullivan and Newman (2014) solve a variant of the NPV-based objective problem by focusing on maximizing metal production. Using an optimization-based heuristic, they generate schedules that maintain feasibility for three different mining methods and that can be evaluated for several end-of-life-of-mine scenarios. Brickey (2015) develops and solves a model with a similar objective that incorporates ventilation requirements. The author solves the model for a two-year horizon at a daily fidelity using the OMP Solver (Brickey et al., 2021), which utilizes the Bienstock-Zuckerberg algorithm (Bienstock and Zuckerberg, 2010) and a toposort heuristic (Chicoisne et al., 2012) to rapidly develop solutions. King et al. (2017) use a similar approach to solve scenarios of the open-pit-to-underground transition problems while maximizing NPV. Using a sliding time window heuristic (Cullenbine et al., 2011), Lopes (2017) expedites solutions for scheduling large real-world instances of a RCPSP-based model for underground stoping and cut-and-fill operations. In their work, Huang et al. (2019) develop a more flexible (expandable) model for scheduling ore extraction and development activities for cut-and-fill mining.

4.2.1 Operations Research Applications in Short-Term Underground Scheduling

OR-based research in short-term underground scheduling has been sparse, compared to long- and medium-term underground scheduling. The available literature reports of two main frameworks for developing short-term schedules. These are the flow-shop and RCPSP-based frameworks. The former is mainly used for equipment allocation while the latter is used for activity scheduling. In flow-shop scheduling, all works or jobs are set up to have the same processing route, i.e., a job can only be processed in a fixed sequence across different machine types (Emmons and Vairaktarakis, 2013). In underground flow-shop problems, the working faces, i.e., active mining areas, represent the jobs, and the mining equipment represent the machines.

Gamache et al. (2005) utilize the shortest-path algorithm to simultaneously dispatch, route and schedule bi-directional mining vehicles in an underground mine. The solution process considers the current status of the mine, the current traffic on all bi-directional road segments of the haulage network and operational constraints. Using dynamic programming, Beaulieu and Gamache (2006) develop an enumeration algorithm that determines the optimal route and schedule for bi-directional underground mining vehicles in the shortest time. The schedule avoids conflicts on the haulage network by taking into account the displacement modes of the vehicles, i.e., either forward or in reverse. Using a similar approach, Song et al. (2015) develop a flow-shop model for scheduling mobile mining equipment that improves working efficiency and reduces the working time of an underground gold mine. The model utilizes four enumeration algorithms, i.e., sequencing, grouping, machine set and machine sharing to determine the schedule with the shortest makespan.

In their work, Schulze et al. (2016) formulate a MIP-based hybrid flow-shop model for scheduling mobile mining equipment in an underground potash mine that minimizes the maximum completion time of excavations. The authors implement heuristic solution procedures for large-scale problem instances. These include the use of multi-start algorithms and a modified version of the Giffler-Thompson procedure (Giffler and Thompson, 1960). Schulze and Zimmermann (2017) extend this work by incorporating mine workers as resources, i.e., both machines and workers are assigned specific mining tasks, and are scheduled simultaneously. The extension also includes minimizing deviations from targeted amounts of potash. Seifi et al. (2019) also consider the simultaneous assignment and scheduling of machines and workers in the same potash mine studied by Schulze and Zimmermann (2017). They implement a two-stage solution approach, the first of which involves application of a MIP where some time-consuming restrictions are neglected. Thereafter, the authors modify the resulting schedule by integrating the necessary time intervals that were neglected in the MIP model. Comparison of results from the two-stage approach with results from the heuristic procedure used by Schulze and Zimmermann (2017) shows improvement in solution gap by the former.

Åstrand et al. (2018) present a constraint programming (CP)-based model for scheduling underground mobile production fleet. The model imposes and exploits the presence of blast windows, which creates periodic equipment unavailability. It also allows for a mix of interruptible and uninterruptible tasks, and supports delays between tasks. The authors solve the model using randomized search heuristics with restarts and without restarts for subsequent comparison. They are, however, only able to solve the smallest presented problem instances, i.e., five working faces with one production cycle. Larger instances have as many as ten working faces with two production cycles. Åstrand et al. (2020) extend this work by incorporating fleet travel times in the CP-based model to provide more realistic schedules. This time around, the authors provide an enhanced scaling of the problem to larger instances by solving a modified version of the problem and transforming the solution back to the original problem domain. They also adopt a large neighborhood search heuristic to improve solution time and quality.

Regarding activity scheduling for short-term planning, the available literature provides scheduling methodologies that are similar to those for long- and medium-term scheduling. Nehring et al. (2010) provide a MIP model that simultaneously schedules production and provide machine allocations for sublevel stoping operations. The model minimizes deviation from targeted ore production. Using a MIP formulation, Campeau and Gamache (2020) develop a RCPSP-like model to create activity schedule in the short term at weekly fidelity based on medium-term objectives. The model maximizes ore tonnage, and prioritizes solutions that finish tasks earlier by discounting the ore tonnage over time. The authors demonstrate that scheduling activities in a preemptive manner, i.e., where activities can be stopped once started and restarted at a later date, provides more realistic and quality solutions than otherwise. Manríquez et al. (2020) improve adherence to short-term production schedules by developing a simulation-optimization framework that incorporates operational uncertainty. The framework is iterative, and in each iteration, a short-term schedule is generated using MIP, followed by a discrete-event-based simulation of the generated schedule. The simulation serves to evaluate the generated schedule and provides useful feedback to generate a new and better schedule in subsequent iterations. Adherence indices utilized in the model to assess solution quality include activity lateness, tardiness, earliness, start and completion periods, along with material movement.

In this paper, we propose a deterministic mathematical formulation for short-term underground production scheduling that is based on the rescheduling variant of the RCPSP structure (Hartmann and Briskorn, 2021, Chakrabortty et al., 2021, Elloumi et al., 2021). We contribute to the scarce literature in the subject area by addressing the short-term scheduling problem as an adjustment of the activity start dates of an already optimized schedule, i.e., the medium-term plan. We utilize this approach to accommodate unforeseen circumstances such as changes in production rate, activity costs and revenues. Incorporating this formulation into existing workflows would help mine planners assess different options as deviations arise.

In this study, we do not opt for the more popular NPV-based scheduling considering that the planning horizon for short-term scheduling is a small fraction of the timeline compared to medium- and long-term scheduling. Generating short-term schedules based on value maximization may lead to situations where the operations cannibalize the future of the forecast to feed the present. Campeau and Gamache (2020) emphasize this concern in their work by stating that at the short-term level of planning, which is usually less than six months ahead, most of the economically influential decisions would have been made. Equipment quantity and the amount of resources available would have already been fixed, and mining methods and mine layout already decided. Thus, at the short-term level, there are few possible variations in planning that could affect the overall economics of the operation.

4.3 Methodology

We develop a formulation for short-term underground production scheduling that provides operationally realistic and flexible decision making options for the mine planning engineer. We achieve this by building a two-component objective function for the formulation that minimizes deviation from the medium-term plan while striving to achieve monthly forecast goals, e.g, ore production. The proposed formulation thus considers two types of deviations: i) activity start time deviations from the medium-term plan (activity deviations), and ii) deviations from forecast target values for operational goals (goals deviations). Activities that are scheduled in the short-term to start at a time close to their medium-term start date are not penalized in the objective function. Activities that get scheduled much earlier or much later than their medium-term start date incur an earliness or tardiness penalty, respectively, in the objective function. The formulation also checks against overachieving or underachieving forecast goals by imposing corresponding penalties on the objective function. The farther the achieved goals are from the forecast values, the greater the penalty imposed. By this approach, we are able to obtain activity schedules at a fine fidelity, e.g., shift, half-shift, hourly, that achieve, or are as close as possible to, forecast targets and also follow the medium-term plan.

In developing this formulation, our goal has been to incorporate flexibility for easy adaptation by other operations (mines employing different underground mining methods and have fluctuating operational conditions). We have thus incorporated scaling factors by which mine planning engineers can assign priorities to the two primary components of the objective function, i.e., activity deviations and goals deviations. We have also made it possible to prioritize one goal over the other, depending on operational conditions and considerations at the mine. This is to contribute to a more realistic scheduling in underground mining operations and provide engineers the ability to adjust the model to meet changing priorities. The objective function also controls bias (skewness) by normalizing penalties from the two terms to be in the range 0 – 1. In this way, both activity deviations and goals deviations are brought to a similar scale prior to solving the model. We create schedules from the model at a 12-hour shift fidelity (time period). We further incorporate sets of consecutively coarser time periods, known as multi-time periods, in the model (Chowdu et al., 2019). A multi-time period can represent a week or a month. The flexibility we incorporate in the model makes it possible for a mine planner to adjust the scheduling fidelity and the multi-time period fidelity according to the needs of the operation. The model assesses goals deviations over each multi-time period rather than over each time period (shift) because shift-to-shift operational performance can vary significantly due to heterogeneity and uncertainty associated with underground mining activities. Implementing goals deviation penalties over the multi-time period (weekly or monthly) allows flexibility in the schedule at the shift-to-shift level while still meeting weekly or monthly forecast targets. The proposed formulation is an improvement upon an existing formulation by Chowdu (2020).

We make improvement by incorporating more realistic penalty functions for minimizing activity and production goal deviations. Activity earliness and tardiness are penalized with exponentially increasing values as deviations increase, while goal penalties are only imposed if certain predetermined production target levels are not met.

4.3.1 Activity Start Time Deviation Penalties

For each activity scheduled in the short-term, a penalty is imposed in the objective function based on how much the short-term start date deviates from the production forecast, i.e., medium-term start date. Activities that begin earlier than their forecast date incur earliness penalties while those which begin later than their forecast date incur tardiness penalties. We adopt a symmetric approach to the calculation of earliness and tardiness penalties (Figure 4.1). That is, an activity that is early by a certain number of time periods incurs the same penalty as one that is tardy by the same number of time periods. No penalty is assigned if an activity is scheduled to start on the same date as the forecast date. We also incorporate the concept of grace period, i.e., the number of time periods an activity is allowed to be early or tardy without incurring penalty. For the case study presented herein, we impose a grace period of 1 day, i.e., two shifts (Figure 4.1). This is essential considering that in medium-term planning activity start dates are of coarser fidelity, e.g., daily, weekly, monthly, than in short-term planning. The use of grace periods thus prevents over constraining the problem when considering finer time fidelity, e.g., shift, half-shift, hourly. Prior to modeling the short-term schedule, we determine the activity deviation penalties for each activity over all the possible start times in the short-term horizon using equation 4.1.

$$pen_{at} = \begin{cases} 0, & |t - \hat{t}_a| \leq 2 \\ \left(\frac{|t-\hat{t}_a|}{n}\right)^{3f} + \left(\frac{|t-\hat{t}_a|}{n}\right)^{f-1}, & 2 < |t - \hat{t}_a| \leq 28 \\ \left(\frac{|t-\hat{t}_a|}{n}\right)^{f} + \left(\frac{|t-\hat{t}_a|}{n}\right)^{f-1}, & |t - \hat{t}_a| > 28 \end{cases} \tag{4.1}$$

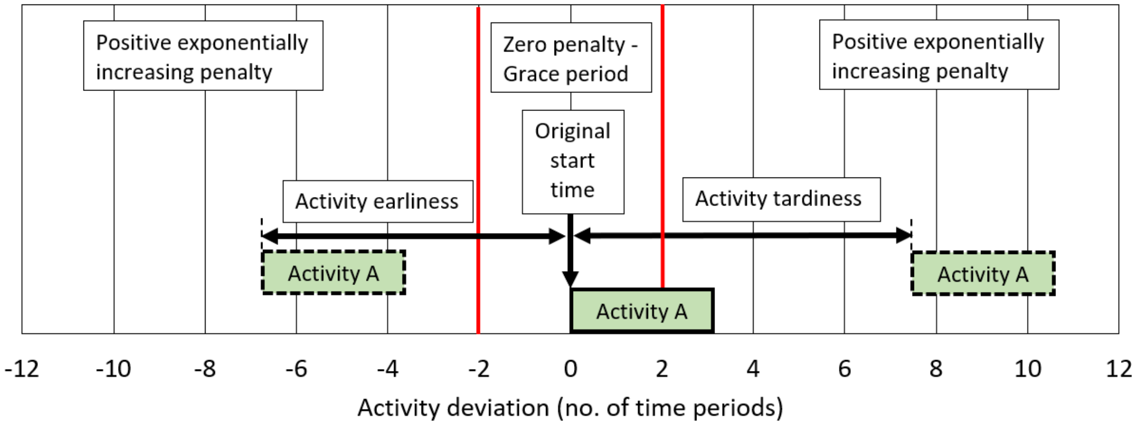


Figure 4.1: Activity Earliness, Tardiness and Grace Period

where pen_{at} = penalty assigned if activity a is scheduled in time period t

t = a given time period (shift) in the short-term scheduling horizon

$\hat{t}_a$ = forecast start time (shift) for activity a

n = number of time periods (shifts) in a multi-time period

f = exponential factor

Equation 4.1 describes an exponentially increasing penalty function. Assuming a 12-hour shift fidelity, i.e., time period, the difference t - $\hat{t}_a$ measures the earliness or tardiness deviation, in shifts, between an activity's forecast start time $\hat{t}_a$ in the medium-term schedule and the potential start time t in the short-term schedule. Dividing this deviation by the number of shifts in a multi-time period yields an earliness or tardiness deviation expressed in terms of the multi-time period. In this study, a multi-time period is assumed to be a 30-day month, resulting in a total of 60 shifts per month. Equation 4.1 is made up of three components. The first component ensures that no penalty is assigned when an activity starts within the grace period, i.e., up to 2 shifts before or after the medium-term start date. The second component assigns a more gentle exponentially increasing penalty for activities whose earliness or tardiness is within two weeks, i.e., 28 shifts, of their medium term start date.

The third component assigns a steeply increasing exponential penalty to activities whose earliness or tardiness goes beyond two weeks. This incentivizes the model to schedule activities close to their forecast start times, i.e., estimated start times in the medium-term plan. Adopting an exponentially increasing function, instead of a simple linearly increasing function, helps us to better manage penalty assignment to reflect operational situations. That is, based on operational conditions, we segregate the penalty assignment over the time periods in a more continuous and realistic manner. We achieve this by discouraging activity earliness or tardiness that goes beyond two weeks by heavily penalizing such, and gently penalizing those whose earliness or tardiness is within two weeks. Figure 4.2 shows a graph for the exponential function, assuming a multi-time period of 60 shifts and an exponential factor of 2. An activity with a forecast start time of shift 60 in the medium term, and a scheduled start time of shift 50 in the short-term will incur an earliness deviation, i.e., t - $\hat{t}_a$, of 10 shifts. This will result in a penalty of 0.17, assuming a multi-time period of 60 shifts and an exponential factor of 2. In order to ensure that the activity deviation penalties are on a similar scale as the goals deviation penalties, we normalize all pen_{at} values to be in the range $0-1$, using equation 4.2.

$$\overline{pen}_{at} = \frac{pen_{at}}{\max_{a,t}(pen_{at})} \; \forall \, a \in \mathcal{A}; t \in \mathcal{T} \tag{4.2}$$

where $\overline{pen}_{at}$ = normalized penalty assigned if activity a is scheduled in time period t

$\max\limits_{a,t}(pen_{at})$ = the maximum penalty assigned to activity a

4.3.2 Goal Deviation Penalties

We assign goal deviation penalties based on the multi-time periods. For a given multi-time period, the assigned penalty is determined by the fraction of the goal, i.e., production

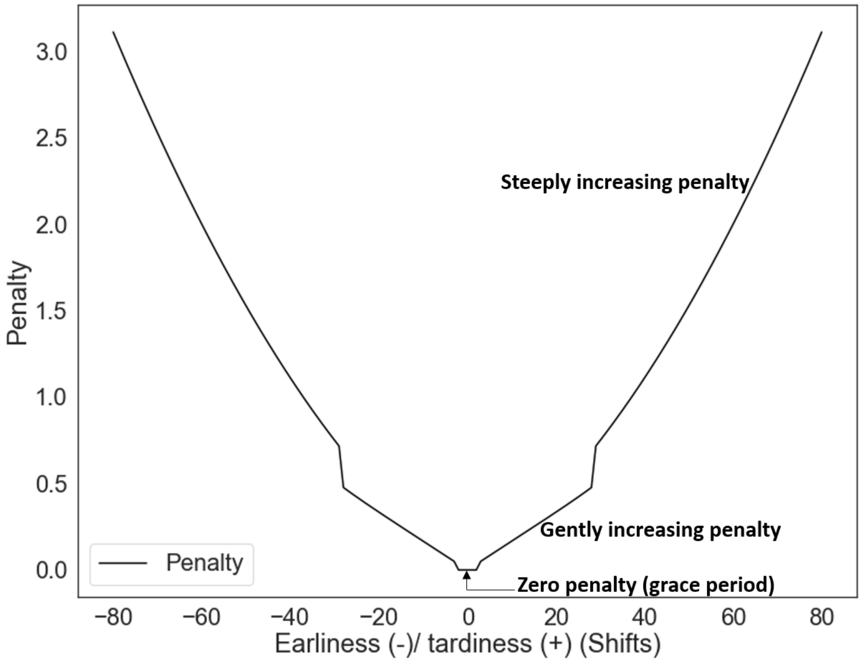


Figure 4.2: Exponential Penalty Function

target, achieved for that period. This fraction can represent under-achievement or over-achievement, either of which we penalize in order to closely stick to the medium-term goals, i.e., ore tonnage and lateral development targets. We define two sets of goal achievement values, i.e., under-achievement and over-achievement. These values are fractions that serve the purpose of adjusting the lower and upper bounds on a given multi-time period goal constraint. The under-achievement values range from 0.80 to 1.00. For each multi-time period, we determine the actual fraction of the goal achieved for that period. We then iterate over the fractions in the set of under-achievement values. When the actual fraction of goal achieved in that multi-time period is lower than a given value, a corresponding penalty is assigned for the deviation. The assigned penalties range from 0.00 to 1.00 so as to be on a similar scale as the activities deviation penalties.

For illustration purposes, consider the following set of values: 0.80, 0.90 and 0.98. Assume the respective penalties for failing to achieve these values in a multi-time period are 0.75, 0.50 and 0.10. Assuming in a given month, representing one multi-time period, the total amount of ore tonnage produced is 42,500 out of a production target, i.e., goal, of

50,000 tonnes, the fraction of achieved ore tonnage will be 0.85, i.e., $\geq 85\%$ of the production target. Iterating over the set of under-achievement values results in a total deviation penalty of 0.6, i.e., 0.5 + 0.1, for ore tonnage in that month. Note that no penalty is assigned for the first value since the achieved fraction of 0.85 exceeds that value.

A similar concept is applied to the set of over-achievement values, defined over the range 1.00 to 1.10. In this case, goal over-achievement is penalized. That is, when the actual fraction of goal achieved in a multi-time period is greater than a given value, a corresponding penalty is assigned. Subsequently, for each multi-time period, a cumulative over-achievement or under-achievement penalty is assigned. This is calculated as part of the objective function, and thus implemented during solution of the model, and not *a priori* like in the case of the activities deviation. The implementation creates a step-wise goal deviation function that increases in magnitude as the goal deviation increases, and vice versa. By this approach, the model is incentivized to prevent large deviations from the forecast production targets. From the foregoing, the overall range of goal achievement values considered in the formulation is from 0.80 to 1.10. We do not, however, penalize values between 0.98 and 1.02. This constitutes a $\pm 2\%$ goal deviation margin, and it represents the amount of ore tonnage or lateral development in excess or shortage that can be allowed without significantly disrupting future operational goals. It is analogous to the concept of grace period in the activities deviation function; it helps prevent the model from being over constrained. Strictly requiring the model to achieve the exact target in a given month may over constrain the problem, leading to longer solution times and poor solution quality O'Sullivan et al. (2015). The model's flexibility allows a mine planner to define specific fractions for the two sets of goal achievement values, depending on short-term production requirements and operational conditions. Additionally, the planner can define the range over which no penalty is assigned for both over-achievement and under-achievement.

4.3.3 Mathematical Formulation

We formulate the model as a RCPSP following the rescheduling variant. That is, we formulate the short-term scheduling problem as an adjustment of the activity start dates of the medium-term schedule at a finer fidelity while minimizing activity and goal deviations. The objective function minimizes these deviations subject to resource and precedence constraints. We include goal deviation constraints to ensure the satisfactory achievement of goals in each multi-time period. The model has three types of decision variables: (i) binary variables y_{at} which determine when an activity starts; (ii) binary variables x^{+}_{gml} which turn on goal over-achievment penalties; and (iii) binary variables x^{-}_{gml} which turn on goal under-achievement penalties.

We obtain the data used in the model from the medium-term mine plan. From this, we deduce the sets of activities, resources, goals, and predecessors. We also deduce from the data all parameters in the model, e.g., activity duration, resource consumption, resource capacities and multi-time period targets. All sets, parameters, decision variables, objective function, and constraints in the model are defined as follows:

Table 4.1: Simple Sets

Symbol	**Description**
$\mathcal{A}$	set of all activities ($a \in \mathcal{A}$)
$\mathcal{R}$	set of operational resources ($r \in \mathcal{R}$)
$\mathcal{E}$	set of equipment resources ($e \in \mathcal{E}$)
$\mathcal{T}$	set of shifts in scheduling horizon (time periods for short-term scheduling) ($t = 1 \ldots \lvert\mathcal{T}\rvert$)
$\mathcal{M}$	set of all multi-time periods ($m \in \mathcal{M}$)
$\mathcal{G}$	set of production and development goals ($g \in \mathcal{G}$)
$\mathcal{L}^{+}$	set of goal over-achievement values ($l \in \mathcal{L}^{+}$)
$\mathcal{L}^{-}$	set of goal under-achievement values ($l \in \mathcal{L}^{-}$)

Table 4.2: Subsets and Indexed Sets

Symbol	Description
$\mathcal{A}^h \subseteq \mathcal{A}$	set of activities available to be scheduled within current scheduling horizon
$\mathcal{A}^c \subseteq \mathcal{A}$	set of activities previously scheduled and carrying over to current scheduling horizon
$\mathcal{A}_r \subseteq \mathcal{A}$	set of activities consuming resource $r \in \mathcal{R}$
$\mathcal{A}_e \subseteq \mathcal{A}$	set of activities utilizing equipment $e \in \mathcal{E}$
$\mathcal{P}_a \subset \mathcal{A}$	set of predecessors for activity $a \in \mathcal{A}$
$\mathcal{T}_m \subseteq \mathcal{T}$	set of shifts $t \in \mathcal{T}$ contained in multi-time period $m \in \mathcal{M}$

Table 4.3: Model Parameters

Parameter	Description
d_a	duration of activity a (number of time periods)
$d_{aa'}$	sum of $d_{a'}$ and minimum delay between activities a and a' (number of time periods)
es_a	earliest start (time period) for activity a
$\bar{c}_{rt}$	maximum operational capacity available for resource r in time period t (tonnes or meters)
$\bar{c}_{et}$	maximum number of concurrent activities utilizing equipment e in time period t
b_{gm}	operational target for goal g in multi-time period m, i.e., medium-term forecast (tonnes or meters)
q_{ar}	consumption of resource r by activity a (tonnes or meters per time period)
q_{ag}	contribution of resource towards goal g by activity a (tonnes or meters per time period)
$\overline{pen}_{at}$	normalized earliness/tardiness penalty for activity a for starting in time period t (unitless; ranges from 0.00 to 1.00)
f_l^+	goal over-achievement value $l \in \mathcal{L}^+$ (unitless; ranges from 1.00 to 1.10)
f_l^-	goal under-achievement value $l \in \mathcal{L}^-$ (unitless; ranges from 0.80 to 1.00)
pen_{gml}^+	penalty assigned if $l \in \mathcal{L}^+$ is achieved for goal g in multi-time period m i.e., over-achievement penalty (unitless)
pen_{gml}^-	penalty assigned if $l \in \mathcal{L}^-$ is not achieved for goal g in multi-time period m i.e., under-achievement penalty (unitless)
$w_{\mathcal{A}}$	scaling factor (relative importance) of minimizing activity deviation (unitless)
$w_{\mathcal{G}}$	scaling factor (relative importance) of minimizing goals deviation (unitless)
$w_{\overline{g}}$	priority scaling factor for goal g (unitless)

Decision Variables:

$$y_{at} = \begin{cases} 1, & \text{if activity } a \text{ starts in time period } t \\ 0, & \text{otherwise} \end{cases}$$

$$x^+_{gml} = \begin{cases} 1, & \text{if } \; l \in \mathcal{L}^+ \text{ is achieved for goal } g \text{ in multi-time period } m \\ 0, & \text{otherwise} \end{cases}$$

$$x^-_{gml} = \begin{cases} 1, & \text{if } \; l \in \mathcal{L}^- \text{ is not achieved for goal } g \text{ in multi-time period } m \\ 0, & \text{otherwise} \end{cases}$$

Objective Function:

$$\begin{aligned} \mathcal{STUG}: \; \text{Minimize } & w_{\mathcal{A}} \cdot \frac{1}{|\mathcal{A}^h|} \cdot \sum_{a \in \mathcal{A}^h} \sum_{t \in \mathcal{T}} y_{at} \cdot \overline{pen}_{at} \quad + \\ & w_{\mathcal{G}} \cdot \frac{1}{|\mathcal{G}| \cdot |\mathcal{M}|} \cdot \sum_{g \in \mathcal{G}} \sum_{m \in \mathcal{M}} \left(\sum_{l \in \mathcal{L}^+} w_{\overline{g}} \cdot x^+_{gml} \cdot pen^+_{gml} \; + \sum_{l \in \mathcal{L}^-} w_{\overline{g}} \cdot x^-_{gml} \cdot pen^-_{gml} \right) \end{aligned} \tag{4.3}$$

Subject to:

$$\frac{1}{b_{gm}} \cdot \sum_{t' \in \mathcal{T}_m} \sum_{a \in \mathcal{A}} q_{ag} \cdot (\sum_{t = max\{t' - d_a + 1, es_a\}}^{t'} y_{at}) + x^-_{gml} \geq f^-_l \qquad \forall \, g \in \mathcal{G}; \; m \in \mathcal{M}; \; l \in \mathcal{L}^- \tag{4.4}$$

$$\frac{1}{b_{gm}} \cdot \sum_{t' \in \mathcal{T}_m} \sum_{a \in \mathcal{A}} q_{ag} \cdot (\sum_{t = max\{t' - d_a + 1, es_a\}}^{t'} y_{at}) - x^+_{gml} \leq f^+_l \qquad \forall \, g \in \mathcal{G}; \; m \in \mathcal{M}; \; l \in \mathcal{L}^+ \tag{4.5}$$

$$\sum_{a \in \mathcal{A}_r} q_{ar} \cdot \left(\sum_{t' = max\{t - d_a + 1, es_a\}}^{t} y_{at'} \right) \leq \bar{c}_{rt} \qquad \forall \, r \in \mathcal{R}; t \in \mathcal{T} \tag{4.6}$$

$$\sum_{a \in \mathcal{A}_e} \left(\sum_{t' = max\{t - d_a + 1, es_a\}}^{t} y_{at'} \right) \leq \bar{c}_{et} \qquad \forall \, e \in \mathcal{E}; t \in \mathcal{T} \tag{4.7}$$

$$\sum_{t'' \leq t} y_{at''} \leq \sum_{t' = es_{a'}}^{t - d_{aa'}} y_{a't'} \qquad \forall \, a \in \mathcal{A}, a' \in \mathcal{P}_a, t \in \mathcal{T} : t \geq es_a \tag{4.8}$$

$$\sum_{t \in \mathcal{T}} y_{at} \leq 1 \qquad \forall \, a \in \mathcal{A} \tag{4.9}$$

$$y_{a1} = 1 \qquad \forall \, a \in \mathcal{A}^c \tag{4.10}$$

$$y_{at} \in \{0, 1\} \qquad \forall \, a \in \mathcal{A}; t \in \mathcal{T} \tag{4.11}$$

$$x^-_{gml}, \, x^+_{gml} \in \{0, 1\} \qquad \forall \, g \in \mathcal{G}; \; m \in \mathcal{M}; \; l \in \mathcal{L}^-, \; \mathcal{L}^+ \tag{4.12}$$

The objective function (4.3) consists of two components. The first component minimizes activity start time deviations from the medium-term plan. The second component minimizes deviations from the forecast target values of operational goals, i.e., ore tonnage (t) and lateral development (m). The objective function achieves this by introducing penalties for the respective deviations. By minimizing these penalties, we obtain schedules that achieve forecast targets and that follow the medium-term plan. Using equations 4.1 and 4.2, the first component applies the respective normalized penalty for an activity a that gets scheduled in time period t. The total penalty resulting from activity deviations is then divided by the number of activities available for scheduling within the current horizon. This yields the average penalty for the deviation of activities from their forecast start dates.

The second component of the objective function applies a penalty for each multi-time period m, depending on whether a given goal g is under-achieved or over-achieved during that period. The severity of the penalty is a function of the severity of the under-achievement or over-achievement of the goal. When the goal is not met, the binary variable x^{-}_{gml} turns on via constraint 4.4 in order to implement the appropriate penalty. The binary variable x^{+}_{gml} turns on via constraint 4.5 for over-achievement. The total goal penalty is then divided by the product of the number of multi-time periods and the number of goals. This yields the average penalty for all goal deviations. Parameters $w_{\mathcal{A}}$ and $w_{\mathcal{G}}$ are weighting factors by which mine planning engineers can assign respective priorities to the two components of the objective function. A higher value for either parameter more heavily weights the impact of the corresponding penalty, and this forces the solver to prioritize accordingly.

Constraints 4.4 and 4.5 ensure the achievement of target values for all goals in each multi-time period. This is achieved by preventing under-achievement or over-achievement for the respective goal achievement values being considered. Constraints 4.6 impose shift-based resource capacity, i.e., ore tonnage (t) and lateral development (m), constraints on the activities. Constraints 4.7 limit the number of concurrent activities that utilize equipment type e in a given time period t. Constraints 4.8 enforce the physical precedence between activities and allows for lags between an activity and its predecessor. Constraints 4.9 ensure each activity is scheduled at most once, while constraints 4.10 enforce the start of carryover activities in the first time period of the scheduling horizon. Constraints 4.11 and 4.12 ensure that the decision variables y_{at}, x^{-}_{gml}, and x^{+}_{gml} are binary.

4.4 Case Study

The case study mine forms part of an underground mining operation that is located in South America. The operation contains six major mineralized zones, with an annual production of approximately 334,000 ounces of gold (Mine Y, 2019). The operation is a multi-mine complex with three high-grade underground operating mines. As part of an expansion project, two additional underground deposits are being developed into mines, one of which is the focus of this study. The operation adopts a combination of transverse and long-hole stoping mining methods with a variation of the Avoca method when the vein width is less than 6 meters. Mining proceeds in an overhand (bottom-up) approach, and mined out stopes are backfilled using waste rock fill, cemented rock fill, or a combination of both.

A medium-term plan is already in place for the case study mine (Mine Y) at a daily fidelity over a period of 5 years. Access to this mine is through a decline that connects from the surface to a ramp system (Fig. 4.3). The decline, along with two raises serve as air intakes while another raise and two drifts that link an adjacent mine, provide air exhaust for ventilation. The total planned airflow through this mine is approximately 200 m^3/s. Based on the medium-term plan, management of the mine would like to produce flexible short-term schedules that can accommodate unforeseen operational disruptions. The scheduling framework should be capable of accommodating disruptions that affect production rate and capacity momentarily, and be able to correct the ensuing deviations from the medium-term plan. To this end, we apply our formulation to data from Mine Y to assess impact of different operational scenarios on the schedule. The dataset is in the form of Deswik CAD and scheduler file formats. From this, we obtain the three-dimensional design of the mine (Fig. 4.3), activity definitions, resource assignment and activity precedence structure.

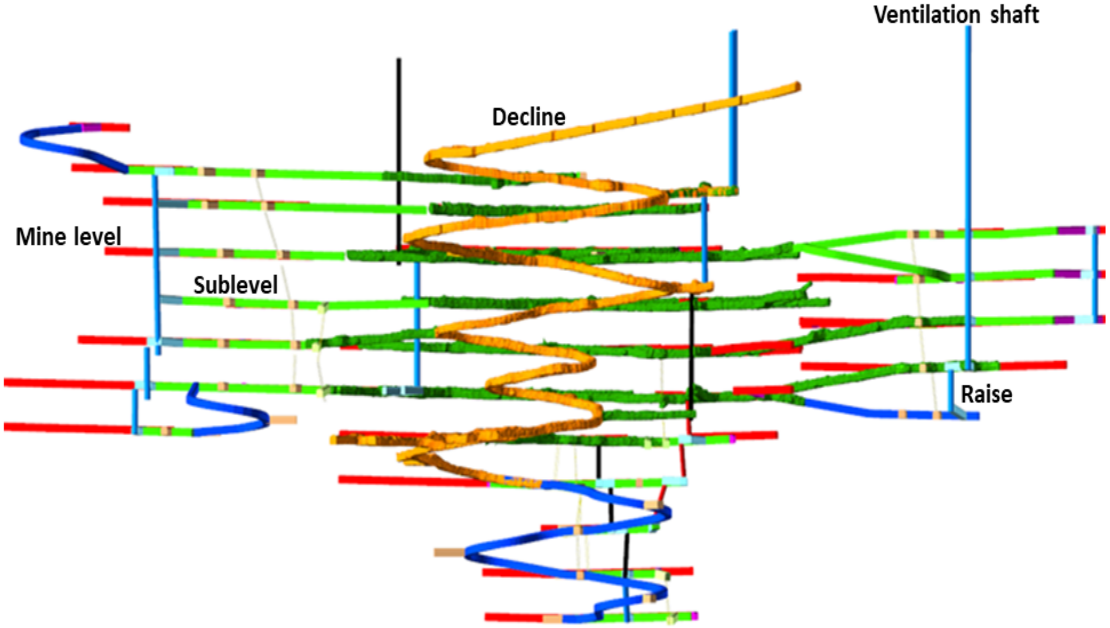


Figure 4.3: General Mine Design and Layout for Mine Y (Source: Mine Y, 2019)

Table 4.4 shows the shift-based resource and equipment capacities used in this case study. The shift-based resource capacities, i.e., the first six resource constraints, are obtained from the daily maximum values using equation 4.13. The division by 2 in the equation is based on the assumption that the resource capacities are evenly divided between the two shifts in a day. The multiplication of the daily maximum value by a factor of 1.10 is based on the assumption that the available resources have a capacity that is 10% more than the daily maximum value. The equipment capacities, i.e., concurrent activity constraints, remain the same for both daily and shift fidelities. Table 4.5 shows the monthly, i.e., multi-time period, goals considered in this study. The table shows the respective target values for the amount of ore extracted and the amount of lateral development completed for each month. These values are obtained from the medium-term plan. Activities considered for scheduling include development drilling, production drilling, stoping and backfill activities. Section 4.4.1 describes the scenarios we consider in this case study. All scenarios are coded with the Python programming language and solved with the Gurobi solver, version 9.0.1 (Gurobi Optimization LLC, 2020). We run the scenarios on a HP EliteDesk 800 G2 TWR computer with 8 cores at a processing speed of 3.4 GHz each, and 16 GB of RAM. We impose on the solver a time limit of 15 minutes, and a target integrality gap of 0.1%. The integrality gap refers to the optimality gap between the objective function value of the relaxed linear-programming solution and that of the integer solution.

Table 4.4: Resource Constraints

No.	Resource Constraint	Daily Maximum	Capacity (Shift)
1	Ore extraction (t)	1,600	880
2	Primary development (m)	12.5	7
3	Lateral development (m)	23.2	13
4	Ramp development (m)	6	3.5
5	*Other development (m)	12.1	7
6	Backfill (m^3)	1,400	770
7	Number of concurrent development advance activities	4	4
8	Number of concurrent ore extraction activities	3	3
9	Number of concurrent production drilling activities	3	3

*Refers to all other development in waste[1]

$$\text{Shift resource capacity} = \frac{1.10 * \text{daily maximum}}{2} \tag{4.13}$$

Table 4.5: Monthly Goals and Target Values (Forecast)

Month	Goal	
	Ore tonnage (t)	Lateral development (m)
1	34,670	383
2	33,356	323

4.4.1 Scenario Considerations

The scenarios we consider are sets of 30-day and 60-day short-term schedules created at 12-hour shift fidelity, with a 30-day look-ahead period in each case. The look-ahead period limits how far ahead one can look in the production forecast and include activities in the model. For instance, with a scheduling horizon of 30 days, the activities we consider for scheduling are those within a 60-day window, i.e., activity horizon, in the forecast, but scheduling is limited to the first 30 days. To do this, we first filter the set of activities to include those whose forecast start dates are within 60 days from the short-term schedule start date. We further filter these activities to include those whose early start dates fall within the available scheduling horizon, i.e., the first 30 days. This ensures that the model contains only activities which could actually be scheduled within the scheduling horizon under consideration. This is for the purpose of improving model tractability and allowing for flexibility in the scheduling process to enhance accommodation of operational disruptions.

The problem instances we consider are shown in Table 4.6. The first instance is a 30-day horizon, i.e., 60 shifts. The second instance is a 60-day horizon comprising 120 shifts. The first scenario is a base case which solves for these instances under expected operating conditions. We further simulate operational disruptions for these instances by reducing ore extraction capacity and development advance rate for specific shifts. We summarize all scenarios as follows:

1. Base case
2. Reduced ore extraction capacity
3. Reduced development advance rate

4.5 Results and Discussion

Using the problem instances outlined in Table 4.6, we solve for all scenarios at a 12-hour shift fidelity. We utilize a grace period of two shifts and an allowable goal deviation margin of $\pm 2\%$. That is, schedules which produce goals within this margin are acceptable

Table 4.6: Problem Instances

No.	Schedule Horizon (shifts)	Number of Activities in Model
1	60	232
2	120	350

Time limit: 900 s (15 minutes)[2]
Target integrality gap: 0.1%[3]

to the mine planner. We present summarized results for the base case in Table 4.7 using the resource constraints and target values in Tables 4.4 and 4.5, respectively. The results show that each instance of the base case satisfactorily achieves the targets for the respective goals. This is because all goal deviations are within ±2% of their respective target values (Table 4.5). Likewise, there are no significant deviations in activity start times as all activities are scheduled within the grace period of 2 shifts. To further illustrate how closely the base case schedule follows the medium-term plan (forecast), we present cumulative plots for both goals over a period of 60 days (Figures 4.4 and 4.5). From the figures, we realize that the base case closely follows the medium term plan with minimal deviation from both ore tonnage and lateral development targets. Thus, under normal operating conditions, this formulation is able to schedule at a finer fidelity while not significantly deviating from the medium-term plan.

Table 4.7: Results for Base Case Scenario

Problem Instance	**Schedule horizon (shifts)**	**Solution time (s)**	**Integrality gap (%)**	**Activities considered**	**Activities scheduled**		**Goals deviation from target (%)**	
					Within grace period	**Outside grace period**	**Ore ton-nage**	**Lateral devel-opment**
1	60	1.5	0.00	133	133	0	-1.78	-1.63
2	120	12.6	0.00	250	250	0	-1.83	-1.70

We further demonstrate how this formulation can be used for rescheduling in the event that operational disruptions occur. We then assess the impact of the disruptions on the ensuing schedules, and make informed decisions where necessary. We begin by simulating

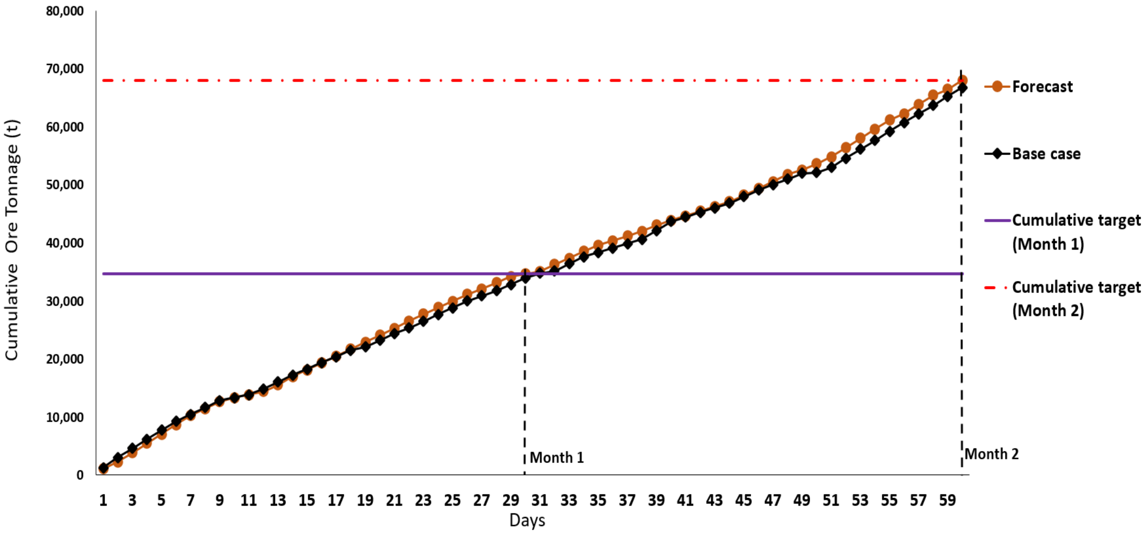


Figure 4.4: Cumulative Ore Tonnage Plot for Base Case Scenario

different scenarios of mill breakdown, leading to reduced ore extraction capacity for different shifts within the first week of the scheduling horizon. Here, the assumption is that there is not enough space to stockpile ore at full production capacity when the mill breaks down. The mine has a limited stockpile space for ore rehandling, which is located on the surface and accessed via a ramp and decline system. Consequently, we assume a 75% reduction in ore extraction, resulting in a new capacity of 220 tonnes per shift as against the regular capacity of 880 tonnes per shift (Table 4.4). This would be hauled to the stockpile over the period that the mill is down. We create new schedules for three cases of breakdown lasting 2, 3 and 4 days respectively. In each case, the breakdown occurs 2 days into the start of the scheduling horizon. So, the first case, termed the best case scenario (because it has the least repair duration), disrupts operations for shifts 5 to 8. The second case, termed the mild case scenario, disrupts operations for shifts 5 to 10, while the third case, termed the worst case scenario, disrupts operations for shifts 5 to 12.

Table 4.8 is a summary of the results for the mill breakdown cases, with emphasis on the ore tonnage since it is the goal that is directly impacted by the reduced ore extraction capacity. Despite the disruptions, all scenarios solve within the acceptable integrality gap of 0.1% and time limit of 900 seconds, signifying a good quality solution. We observe that

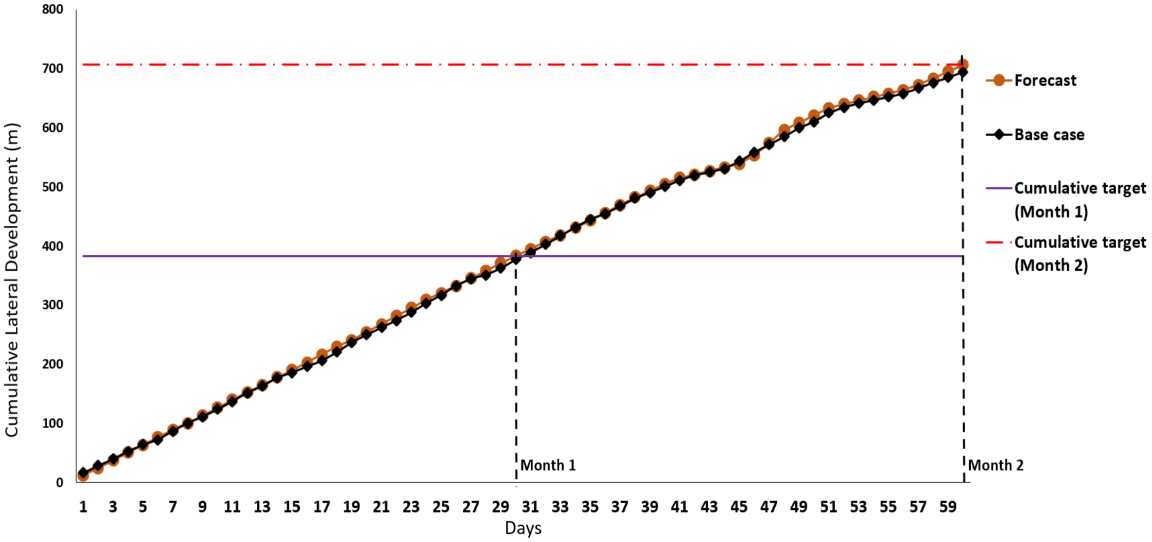


Figure 4.5: Cumulative Lateral Development Plot for Base Case Scenario

the amounts of ore tonnage produced by the best case and mild case schedules are all within the acceptable goal deviation margin of $\pm 2\%$. So, despite the reduced ore extraction capacity in the first week for these cases, the new schedules are able to make up for the deficit, even within the first month. This is further illustrated in Figure 4.6, where the best and mild cases get on track, i.e., follow the base case, in the 5th week. Figure 4.6 is a cumulative ore tonnage plot built from the 30-day schedules for the respective cases. In making up for the deficit, the rescheduled instances for the best and mild cases involve significant movement of activities outside the grace period, when compared to the base case scenario (Tables 4.7 and 4.8). We show some activity movement for the reduced ore extraction capacity scenarios relative to the base case in Figure 4.7. The figure shows the start times for stoping and production drilling activities in the respective 30-day schedules. We observe that relative to the base case, all other scenarios have their activity start times pushed forward to accommodate the reduced ore extraction capacity in the first week. Generally, the best case shows lesser activity movement compared to the mild and worst cases.

Regarding the worst case, we observe the model's attempt to get back on track as the ore tonnage deviation improves from -5.00% to -3.39% over the 1st and 2nd problem instances in Table 4.8. This is corroborated by the trend in Figure 4.6; it attempts to approach the base case with time. We also observe significant movement of activities in the model's attempt to make up for the deficit incurred in week 1 (Figure 4.8). Despite this, the deviation in ore tonnage at the end of the 60-day schedule is above the ±2% margin. In a circumstance of prolonged mill breakdown as this, the mine planner may accept the deficit for the current horizon, and adjust the target when solving for the next horizon, so as to make up for the current horizon's deficit. In doing this, the planner must ensure the adjustment is within the bounds of the resource capacity constraint for the goal under consideration.

Table 4.8: Results for Reduced Ore Extraction Capacity Scenarios

Case	**Problem instance**	**Schedule horizon (shifts)**	**Solution time (s)**	**Integrality gap (%)**	**Activities scheduled within grace period**	**Activities scheduled outside grace period**	**Ore tonnage deviation from target (%)**
Best case	1	60	12.4	0.02	103	33	-1.71
	2	120	223.6	0.00	192	57	-1.79
Mild case	1	60	16.7	0.00	91	51	-1.85
	2	120	227.3	0.00	168	82	-1.77
Worst case	1	60	22.1	0.07	85	52	-5.00
	2	120	294.8	0.09	171	76	-3.39

We also consider another form of operational disruption that impacts development advance rate. We consider a cluster of development drilling activities located in a poor ground zone, e.g., area where the rock mass is highly fractured or other characteristic has caused difficulty in conducting an activity. In such situations, the development advance rate is often reduced. We solve for two scenarios representing a 25% and 50% reduction in the development advance rate, respectively. The former scenario is termed the mild case, and the latter is termed the worst case. We show the impact of these scenarios on the development advance rate and duration in Table 4.9. The activities listed therein are all development drilling activities that are spatially close to each other, and occur within the first four days of the scheduling horizon. For the mild case, a 25% reduction in the rate leads to a 33.3%

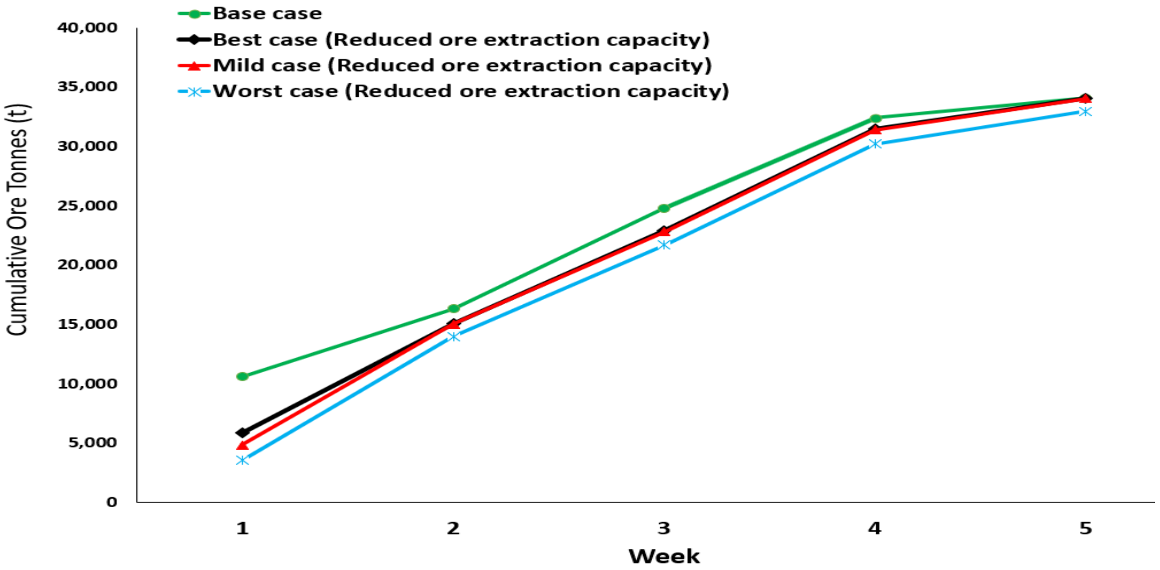
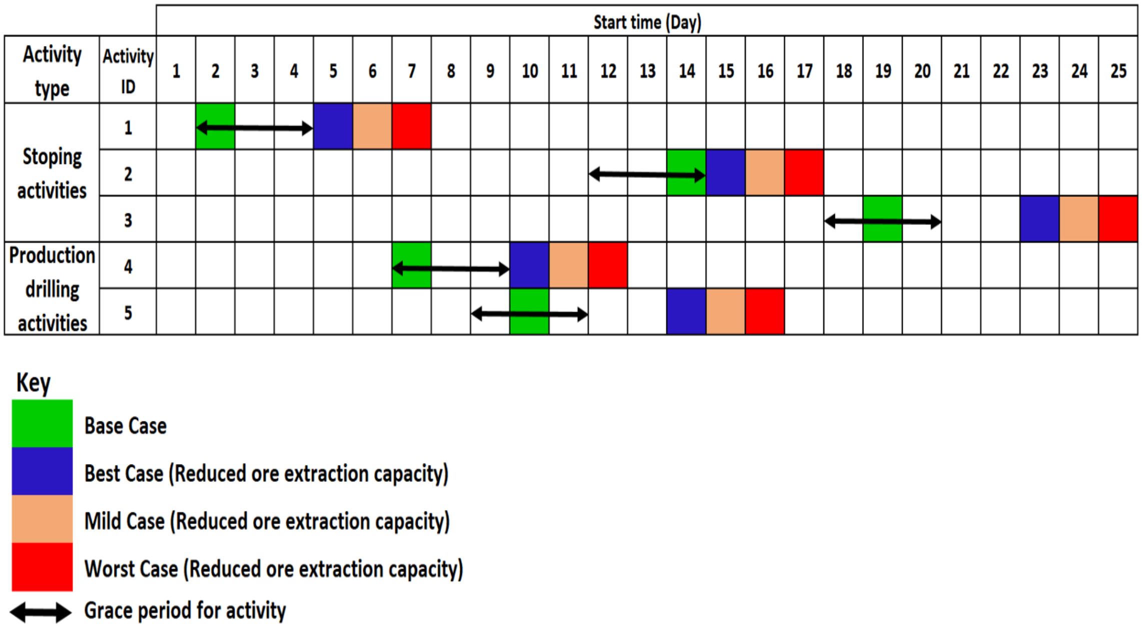


Figure 4.6: Impact of Reduced Ore Extraction Capacity on Schedule



		Start time (Day)																								
Activity type	Activity ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Stoping activities	1		🟩	↔	↔	🟦	🟧	🟥																		
	2												↔	↔	🟩	🟦	🟧	🟥								
	3																		↔	🟩	↔			🟦	🟧	🟥
Production drilling activities	4							🟩	↔	↔	🟦	🟧	🟥													
	5									↔	🟩	↔			🟦	🟧	🟥									

Key
🟩 Base Case
🟦 Best Case (Reduced ore extraction capacity)
🟧 Mild Case (Reduced ore extraction capacity)
🟥 Worst Case (Reduced ore extraction capacity)
↔ Grace period for activity

Figure 4.7: Activity Movement of Selected Activities for 30-Day Schedules

increase in duration. The worst case, which causes a 50% decrease in the rate, leads to a 100% increase in duration.

Results for the 30-day and 60-day schedules for these scenarios are in Table 4.10, with emphasis on lateral development since it is the goal that is directly impacted by development drilling activities. We observe that all scenarios satisfactorily achieve their respective

Table 4.9: Impact of Worst and Mild Case Scenarios on Development Advance Rate and Duration

Activity ID	Initial rate (m/d)	Initial duration (hrs)	Mild case		Worst case	
			New rate (m/d)	New duration (hrs)	New rate (m/d)	New duration (hrs)
1	5.4	15.6	4.1	20.7	2.7	31.1
2	5.4	15.6	4.1	20.7	2.7	31.1
3	5.4	15.6	4.1	20.7	2.7	31.1
4	5.4	15.6	4.1	20.7	2.7	31.1
5	5.4	15.6	4.1	20.7	2.7	31.1

lateral development goals, i.e., each goal achievement is within the $\pm 2\%$ allowable goal deviation margin. All scenarios are able to make up for the reduced development advance rate without moving activities outside the grace period. These results are similar to the base case scenario (Table 4.7), considering the number of activities scheduled and the goal deviations; the mild case shows the same deviation values. This goes to show that the model is robust to disruptions in development advance rate–even for the worst case, and only needs minor adjustment to get on track. We further corroborate this observation with a cumulative plot from the 30-day schedules for the first 5 weeks (Figure 4.8). The figure shows that the base case and the mild case are superimposed on each other while the worst case makes up for the deficit and catches up in week 5. We investigate activity movement among the three scenarios using the 30-day schedules. We show, in Figure 4.9, the start times for the development advance activities in poor ground. We observe that all five activities have the same start times in the base case and mild case. Relative to the base case, the worst case only offers slight adjustment for activities 2 to 5, and all adjustments are within the grace period of two shifts. The foregoing suggests that the short-term schedule is not as sensitive to these development advance disruptions as it is to the ore extraction capacity disruptions.

Table 4.10: Results for Reduced Development Advance Rate Scenarios

Case	Problem instance	Schedule horizon (shifts)	Solution time (s)	Integrality gap (%)	Activities scheduled within grace period	Activities scheduled outside grace period	Lateral development deviation from target (%)
Mild case	1	60	1.4	0.00	131	0	-1.63
	2	120	13.7	0.00	248	0	-1.70
Worst case	1	60	0.1	0.00	131	0	-1.78
	2	120	9.9	0.00	249	0	-1.60

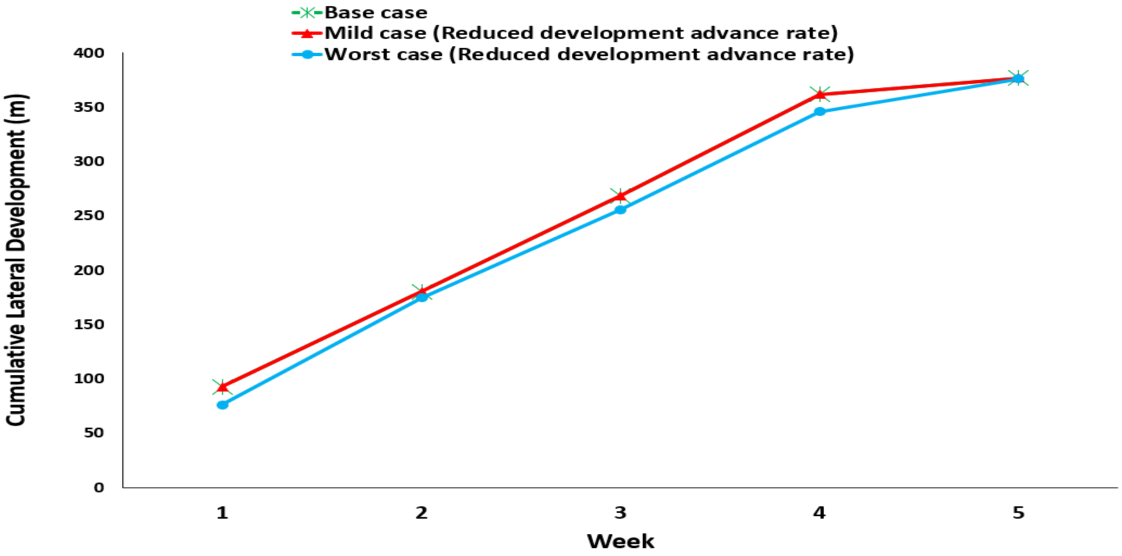


Figure 4.8: Impact of Reduced Development Advance Rate on Schedule

4.6 Conclusion and Future Work

We present the underground short-term production scheduling problem as a rescheduling of the medium-term plan at a finer fidelity. The goal is to develop a tool that can help the mine planner generate short-term schedules that achieve forecast targets without significantly deviating from the sequence of activities in the medium-term plan. With this goal in mind, we develop a formulation that is able to closely follow production forecast under normal operating conditions. The strength of this tool lies in its ability to make up for deficits resulting from operational disruptions. We demonstrate this by simulating disruptions in-

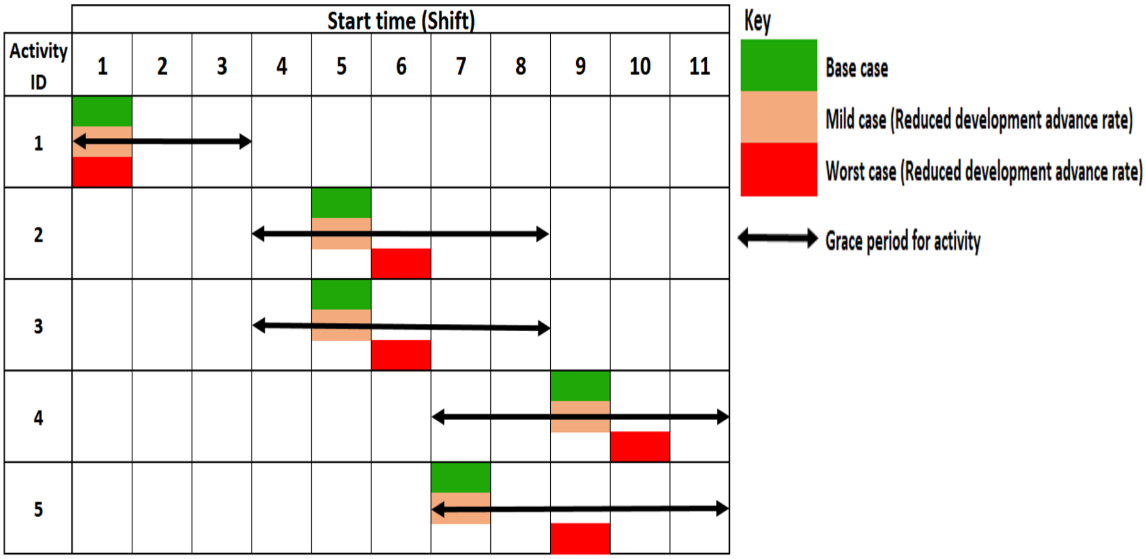


Figure 4.9: Start Times for Development Advance Activities in Poor Ground

volving reduction in ore extraction capacity and development advance rate. Aside from its rescheduling capability, this tool can help mine planners conduct further analysis on the impact various disruptions have on the schedule. It can help identify those conditions or disruptions that are more detrimental to the achievement of forecast targets, or otherwise.

In the future, we seek to incorporate in the formulation respirable dust, diesel particulate matter, and ventilation constraints in order to create more realistic schedules, and to enhance miners' health and safety. We also seek to capture elements of uncertainty such as activity duration and activity rate in our future work to provide better representation of real-world scenarios. With the advancement of internet-of-things (IoT) and operational technology (OT) systems, mine production scheduling can be revolutionized via real-time update and incorporation of relevant parameters to rapidly create schedules and make informed decisions quickly.

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Chapter 5

Conclusion

The mining industry is often viewed as extremely dangerous, with many heath and safety hazards. While this is true to the nature of the mining environment, the focus on implementing safety measures, and creation of a strong safety culture that has developed over the last century in the mining industry, has reduced the fatality rate to 12.94 per 100,000 employees in 2021 (NIOSH, 2021). This can be compared to Uber and Lift drivers, the ride-sharing services, which have a combined fatality rate of 14.6 per 100,000 employees (DuChene, 2019). While any fatality is too many, the mining industry has taken many successful steps in reducing hazards and improving safety of the miners. Yet, the industry is determined to continue to reduce the fatality and injury rates to zero. Advances in technology have enhanced this quest through endeavors such as advanced injury analytics using machine learning, the use of internet-of-things (IoT) and computer-vision systems for hazard recognition and mitigation, and the real-time monitoring of mine air pollutants such as dust and diesel particulate matter.

To this end, researchers have utilized various machine learning techniques to derive valuable information implicit in mine injury and accident data. The goal has been to improve our understanding of mine safety, identify risks, and work out a mitigation plan. Utilizing the Mine Safety and Health Administration (MSHA) injury data for the period 2007 - 2010, a multiclass logistic regression model is developed that ranks the safety risk of different injury types based on miner's demographics such as age, experience on the current job (year), mine type (coal vs. non-coal) and type of accident suffered. The model is a useful tool for assessing miners' susceptibility to different types of injury, i.e., nonfatal injury with no days lost or restricted activity (NDLR), nonfatal injury with days lost and/or days of restricted work activity (DLR), and fatal and total permanent or partial permanent disability (FP). The model identifies the following as significant factors to injury occurrence: miners' age, mine type (coal vs non-coal), experience on the current job (years), shift start time, employment type (operator vs. contractor), mining district, and accident type. Regardless of the overall mining experience of a miner, the initial year in a new job incurs the highest DLR risk. The multiclass logistic regression proves to be a tool that can be used beyond basic statistics in providing robust mine accident and injury analysis. Using this tool, safety managers can identify areas that need prioritized training or attention. Periodic analysis with this tool and taking pragmatic measures, thereafter, will promote a strong safety culture and risk mitigation in the mine environment. A number of data quality issues make modeling and subsequent analysis challenging. These include missing records, inconsistency and subjectiveness in the data collection regime.

Mine workers are exposed to a variety of hazards within the mining environment. These include respirable dust and diesel particulate matter (DPM) exposure, heat, fires, harmful gases, and noise. The literature provides detailed information on research findings that touch on various hazards encountered in the mining industry. A review by Donoghue (2004), in particular, touches on most of the hazards miners are exposed to, and summarizes the sources, impact and control measures thereof. In all this, both researchers and stakeholders agree to the continuous need for new and novel approach to maintaining effective control of these hazards. Subsequently, risk management and sustainability have evolved over the years and become central to the way mining companies operate. There is the growing need to integrate health and safety needs of workers into conventional procedures of operation, and thus develop a more proactive risk management system for the industry.

In view of the foregoing, the author devises a proof-of-concept framework, taking advantage of the advances in technology, to incorporate some of these hazards into the conventional process of production scheduling in underground mines. The long-term goal here is to combine ventilation with production scheduling by individually considering exposure to dust, heat or DPM as mathematical constraints in the schedule. The author begins with the case of respirable dust exposure, and documents results and findings of the first phase of the framework in this dissertation. This phase proceeds with an acknowledgment that production activities in underground mines generate respirable dust which impacts workers' health and productivity. For instance, respirable dust, in the long term, causes lung diseases with varied health impact such as swelling in the lungs, shortness of breath, scarring of the lungs (fibrosis) and death. The study points out the linkage between respirable dust generation in underground mines and production scheduling–they are both associated with activity type and activity rate. Building on this, the author develops an artificial neural network (ANN) model for predicting respirable dust concentration for an underground metal mine with input parameters that are derived from production activities. Though the study successfully demonstrates the potential of using ANN to sufficiently predict respirable dust concentration in underground mines, some challenges are encountered in the modeling process. The main challenge is the lack of direct activity-based dust samples, the reason being that dust sampling in underground mines is generally done using a personal dust collection system worn by a miner rather than being sampled at the working face of individual production activities. Other challenges include limited features and samples for modeling. These challenges are surmountable and subsequent mitigation will go on to improve results of the modeling. Thus, correspondence with industry partners is ongoing to collect additional data that directly correspond with the different activity types that are considered in production operations. Future work, i.e., second phase of the framework, will determine additional variables to include as model features to help improve model complexity and performance. Thereafter, mathematical constraints will be developed that will make it possible to include in short-term underground production schedules, predictions from the ANN model along with ventilation requirements. This will make it easier to identify high dust production activities in a proactive manner. It will enhance efficient management of available ventilation and dust control measures to improve miners' safety while optimizing production. Future work will also look at extending this proof-of-concept framework to other hazards such as DPM and heat.

Underground mining is characterized by varied activities that include development drilling, production drilling, stoping (ore extraction), and backfilling activities. These activities require careful sequencing in order to maximize the value of operations. Operations research tools have made it possible to produce schedules that determine the start dates for these activities in a way that achieves the operations' objectives while adhering to precedence and resource constraints. The objectives range from maximizing NPV, minimizing production costs, or minimizing deviations in production, among others. The precedence constraints serve to impose an order in which activities can be carried out. The resource constraints represent production and processing limits, and include supply and demand limitations on tonnage of ore mined. The resource constraints ensure that activities that are ongoing during a given time period do not exceed the resources available to accommodate them. Typical resources in an underground production scheduling problem include labor, mining equipment, and ventilation capacity.

Operations research tools have seen application in all three levels of mine production scheduling, i.e, short-, medium-, and long-term scheduling. The long-term schedule establishes the overarching goals for the operation, e.g., annual production targets, based on corporate policy. The medium-term schedule utilizes this information to develop a sequence for the activities at a finer fidelity, e.g., monthly, for up to a period of 5 years. This is essential in forecasting targets for the operation. Mine planners develop the short-term schedule to guide the day-to-day operations towards achieving the forecast targets. Thus, the short-term schedule sequences activities at a very fine fidelity, e.g., hourly, shift, daily, over a time horizon spanning several weeks to months. The focus is on efficient utilization of resources, e.g., equipment and labor, to achieve shift, daily, or weekly production targets.

Utilizing the resource-constrained project scheduling problem (RCPSP) modeling concept, a mathematical formulation is developed for generating short-term schedules for an underground mining operation. The formulation is able to achieve forecast targets without significantly deviating from the sequence of activities in the medium-term plan. This formulation gives the mine planner the ability to assess different scheduling options as deviations arise. The formulation's strength lies in the ability to minimize deviations from the medium-term activity start dates and production goals. Additionally, mine planners are able to prioritize one production goal over the other depending on operational needs. By this, the formulation provides the mine planner with a more flexible and realistic approach to short-term planning in underground operations. The dissertation demonstrates the formulation's ability to assess impact on the schedule as operational disruptions arise. This proceeds with the simulation of reduced ore extraction capacity scenarios and reduced development advance scenarios. Analysis shows how the disruptions impact the schedule, and how the new schedule makes up for the ensuing target deviations. Future work will consider improving upon the model by incorporating in the formulation respirable dust, diesel particulate matter, and ventilation constraints to enhance miners' safety.

5.1 Future Work

The mining industry is progressively looking to achieve zero injuries and fatalities in the work place. In response to this, the National Institute for Occupational Safety and Health (NIOSH) and several researchers have been working towards novel ways to contribute to the zero-injury drive. Going forward, there is the continual need to adopt new technology for mine injury and accident analysis. With advances in technology, continuous stream of personnel demographics can be supplied to a database and analytics system for real-time assessment of risk, and proactive steps taken to avert potential injuries and accidents. Potential future work would be the evaluation of different dependent variables in the MSHA injury data to draw more insight into injury and accident occurrence on mine sites. Different machine learning techniques could be applied on the data to conduct comparative assessment of the ensuing results, and to improve our understanding of the relationship between injury occurrence and personnel demographics.

As part of the second phase of the proof-of-concept framework discussed in Chapter 2, there is the foremost need to obtain a larger sample size through continued correspondence with stakeholder mining operations. Obtaining respirable dust samples that are activity-based rather than personnel-based would contribute to significant improvement in the ANN model's performance. There is also the need to derive additional features aside from activity type and activity rate to improve the model's estimation of respirable dust concentration. Predictions from the finalized model would be incorporated along with ventilation requirements as mathematical constraints in the short-term production schedule formulation of Chapter 3. Successfully achieving this will set the pace to consider same framework for DPM and heat to provide more proactive measures of managing workers' exposure to these hazards. At the moment, these hazards are primarily managed from an operational level in the short-term, and not considered as part of the scheduling process. The ability to consider them as part of the production scheduling process will go a long way to help with mitigation by accounting for activity-based emission of these hazards, and subsequently scheduling requisite resources, e.g. ventilation, to help reduce impact. Future work could also consider capturing elements of uncertainty such as activity duration and activity rate in the short-term model formulation to provide better representation of real-world scenarios. Furthermore, making use of the advances in technology, e.g., internet-of-things (IoT) and operational technology (OT), can help provide real-time update and incorporation of relevant parameters to quickly generate short-term schedules for underground operations.

Disclaimer: This bibliography is limited to the non-journal article chapters of this dissertation. All journal articles in this dissertation have a self-contained bibliography.

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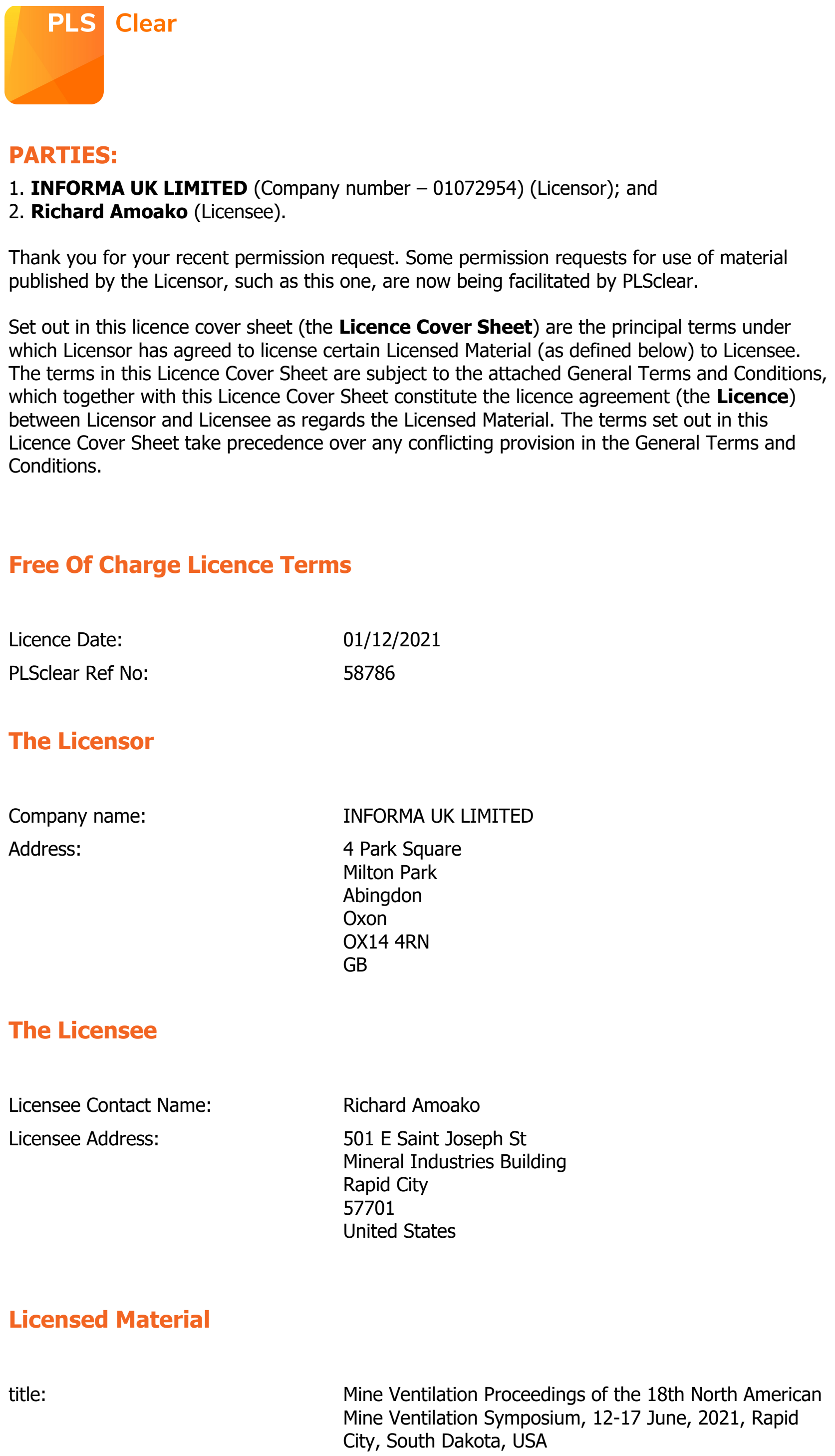

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