University of Nevada, Reno

Application of Integer Programming for Mine Evacuation Modeling with Multiple Transportation Modes

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Mining Engineering

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ABSTRACT

The safe evacuation of miners during an emergency within the shortest possible time is very important for the success of a mine evacuation program. Despite developments in the field of mine evacuation, little research has been done on the use of mine vehicles during evacuation. Current research into mine evacuation has emphasized on miner evacuation by foot. Mathematical formulations such as Minimum Cost Network Flow (MCNF) models, Ant Colony algorithms, and shortest path algorithms including Dijkstra's algorithm and Floyd-Warshall algorithm have been used to achieve this. These models, which concentrate on determining the shortest escape routes during evacuation, have been found to be computationally expensive with expanding problem sizes and parameter ranges or they may not offer the best possible solutions.

An ideal evacuation route for each miner must be determined considering the available mine vehicles, locations of miners, safe havens such as refuge chambers, and fresh-air bases. This research sought to minimize the total evacuation cost as a function of the evacuation time required during an emergency while simultaneously helping to reduce the risk of exposure of the miners to harmful conditions during the evacuation by leveraging the use of available mine vehicles. A case study on the Turquoise Ridge Underground Mine (Nevada Gold Mines) was conducted to validate the Integer Programming (IP) model. Statistical analysis of the IP model in comparison with a benchmark MCNF model proved that leveraging the use of mine vehicles during an emergency can further reduce the total evacuation time. A cost savings analysis was made for the IP model, and it was found that

the time saved during evacuation, by utilizing the IP model, increased linearly, with an increase in the number of miners present at the time of evacuation.

DEDICATION

I dedicate my thesis work to my father, Yaw Asare (late), and my guardian, Ernest Opoku-Ansah (late). I would not have made it this far without them.

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CHAPTER 1 : INTRODUCTION

1.1 Motivation

Various factors, including explosion, fire, ground fall, floods, mining-induced seismicity, and the inrush of hazardous gases, can lead mine disasters (Kowalski-Trakofler et al., 2009). Even though many precautions have been taken in the modern era to reduce the likelihood of mining catastrophes, these events nevertheless happen on a regular basis all over the world.

According to the Statistica Research Department, there were ten occupational fatalities in the coal mining business in the United States in 2021, which is a 200-fold reduction from a century earlier. Mining is still a dangerous work no matter where you are, in both developed and undeveloped nations. Due to a variety of errors made during the evacuation process, many lives have been lost during mining emergencies.

In recent years, the world's mining corporations and safety regulatory agencies have concentrated their efforts on improving the evacuation procedure. This has been accomplished by improving emergency response plans and implementing programs for the mining workforce's mine rescue training and evacuation. Virtual reality simulators for mining evacuation training have shown to be a more affordable and secure substitute for conventional training techniques (Andersen et al., 2020).

The use of refuge chambers and safe havens, fresh air bases, and guidance systems for low visibility situations are all part of mine emergency response strategies. However, depending on the severity of the emergency and other conditions, the miners' initial response may not be sensible during a crisis (Brenkley et al., 1999)

To learn more about what transpires in the first essential seconds of a mine emergency, researchers at the National Institute for Occupational Safety and Health (NIOSH) conducted interviews with seven focus groups and ten individuals. The project's objective was to gather information about responses given on-site during the early stages of a mine disaster to enhance response.

According to the findings, there were recurring themes in the initial response, including the significance of mine emergency preparedness and training, amount and quality of communication providing information for decision-making, leadership, and trust, as well as specific personal difficulties (Kowalski-Trakofler, Kathleen, et al., 2010). This project demonstrated the need for the adoption of optimization models to reduce the influence of the above factors and dynamically ensure the optimality of miner movements during an emergency.

Mathematical programming can be used to describe the evacuation problem in operations research. The mine evacuation problem is currently being addressed using shortest path methods like Dijkstra's Algorithm, Floyd-Warshall Algorithm, or Ant Colony Optimization. However, these methods (Dijkstra and Floyd-Warshall) are computationally inefficient, or they might not offer the best answer (Ant Colony Optimization) (Meij, 2020). Additionally, the impact of readily available mine vehicles on the evacuation process was not considered by researchers utilizing these methodologies.

To further shorten the required evacuation time, the author hypothesizes that available mine vehicles should be included in the evacuation process during a mine emergency. Using an integer programming approach, this research aims to reduce the total amount of time required for evacuating a mine by utilizing available mine vehicles and optimizing the routing of these vehicles. Miners and vehicles are now easily located and tracked via wireless positioning systems and other technological advancements. These systems can be used in conjunction with the optimization model discussed in this thesis to track the whereabouts of miners and mine vehicles and to ensure efficient and timely evacuation during emergencies.

1.2 Enabling Technologies

Instances of the Integer Programming (IP) model developed in this thesis can be solved in real-time by making use of enabling technologies such as mobile crowdsourcing with smart devices, indoor positioning systems, and an efficient programming language, framework, and a solver to navigate miners to safe havens during an emergency. These enabling technologies working in tandem with the IP model will help minimize the evacuation time, eliminate indecision, and help reduce the exposure of miners to potentially dangerous conditions during evacuation.

1.3 Research Questions and Objectives

1.3.1 Research Questions

This research seeks to answer the following questions:

- Can the total evacuation time be further minimized?
- Is it possible to incorporate other transportation modes besides walking?
- Can the available mine vehicles be optimally routed during a mine emergency?
- Is it possible to combine both foot and vehicle modes during the evacuation?

1.3.2 Research Objectives

The following are the objectives of the thesis:

- To leverage the use of mine vehicles during evacuation.
- To optimally route the available vehicles during evacuation.
- To combine both foot and vehicle modes during evacuation.

1.4 Thesis Structure

This thesis is part of a NIOSH funded research into smart mine evacuation involving the use of smart devices with software implementing an optimization model, a relational database which stores the real-time location of miners and a server for hosting the database. The results obtained from this thesis will ultimately be incorporated into a software which will provide real-time navigation for the miners during evacuation.

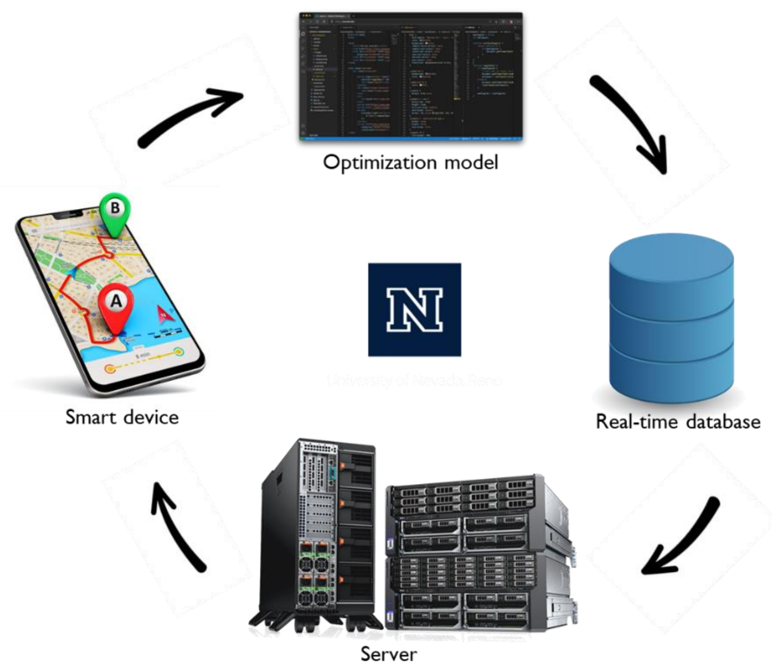

Figure 1 A Big Picture Overview of the NIOSH Research Grant.

To answer the research questions and achieve the research goals, the thesis is structured as follows:

Chapter 2 provides an overview of the big picture of the research. Mobile crowdsourcing, its challenges and potential solutions are discussed. Indoor positioning systems which are useful for evacuation during emergencies are also discussed in this chapter. Additionally, the trigger events for mine evacuation, mine evacuation management, current mine evacuation methods and algorithms are presented.

Chapter 3 describes the mine evacuation model developed for the research. An overview of mixed-integer / integer programming is given followed by a detailed description of the mathematical formulation of the IP model developed, the assumptions made in the study, and the optimization framework used. The benchmark MCNF formulation is described, and finally, a case study for validating the model is described.

Chapter 4 details the results obtained from implementing different scenarios of the case study with both the IP model and the benchmark MCNF.

Chapter 5 concludes the study by summarizing the results obtained and describing the impact of the IP model and its advantages over the benchmark MCNF model. Further recommendations and suggestions for future work are then presented.

CHAPTER 2 : LITERATURE REVIEW

This chapter contains a literature review of the enabling technologies including mobile crowdsourcing, indoor positioning systems for locating miners and vehicles in underground mines, the trigger events that lead to mine evacuations, various algorithms used in smart evacuation research and some conventional evacuation methods used in mines.

2.1 Mobile Crowdsourcing

The word "crowdsourcing" was first used in 2006 by Jeff Howe, a writer for WIRED, to describe the process by which certain firms built their business models by utilizing the wisdom of crowds. This process involved collaboration, aggregation, teamwork, consensus, and creativity (Brabham, 2008).

Mobile crowdsourcing (MCS), a novel paradigm that combines crowdsourcing and smartphone-based mobile technologies, offers substantial flexibility because of the rapid development of smartphones with rich built-in sensors and numerous ratio interfaces (Wang et al., 2017). As a result, novel crowdsourcing applications are made possible by the multi-sensing capabilities of smartphones, which include geolocation, movement, audio, and visual sensors (Chatzimilioudis et al., 2012).

Based on the kinds of events being accessible and tracked, MCS sensing applications can be roughly divided into two categories, personal and community sensing (Wang et al., 2017). Personal sensing applications monitor phenomena that are exclusive to an individual, whereas community sensing applications monitor widespread phenomena that are difficult for a single person to effectively quantify. The two subtypes of community sensing are participatory and opportunistic. In participatory sensing, the person taking part directly contributes to the sensing action, such as taking photos of certain events. In opportunistic sensing, the user is unaware of any running programs, everything is handled by the crowdsourcing application.

Various sectors of study and research have leveraged opportunistic sensing using crowdsourcing applications on smartphones to gather the information needed to solve challenging challenges and complete tough tasks. Mobile crowdsourcing and smartphone sensing have made important contributions to disaster management and evacuation.

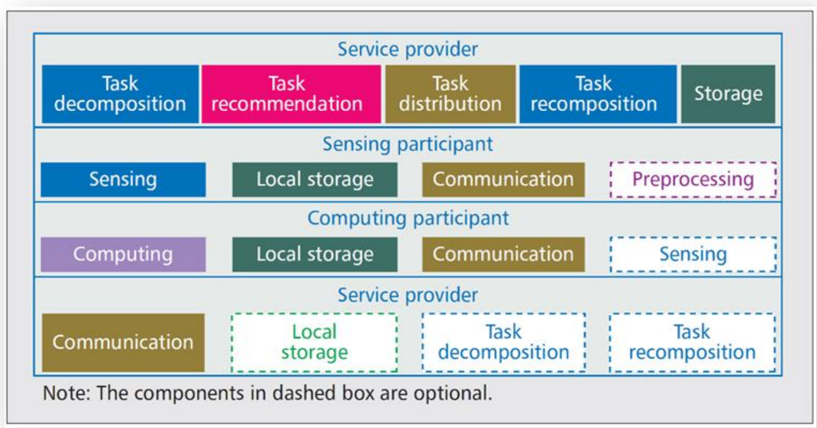

Figure 2 Components of Each Entity in Mobile Crowdsourcing (Yang et al., 2015).

Making time-sensitive decisions with little information is necessary for real-time catastrophe response, which is an essential paradigm for disaster response (Callaghan, 2016). The possibility of finding solutions in real-time is increased by increasing the number of inputs because the knowledge accessible in the early phases of a crisis may be probabilistic. Chris William Callaghan developed a probabilistic innovation theory, which asserts that there is a probability-based relationship between scientific breakthroughs and the resources used to achieve them, or between any solvable research problem and the volume of inputs used to solve it.

However, it is anticipated that this association will likely become more apparent with large levels of problem-solving input. Researchers have developed "SensoRecivico," "Crowdsafe," and "Clark," to name a few, as crowdsourcing systems that deliver practical services via smartphones, using the built-in sensors in smartphones as crowdsourcing instruments (Felemban et al., 2020).

Smartphone-based mobile crowdsourcing and sensing enable the production of large amounts of problem-solving input required to offer immediate solutions to issues pertaining to disaster management and evacuations. Time-sensitive decisions must be made during mine evacuations to ensure the safety of the crew and equipment.

Three primary stakeholders, the crowdsourcer, crowdworkers, and a crowdsourcing platform, make up the MCS architecture. When a task is crowdsourced, the crowdsourcer submits it to a crowdsourcing platform and may choose to score the accuracy of the data the crowdworkers provide (Wang et al., 2017).

The "direct mode" of crowdsourcing uses a centralized type of control, where a crowdsourcing platform uploads a task, breaks it into smaller "micro-tasks," and then organizes crowdworkers to do the tasks sequentially or concurrently. In general, crowdworkers do not directly communicate and work together. Time and location-sensitive tasks may not be handled well by the direct approach (Wang et al., 2017).

By assigning team leaders and followers who share similar interests and collaborate more effectively on mobile crowdsourcing tasks, researchers have made progress toward developing frameworks and algorithms that help to optimize mobile crowdsourcing to perform effectively in time-sensitive and location-sensitive tasks (Hamrouni et al., 2019).

Over the past decade, mobile digital communication devices have replaced analog landlines for use in emergency evacuations. More than 88% of US citizens own a mobile phone (Oxendine & Waters, 2014), making it possible for first responders and citizens to communicate more effectively and reduce the risk to evacuees during evacuations. Over 40% of cell phone owners, according to a 2011 Pew Research Center study, utilized their phones in an emergency.

For directions to their destination, evacuees typically rely on their past knowledge of the area, a cell phone with aided GPS, or an online mapping tool (such as Google Maps). They are given the quickest paths to secure locations in the resulting directions. However, these instructions frequently overlook the risk that may be present along the suggested route (Oxendine & Waters, 2014). Despite continued research efforts, 444 fatal landslides that took place worldwide in 2016 resulted in as many as 2,250 deaths. Scientists and professionals are beginning to embrace smartphone technology as a tool to better mitigate and manage disasters because of the technology's growing affordability and availability, particularly in developing nations (Choi et al., 2018).

A growing tendency toward modeling information in crisis response can be seen in the use of statistical models to model risk, such as in cases of tornado risk (Callaghan, 2016). The process of modeling various crises and response dimensions depends on the caliber and quantity of data gathered and processed.

Since the advent of the personal computer and computer-supported design, computational geometry has focused on locating the nearest neighbors. Utilizing strategies like divide-and-conquer and Voronoi diagram-based pre-processing, several methods have been created. (Piegl & Tiller, 2002) developed a method to find the k-nearest neighbors in 2-D without pre-processing. This technique can be used in evacuation models to determine where various people are in relation to escape routes in an emergency.

A research project called the RESCUER project sought to support emergency and crisis management during massive events like the World Cup by gathering crowdsourced information, such as photos and videos from eyewitnesses of dangerous events, fusing similar data coming from eyewitnesses and giving the command center an emergency response toolkit to manage emergencies effectively.

By offering crowdsourced maps, the software product, Collabmap, uses crowdsourcing to assist emergency planners. With the help of existing maps or aerial photos, the crowdworkers identify buildings or routes, add, and confirm escape routes that might not be shown on the existing maps, and identify any missing escape routes (Ramchurn et al., 2013).

Mobile crowdsourcing has also been used in evacuation simulations for building fire emergencies (Bajaj & Singh, 2015). In comparison to the manual process of filling out fire drill reports, it was found that the mobile crowdsourcing drill gave a more precise evacuation time and monitoring of the participation of residents. The results revealed a somewhat significant difference between the manual and crowdsourced data-derived evacuation timings. Additionally, it revealed that almost 50% of the residents did not take part in the drill, a fact that the drill reports did not adequately document.

Different techniques have been developed by researchers to evaluate the accuracy of sensed data from smartphones. A tree-modeling based data mining technique was developed by (Li, Sun, et al., 2019) to identify abnormalities in crowdsourced network data. Mobile crowdsourcing has become an essential tool in disaster evacuations because of this and other scientific advancements.

It is challenging to use mobile crowdsourcing for location services inside an underground mine. Devices are located using the Global Positioning System (GPS) in open areas with minimal to no interference between the devices and the GPS satellites in orbit. There are two (2) basic approaches to applying positioning techniques: self-positioning and remote positioning. The mobile device uses signals transmitted by the antennas (i.e., terrestrial or satellite) to determine its position in the first method (self-positioning). When using remote positioning, the location of the mobile device is determined by analyzing the signals that are sent to and received from a group of receivers. The signals coming from or reflecting off the mobile device to be located are measured by these receivers, which are deployed at one or more places. The position of the mobile device is estimated from geometric relationships using these signal observations to establish the length and direction of individual radio channels (Zeimpekis et al., 2002).

Mobile crowdsourcing has difficulty locating devices in enclosed spaces like deep mines because GPS sensing is not possible there. Researchers have developed a variety of methods to help with device location prediction in underground and indoor environments. These methods have been applied in a few indoor evacuation scenarios and offer results on device locations that are reassuringly accurate. There are many methods for measuring signals, but the ones that are most usually applied are the angle of arrival, time of flight, time of arrival, time difference of arrival, received signal intensity indicator, and channel state information (Zare et al., 2021).

Similar technologies are currently used by numerous mines to convey text messages to underground workers. The primary distinction between these three situations is the method of information transmission: cell phones for weather alerts, roadside electronic monitoring for traffic dangers, and personal transponders for mining data. All these messages have one common goal when utilized in an emergency or dangerous situation, to guide the miner in making safer decisions (Ur Rehman et al., 2020a).

When someone is given a task that requires them to work somewhere other than their usually assigned location, they should be informed of the area's escape route at the time of the assignment. However, in accordance with regulations, individuals who typically work in many mine sites should get instructions concerning the locations of all escape routes at least once every 12 months.

To locate people during an emergency and propose Augmented Reality (AR) escape routes, RescueMe, an indoor mobile augmented reality evacuation system, uses sensed data from smartphones that are crowdsourced and collected (Ahn & Han, 2011). The solution uses individualized pedometry to forecast device placement and direct evacuees using augmented reality.

Solutions for indoor GPS have been developed for use in open spaces without considerable obstructions. Several pseudolites provide the navigation signal (pseudo-satellites). These gadgets produce a signal for navigation akin to GPS. To build pseudolite-compatible receivers with the fewest modifications possible to current GPS receivers, the signal is created to be comparable to the GPS signal. To navigate, at least four pseudolites must be visible, much like in the GPS, barring the usage of additional tools like altitude helping (Zeimpekis et al., 2002).

2.1.1 Challenges in Mobile Crowdsourcing

According to a recent survey, most US citizens support the gathering of location information in times of disaster. On how to use the location data however, there was debate (Oxendine & Waters, 2014). A significant issue in MCS is how to safeguard a mobile user's location privacy in location-based services.

The potential for violating user privacy by recording and disclosing sensitive information (intentionally or unintentionally) is one of the main issues with autonomous sensing (Wang et al., 2017). Within an MCS framework, data and tasks may reveal personal information.

The reliability of crowdsourced data is also extremely important for any mobile-crowdsourcing-based model. Below is a summary of the effects of unreliable data from crowdsourcing. Incorrect or erroneous data may be reported by crowdworkers with malicious intent; this is known as a pollution attack. Crowdworkers can maliciously configure mobile devices to jam data.

It is challenging to spot dishonest computer users who might produce false findings. When a mathematical model or algorithm is used to interpret data and produce an output, the output's dependability is proportional to the algorithm's correctness and dependability. The service provider may get the crowdsourced data via networks such as 3G/4G and Wi-Fi. Due to human involvement in data transmission, data may be altered by intermediary devices (Yang et al., 2015).

2.1.2 Potential Solutions to Mobile Crowdsourcing Challenges

To lessen the likelihood that one user will reveal his real location, several academics have advocated location privacy preservation by the insertion of noise into the reallocation of data. (Chi et al., 2017) introduced a location privacy-preserving technique called CKD that combines k-anonymity with differential privacy-preserving to stop the leakage of mobile users' location information. In addition, the Stackelberg game is used to resolve the trade-off between privacy protection and service quality.

The long-term evolution package for the fourth generation of mobile broadband technology is known as LTE, also referred to as 4G LTE. It has a range of techniques for load balancing, congestion control, and traffic priority and can operate in a range of frequencies. Comparing 4G LTE to earlier 3G standards, the former offers higher peak bit rates and significantly lower latency (Mueller et al., 2019).

As the internet of things (IoT) and 5G (the fifth generation of mobile broadband technologies) gain popularity, private LTE is emerging to provide flexible and easily adjustable wireless coverage for a range of applications and sectors. By 2025, the private LTE/5G market is expected to triple, according to mobile industry analysts. For a localized region, such as a mine or a stadium, private LTE establishes an LTE service using nearby cellular towers and cell sites. Multiple Wi-Fi connection points would have been needed to cover the same region as LTE. Users choose private LTE because of its capacity, coverage, security, and user control over public LTE and Wi-Fi networks. In areas with no existing infrastructure, private LTE networks can act as a cost-effective stand-alone network or as a supplement to existing networks to ease congestion and increase security.

Nowadays, LTE coverage is often good in open-pit mines all around the world. The widespread adoption of 5G technology is anticipated to bring about a revolutionary improvement soon. The installation of private LTE networks at many open-pit mines will benefit these mines, even if many companies have restrictions on the use of any sort of smartphone at the mine site. Companies are carefully considering private LTE as an essential infrastructure for their operation since it offers a wide range of operational applications for mines at extremely low operating costs and great security compared to alternatives like Wi-Fi (Mueller et al., 2019).

Rapidly expanding private LTE networks are being installed in surface and underground mines and the advantages include greatly lowering the number of fixed Wi-Fi access points to just a few LTE radio sites while also enhancing security, overall network capacity, and system performance. As 5G gradually enters the mainstream, 5G elements are now being integrated into LTE development, which is still primarily a 4G technology.

2.2 Indoor Positioning Systems

Indoor positioning technologies make use of pedestrian dead reckoning, wireless fidelity (Wi-Fi), Bluetooth, geomagnetism, inertial sensors-based localization, ultrawide band, radio-frequency identification, and ultrasound or sound (PDR) (Jang & Kim, 2019). Smart evacuation for underground mines requires an efficient indoor positioning technology for implementation. The advantages of various technologies and their drawbacks are highlighted in the subsections below.

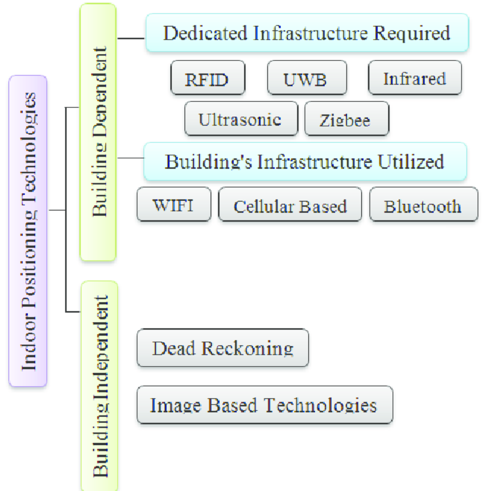

Figure 3 Classification of Indoor Positioning Technologies (Alarifi et al., 2016).

2.2.1 Wi-Fi

Wi-Fi is the technology that, when compared to other networks, offers the most benefits. Its primary benefit is that it is universal. There is no requirement to add extra hardware to mobile devices or put extra hardware in the indoor space. Wi-Fi is also easier for many people to use than other technologies because it is more widely used. As a result, the Wi-Fi infrastructure has garnered the most study interest and given rise to the most existing studies (Jang & Kim, 2019).

A Wireless Local Area Network (WLAN), also known as an 802.11b network, can be used to locate a miner or a vehicle underground. Miners can travel with a smart device that can access the internet. The link between the miner and the smart device is stronger the closer the miner is to a wireless access point (Meij, 2020).

2.2.2 Radio Frequency Identification (RFID)

The phrase "Radio Frequency Identification" (RFID) refers to a system that wirelessly transmits an object's or person's identification using radio waves. In large systems, the RFID technology is most frequently used to autonomously identify objects. RFID is founded on the exchange of various radio frequency signals between its two primary parts, RFID readers and RFID tags. RFID readers and RFID tags both receive radio impulses that are emitted by RFID tags. The RFID tags are made up of a radio antenna and a microchip, which can usually hold up to 2 kilobytes of data (Al-Ammar et al., 2014).

Making a connection between tags and readers is how RFID devices operate. Electromagnetic waves are used to make this connection. Tags, which have information about the wearer, can be worn by miners or affixed to vehicles. This information is transmitted to the readers through the antenna, and the readers in turn are linked to a computer that processes the information (Meij, 2020).

2.2.3 Ultra-Wideband (UWB)

UWB is a radio frequency signal that is higher than 20% of the center carrier frequency or has a bandwidth greater than 500 MHz, according to the Federal Communications Commission (FCC). By primarily using the time of arrival (TOA) or time difference of arrival (TDOA) of the RF signals to calculate the separation between the target and the reference location, UWB can be used for positioning (Al-Ammar et al., 2014).

Due to its high bandwidth and signal modulation, UWB technology, unlike other positioning technologies like infrared and ultrasonic sensors, does not require a line-of-sight and is unaffected by the presence of other communication devices or outside noise.

UWB has been used to successfully implement numerous IPSs. The Ubisense system is one popular positioning device that makes use of UWB. In a Ubisense system, a user wears tags that send UWB signals to fixed sensors, which then utilize the time of arrival (TOA) technique to determine the user's positions (Alarifi et al., 2016).

2.2.4 Infrared (IR)

When compared to indoor positioning based on visible light, infrared wireless communication uses the invisible spectrum of light just below the red edge of the visible spectrum, making it less intrusive. Direct IR and diffuse IR are the two methods that IR can be used. IrDA (Infrared Data Association) is a type of direct infrared that makes use of an ad hoc point-to-point data transmission protocol intended for extremely low power communications.

IrDA needs up to 16 Mbps line of sight communication over very short distances between devices. Diffuse IR, on the other hand, has a greater reach (9–12 meters) than direct IR because its signals are stronger. Wide-angle LEDs used in diffuse IR emanate signals in multiple directions (Al-Ammar et al., 2014).

2.2.5 Ultrasonic

A mechanical vibration called an ultrasound is an oscillation of pressure that travels through a medium. It has a limited range and does not interact with electromagnetic waves (Al-Ammar et al., 2014). Time of Arrival (TOA) measurements of Ultrasound (US) pulses that travel from a US emitter to a US receiver can be used to determine the distance or range between two devices.

Due to the unique decay profile of the airborne acoustic channel, the US TOA working range is 10m or less as opposed to radio waves. Due to radial intensity attenuation and absorption, which corresponds to an inverse quadratic attenuation in 3D space, doubling the distance causes the signal's sound pressure level to attenuate by 6 dB (Mautz, 2012).

2.2.6 Zigbee

The ZigBee standard offers network, security, and application support services. It is a wireless personal area network with a limited range and low data rate. Simple ZigBee nodes are inexpensive, simple, and compact. It is made up of a microprocessor and a multichannel two-way radio on a single silicon chip. By coordinating with nearby nodes and exchanging messages, this technology accomplishes positioning. Full Function Device (FFD) and Reduced Function Device (RFD) are the two physical device kinds used for ZigBee nodes (Al-Ammar et al., 2014).

Usually, RSSI numbers are used to estimate the distance between two ZigBee nodes. ZigBee is susceptible to interference from a variety of signal types using the same frequency because it uses unlicensed ISM bands, which can impair radio transmission (Mautz, 2012).

2.2.7 Bluetooth

Wireless personal area networks use the Bluetooth specification (WPANs). ZigBee is an open standard, whereas Bluetooth is a private format run by the Bluetooth Special Interest Group (SIG). Bluetooth is intended to be a very low power peer-to-peer communication technology that uses the 2.4 GHz ISM frequency. One of the Bluetooth

Special Interest Groups (SIG), the Local Positioning Group, researches into the use of Bluetooth wireless technology for positioning (Al-Ammar et al., 2014).

A signal comparable to that of Wi-Fi is used by Bluetooth. Bluetooth can use multiple bands, whereas Wi-Fi only uses one. This makes it helpful in situations where there is a lot of "background noise" on the transmission frequencies. Other benefits of Bluetooth systems include excellent signal detection, affordable deployment costs, and ease of application development for Bluetooth-enabled systems. Additionally, Bluetooth-enabled devices can communicate with one another. This means that during an evacuation, smart devices can inform you if any co-workers are close by (Meij, 2020).

2.2.8 Image Based Technologies

Camera and computer vision-based technologies, also known as optical methods, are used in image-based indoor positioning. The performance of various camera kinds, including omnidirectional, three-dimensional, and mobile phone cameras, varies depending on how much information can be gleaned from their images. The creation of image processing algorithms, detector technology progress, data transmission rate increases, and computational power increases are just a few of the variables that influence the success of image-based technologies (Al-Ammar et al., 2014).

This system presupposes that when miners work in the mine, they don cap lamps on their helmets. A miner can be recognized by looking at the distinctive pattern of the light by giving each of the lights emitted from these lamps a distinctive form. Special cameras are used to read the lights, and a computer at the base location receives this information (Meij, 2020).

2.3 Trigger Events for Mine Evacuation

Trigger events in mining are events that result in mine emergencies requiring the evacuation of miners. These events may be caused by man or nature. The probability of human-caused events occurring in a mine is largely dependent on the safety culture at the mine site. When these events occur, the authorities get involved to implement a suitable evacuation plan depending on the type and location of the event. Described below are the major trigger events that warrant a mine evacuation when they occur.

2.3.1 Fires and Explosions

In the 61 fires that occurred in deep metal and non-metal mines in the USA between 1991 and 2000, 10% were classified as electrical, 5% as friction, 46% as equipment fires, 2% as spontaneous combustion, 16% as cutting and welding fires, and 21% as other fires (Meij, 2020). The emergency response to fires can be divided into three phases. The miners who are on site when the fire breaks out are the first to arrive. Even though these miners may lack experience and expertise in fighting fires, it is crucial that they act right away because a fire can expand quickly. Therefore, miners should receive appropriate training on how to handle a fire, such as by learning how to use a fire extinguisher (Meij, 2020).

The fire brigades are the second response to an underground mine fire. These are workers who have received specialized training and equipment. Every shift that is worked in the mine should have a fire brigade on standby. Sustained responders, also known as mine rescue teams, attempt to free individuals who become trapped in the mine during the fire in the third stage (Meij, 2020).

A general framework for fire/explosion risk assessment in mines based on the quantification of the likelihood of occurrence and gravity of the consequences of such undesirable events and employing the root-cause analysis method was developed by (Cioca & Moraru, 2012). It is stressed that, should a combustible atmosphere develop, even a small fire should be considered a significant threat in terms of explosion initiation. The framework is based on known underground explosion hazards, fire engineering principles, and fire test criteria for potentially combustible materials used in mines.

The lives and possessions of people are seriously threatened by coal mine fires. Advanced fire suppression methods, such as the injection of inert gases or liquid nitrogen, dynamic pressure balancing, reversal of underground mine ventilation, application of nitrogen foam, inertization of gas, water mist, etc., may be used to combat fire outbreaks (Ray & Singh, 2007).

A database with 782 mine accidents in China from 1950 to 2016 was created and examined to determine the characteristics of large-scale coal mine accidents. According to the number of accidents per year, the historical evolution of large-scale coal mine accidents was divided into four phases. Due to their interchangeability, comparable gaseous hazards, and identical thermochemical essence of combustion, explosions and fires were the most common causes of accidents and were therefore considered to be thermodynamically driven events (Zhu et al., 2019).

There were about 500 significant gas and dust blasts in American mines between 1880 and 1981. However, most of these explosions occurred in coal mines, which have a more significant source of ignition due to the prevalence of coal dust. Nevertheless, more than one hundred people have died because of mine blasts in both metal and non-metal mines (Meij, 2020).

2.3.2 Floods

Inundations or flooding of underground mines can occur for a variety of reasons. Event-controlled flooding, unintentional flooding, and spontaneous flooding are the three main groupings of flooding. Inrushes, also known as spontaneous inundation, are connected to karst groundwater. According to (Meij, 2020), different circumstances can result in accidental inundations. These circumstances are:

- Contact with surface unconsolidated deposits or surface water.
- Strata water entering the workings.
- Old shafts being cleared.
- Contact with ancient, abandoned workings.
- Leakage from a borehole or failure of a subterranean dam's seal.

Since the 1950s, China has seen hundreds of mine flooding incidents. Submerged working faces and even entire coal mines are the result of these flooding accidents, which cause enormous financial losses. According to reports, 285 of China's 601 state-owned mines are at risk from water inrush. As mining depths increase, the water pressure grows steadily stronger, increasing the risk of a water inrush (L.-G. Wang et al., 2007).

As groundwater gradually fills the mining voids, according to (Goldbach, 2009), many South African gold mines will flood when they close. According to preliminary research, mine flooding can cause an increase in seismic activity. Such flooding-induced seismicity may put nearby mines and surface communities in danger and have significant negative environmental, social, and economic effects.

2.3.3 Mining-Induced Seismicity

According to (Hasegawa et al., 1989), the expansion of regional seismograph networks into active mining areas has improved the monitoring of mine-induced seismicity in Canada. However, as mining extends to greater depths and at accelerated rates of extraction, the severity and in some instances frequency of mine-induced tremors has grown. Currently, installing a network of seismometers in and on the surface above mines having microearthquake activity is the most feasible and practical method to monitor these tremors due to the complex design and wide geographic extent of many mines (Hasegawa et al., 1989).

In Chinese mines, a new issue has been active seismicity and rock bursting. Rock burst hazards are primarily caused by deep mining and the activity of the current tectonic stress field. (T. Li et al., 2007) found that the lack of mine seismicity-monitoring networks in most mines and the requirement for improving the accuracy of the monitoring systems for mines that have such systems are the main issues with reducing the risk of rock bursts in China.

The recent creation of alternative techniques for automated seismic event location was prompted by the growing interest in micro-seismic monitoring applications. Time-reversed seismograms are used as sources in some methods based on wave-field backpropagation. These techniques require a lot of computation, and when dealing with noisy data and highly heterogeneous models, energy focusing can be ambiguous (Grigoli et al., 2013).

2.3.4 Fall of Ground

Unexpected roof failures in coal mines can result from a variety of causes. These include, to name a few, geologic flaws in the roof rock, moisture-induced shales degradation, extremely high loading conditions, multiple seam mining, and insufficient support. Understanding the causes of any engineering failure is a big step toward a solution. Sometimes it is impossible to determine what caused a roof to fall, but often, the causes can be found by looking into the fall cavity, the state of the nearby roof, and the geotechnical environment.

To demonstrate the causes and circumstances preceding a roof fall, NIOSH has examined roof failure in several coal mines. According to roof fall surveillance statistics, a disproportionately high proportion of roof falls occur at mines with flimsy roofs (Molinda & Mark, 2010).

One of the biggest risks in underground coal mines is still roof falls. Although the number of deaths from roof falls fell to an all-time low of two in 2003, the Mine Safety and Health Administration received reports of more than 1,400 major roof collapses. These roof collapses have the potential to endanger miners, harm machinery, obstruct ventilation, and impede vital emergency escape routes. The frequency of roof collapses varies among coal mines (Mark et al., 2004).

The minimal level of ground fall results in no injuries, minimal equipment damage, and minimal disruption of the mining activity. No severe injuries occur at the medium level, but there is significant property damage and an interruption of operations. At the highest level, there is extensive property and equipment destruction, as well as injuries, because of the ground fall (Meij, 2020).

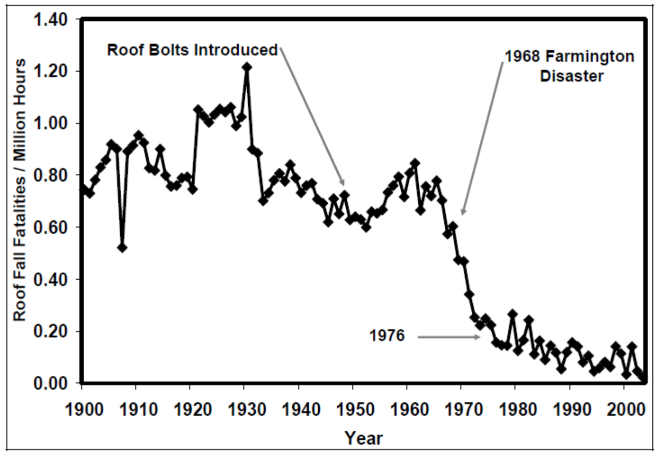

Figure 4 Roof Fall Fatalities in Underground Coal Mines, 1900-2005 (Mark et al., 2011).

2.3.5 Inrush of Hazardous Gases

Equipment and labor are needed for underground mining operations. There is a chance that the subsurface atmosphere will contain explosive gases or poisonous gases that will replace the oxygen that is needed for living. In an underground coal mine, numerous mishaps can result in fatalities and significant property damage. Numerous factors, such as a sudden increase in toxicants like carbon monoxide (CO), hazardous flammable gases, particularly methane (CH_4) or firedamp, and insufficient oxygen for mine employees to breathe, are to blame for these accidents.

The main requirement is to frequently check the levels of gases like oxygen, methane, carbon dioxide, carbon monoxide, etc. to maintain the ideal atmosphere in underground mines. This provides information on both short and long-term trends in the subsurface atmosphere and enables miners to receive early warnings of explosive and toxic atmospheres wherever they typically work or travel. No mine worker should approach a location with poor air circulation, such as blind headings, unless the air has been checked to ensure that it is safe to breathe and is devoid of dangerous gas concentrations (Kumar et al., 2013).

Due to its effectiveness, simplicity of upkeep, dependability, and durability, diesel engines are frequently used in underground mining equipment. However, it poses a serious threat to miners and mining activities because it emits dangerous gases (CO, NO, and CO2) and tiny particles that are easy for miners to breathe in (Kurnia et al., 2014).

A crucial problem is measuring the air quality in a deep underground mine. This procedure is very challenging due to the high cost of ventilation and the geometry of the mine under consideration. As a result, warnings about gas dangers must be displayed on portable, personal devices for miners (Zietek et al., 2020).

2.4 Mine Evacuation Management

During a mine emergency, several factors influence the management of an evacuation exercise. Evacuation planning, decision making, training and human behaviour are some of these factors. The success of a mine evacuation exercise depends on the optimization of these factors.

2.4.1 Egress Behaviour During Mine Evacuation

(Gwynne et al., 2010) categorized evacuee performance during a building evacuation into five components.

- pre-response or pre-escape time, which is the period before an evacuation.
- Travel speeds, or the rate of movement of evacuees.
- Route accessibility - the evacuees' possible routes.

- Route usage/choice - the ways that the evacuees chose from those that were offered.
- Flow conditions or constraints, which refer to the connection between velocity, flow, and population.

Research has shown that specific factors (occupant characteristics, environmental factors, and even building design) impact how long occupants will take to act during pre-response times (Gwynne et al., 2010).

The majority of Kuligowski and Gwynne's study was devoted to building evacuation during a fire. (Kowalski-Trakofler, Vaught, et al., 2010) went into detail about the initial responses during the evacuation of an underground mine. Figure 5 shows a visualization of their take on emergency reaction.

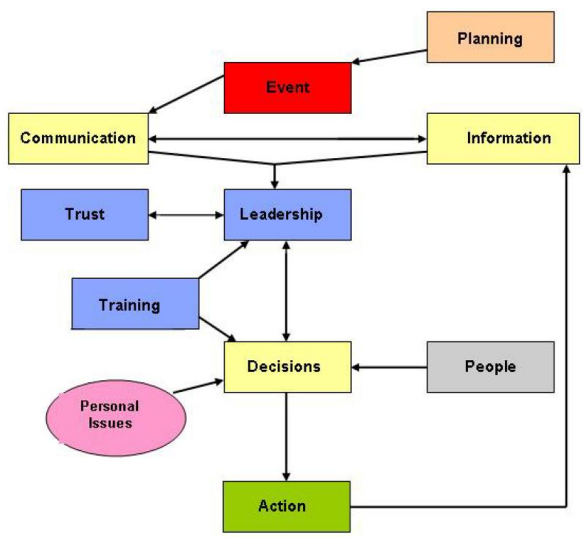

Figure 5 First Moments in Mine Escape (Kowalski-Trakofler, Vaught, et al., 2010).

2.4.2 *Evacuation Planning*

The creation of an emergency response plan for a mining operation is subject to government regulation in the United States (Kowalski-Trakofler, Vaught, et al., 2010). This response plan should be viewed as a dynamic, ongoing process. An emergency response plan's preparation is its most crucial component. In general, there are three different kinds of information that miners need in the event of an evacuation. First, there is technological knowledge, which entails that miners should be familiar with how to use self-contained self-rescuers (SCSRs), lifelines, and refugee chambers. Second, there is mine-specific information, which includes understanding the layout of the mine and its emergency response strategy. Finally, mental knowledge includes the capacity to reason under pressure and adjust to shifting conditions (Meij, 2020).

Figure 6 Self-Contained Self-Rescuer - DEZEGA Ci-30 KS. Credit: MineARC Systems.

The emergency strategy for the mine where they work should be understood and followed by both the rescue team and the miners. Some organizations define emergency response planning as the process of creating a written strategy that can be used whenever an emergency arises. An emergency response strategy is merely a component of this ongoing, dynamic process (Onifade, 2021).

Figure 7 Hard Rock Refuge - MineSAFE Standard Design. Credit: MineARC Systems.

The following factors are crucial according to the survey conducted by (Kowalski-Trakofler, Vaught, et al., 2010):

- Having a strategy will aid in handling the emergency.
- The miner needs to be well-versed in the emergency strategies.
- Everyone should be trained on the response strategy.
- Emergency preparedness ought to be a top concern.

2.4.3 Training

Training is regarded as being an essential component of the emergency response planning process, and it can take various forms. Additionally, it provides an opportunity for rescuers to connect and form bonds. Training should go beyond memorization and inert instructional techniques (Meij, 2020). The core of training programs should be dependence on self-rescue in simulated emergencies (Kowalski-Trakofler, Vaught, et al., 2010).

In underground coal mines, evacuation drills are conducted four times a year because it's important for all employees to be familiar with the right emergency protocols. The instruction, however, seriously interferes with the mine's ability to operate. The mine must stop working so that workers can be trained on appropriate evacuation procedures.

Self-rescue is particularly crucial because studies have shown that miners have a better chance of survival if they have a self-escape plan. The survival rate decreases if rescue teams are the main emphasis. The miners themselves advocate that training should include both emergency reaction and emergency decision-making. Additionally, they advocate for practical instruction, for instance, in how to use a fire extinguisher (Meij, 2020).

2.5 Current Mine Evacuation Methods

2.5.1 Conventional Evacuation Methods

To alert miners to a fire or other emergency that could impact the entire mine, underground mines use a variety of methods, including stench gas, audible or visual alarms, telephones, and messengers. These systems frequently lack speed, dependability, and site coverage (Conti et al., 2005).

Conventional methods have been used over the years for wayfinding during mine evacuation. All underground miners are required by U.S. Federal Regulations to travel escape routes and practice fire drills every 90 days, but this does not adequately prepare them for the challenges they might face in actual escape scenarios, such as smoke-filled entrances. Rescue team members may use a continuous lifeline during rescue efforts in an emergency. The team members are fastened to a team lifeline while looking for lost people or exploring a dangerous smoke-filled environment. When navigating through dark, smoke-filled passageways, the team members can quickly locate themselves along the lifeline thanks to the various colored light wires (Conti, 2001).

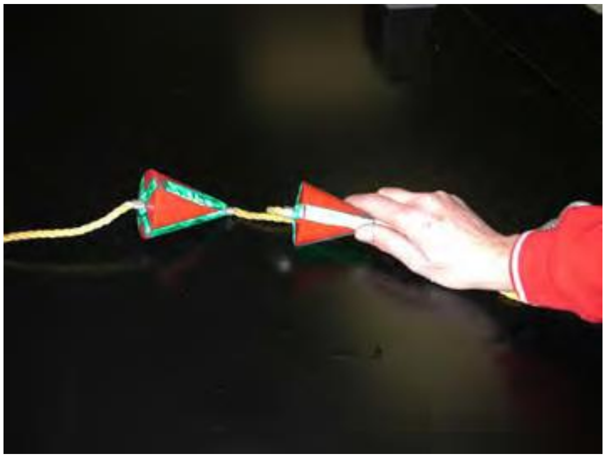

Figure 8 Continuous Lifeline for Escape (Conti, 2001).

In addition to mines with deep workings, where gradients and extreme heat stress conditions can make evacuation extremely difficult, escape plans must consider a wide variety of operational scenarios. When there is no sight, skilled miners can use suitable structures like rails, cables, and conveyors as a lifeline. Utilizing dedicated lifelines which often connect directly to refuge chambers that run alongside travel lanes and return escapeways is an alternative strategy.

Active electronic guidance systems, which use visible and audible signals to guide personnel, have been developed to offer a more effective method of guidance. These systems employ several roof or rib-mounted beacons that emanate an audible and visual indication in a cyclical pattern that starts at the working face and ends at the refuge chamber. The expense of these systems requires that the beacons be placed as far apart as is deemed necessary, usually at intervals of 50 meters or less where there is directional ambiguity, such as at intersections.

IMC has created an efficient escape beacon system in collaboration with the UK Health and Safety Executive and Mines Rescue Service. IMC’s egress beacon system employs a series of bi-color indicators and acoustic senders along with a cutting-edge strategy of providing inductive power transmission to each beacon unit. The IMC system is robust, fail-safe, and may provide the most affordable choice of any "active" wayfinding system.

The beacons are fastened to the tunnel wall so that when they are turned on, based on the direction of travel, each beacon emits either a red or a green light. A series of green lights will appear when the subject is moving in the proper direction toward the refuge chamber or safe area. In contrast, a series of red lights is seen when the subject is moving away from the safe area (Brenkley D et al., 1999).

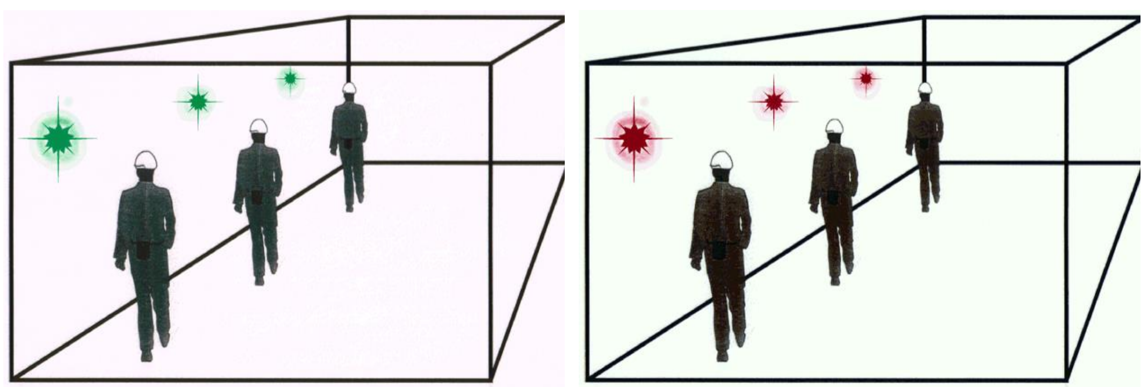

Figure 9 (a) Assigned Escape Route (b) Opposite Direction (Brenkley D et al., 1999).

2.5.2 Smart Evacuation Methods

Smart mine evacuation methods rely on the use of smart technologies such as smart devices during mine evacuation. These methods require real-time localization of miners, which can be obtained from effective indoor positioning systems. Virtual reality and simulations have been used to evaluate the efficiency of smart evacuation methods in mine evacuation.

Installing exit signs that can alter the direction indicator based on the current emergency will enable smart evacuation without personalized instruction. This can be accomplished using fire sensors such as smoke detectors, computing the miners' safest and quickest path on each level in the mine, and sending this information to the intelligent exit signs (Gaab & Sattarvand, 2019).

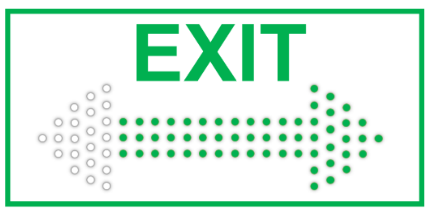

Figure 10 Schematic Design of a Smart Exit Sign with LED's (Gaab & Sattarvand, 2019).

(Ur Rehman et al., 2020) investigated in a study, the impact of emergency alerts on the decision making of miners during evacuation. The underground miners were given simulated alerts with increasing levels of information about a potential fire, cave-in, or explosion emergency as part of the survey. The findings showed that the content of the message alerts significantly influenced the decisions made by miners, with more miners deciding to leave when more information was given about the urgency of the situation.

This study further emphasized the need for smart technologies to aid miners during mine evacuation.

2.6 Algorithms

A few algorithms and mathematical models have been used by researchers to model the evacuation processes. The most frequently used algorithms and models are described in this chapter.

2.6.1 Dijkstra's Algorithm

Finding the shortest path from a starting point in a graph to a destination is solved by the Dijkstra's algorithm, which bears the name of its inventor, E.W. Dijkstra. The algorithm is sometimes referred to as the single-source shortest paths problem because it turns out that the shortest paths between any two locations in a graph can be found simultaneously (Javaid, 2013).

In implementing Dijkstra's algorithm, every node j receives a pair of labels (p_j, d_j), where p_j is the node in the existing shortest path from 1 to j that comes before node j and d_j is the length of this shortest path. The shortest path from point 1 to a node that is permanently labeled has been discovered, while some labels are referred to as temporary, meaning they could change at a later stage. The extent of the arc (j, k) is indicated by d_{jk}. The following steps highlight the Dijkstra's algorithm:

- Permanently affix the markings (Ø, 0) to node 1. Label each node j with temporary labels so that (1, j) is an arc in the graph (1, d_{1j}). Give temporary labels (Ø, ∞) to all other vertices in the graph.
- Assume that node j has a temporary label of d_j, i.e.

d_j = min {d_l: node l is a temporary label}

- If $d_k > d_j + d_{jk}$ for every node k such that (j, k) is in the network, then relabel k as follows:

  p_k = j, $d_k = d_j + d_{jk}$.

Consider node *j's* labels to be permanent.

- Re-do the second step until all the nodes in the graph are all labelled permanently. By reading off the labels p_j, one can determine the shortest paths (Javaid, 2013).

For emergencies involving toxic leakage, the optimization of the evacuation path is crucial. By merging the Dijkstra algorithm and computational fluid dynamics (CFD) code, (J. Wang et al., 2022) suggested a method for route optimization under real-time toxic gas dispersion. To model the dispersion of toxic gases, the CFD code was used to forecast the spatial-temporal distribution of concentrations, which is connected to the estimation of the inhaled dose. The modified Dijkstra algorithm incorporated the CFD concentration predictions as weights for arcs to determine the best route with the least amount of overall inhaled dose (J. Wang et al., 2022).

Network routing protocols, most notably Open Shortest Path First (OSPF), frequently use Dijkstra’s algorithm. The network is divided into network groups to find the shortest path in large networks (Eka Putra & Rohendi, 2017).

There are many variations of the Dijkstra algorithm. The original one finds the shortest path between two nodes, however, the more popular variation fixes one node as the source node and determines the shortest path from the source to all other vertices in the graph, producing the shortest path tree (Rahayuda & Santiari, 2021).

Bidirectional Dijkstra is a variant of the Dijkstra algorithm, which divides the matrix of two graphs before conducting independent searches with the Dijkstra algorithm. Compared to the standard Dijkstra algorithm, bidirectional Dijkstra can handle searches more efficiently. Multi-core technology and the two-way Dijkstra algorithm serve as the foundation for the bidirectional algorithm. On real road networks and social network graphics, bidirectional Dijkstra can operate in practice up to 25000 times faster than the standard Dijkstra algorithm (Rahayuda & Santiari, 2021). Dijkstra's algorithm is however computationally inefficient, having a running time of $O(n^3)$ (Meij, 2020).

2.6.2 Floyd-Warshall Algorithm

Robert W. Floyd discovered this algorithm in 1967. The directed graph (V, E) in the Floyd-Warshall algorithm consists of an edge list and a node list. The weight of a path is equal to the sum of its edge weights. The smallest weights of all paths linking a pair of points are determined by the algorithm, which simultaneously performs the calculation for all pairs of points (Ramadhan et al., 2018).

The Floyd-Warshall algorithm is popular for calculating the shortest paths between all pairs of vertices in an edge-weighted directed graph. For graphs with n vertices, this method has a worst-case runtime of $O(n^3)$. If there are no negative cycles in the input graph, the Floyd-Warshall method returns the right answer. Finding the shortest path in the presence of a negative cycle is an NP-hard problem, and the Floyd-Warshall algorithm may not produce the desired outcome, depending on the instance (Hougardy, 2010).

The Floyd-Warshall algorithm was applied to the shortest routes problem for a fire evacuation by (Lesmana et al., 2019). They implemented the algorithm using the El Royale Hotel Bandung as a case study. The result was a system for fire evacuation which calculates the shortest possible routes from every room in the hotel to the assembly point.

Floyd-Warshall-Algorithm

Input: A digraph G with $V(G) = \{1, \ldots, n\}$ and weights $c : E(G) \rightarrow \mathbb{R}$

Output: An $n \times n$ matrix M such that $M[i, j]$ contains the length of a shortest path from vertex i to vertex j.

$M[i, j] := \infty \ \forall i \neq j$
$M[i, i] := 0 \ \forall i$
$M[i, j] := c((i, j)) \ \forall (i, j) \in E(G)$
for $i := 1$ **to** n **do**
  for $j := 1$ **to** n **do**
    for $k := 1$ **to** n **do**
      if $M[j, k] > M[j, i] + M[i, k]$ **then** $M[j, k] := M[j, i] + M[i, k]$
for $i := 1$ **to** n **do**
  if $M[i, i] < 0$ **then** return('graph contains a negative cycle')

Figure 11 Floyd-Warshall Algorithm (Hougardy, 2010).

2.6.3 Genetic Algorithms

A genetic algorithm is a computational model of biological evolution. These algorithms are helpful in both problem-solving and evolutionary system modeling. Genetic algorithms can evolve remarkably intricate and interesting structures, despite the computational environment being considerably simplified when compared to the natural world (Forrest, 1996).

(Goerigk et al., 2011). developed a multi-criteria optimization model for evacuation in urban areas during natural disasters. Due to the large size of the real-world problem, a genetic algorithm, NSGA-II type, was used to generate good quality feasible solutions in reasonable computation time. The ability to calculate a set of solutions in a single run has made genetic algorithms the technique of choice for solving large-scale multicriteria problems.

An evacuation plan generator based on a genetic algorithm was developed by (Al-Qhtani et al., 2017). The genetic algorithm produced a nearly optimal evacuation plan. With their system, each evacuee was directed to the closest designated exit in the shortest amount of time using the entered facility configuration.

A technique to design the level of service (LOS) for facilities in buildings for the purpose of evacuation planning was developed by (Y. Li, Cai, et al., 2019) using genetic algorithm optimisation. Heuristic approaches such as genetic algorithms have the advantage of considerably reduced computational cost when compared to LP approaches, but they cannot guarantee exact solutions.

2.6.4 Ant Colony Algorithms

Marco Dorigo and his co-workers published the first ACO algorithms in the early 1990’s. The study of ant communities served as an inspiration for the creation of these algorithms. Ants are social creatures who reside in colonies, and their actions are dictated by the survival of the colony rather than individual survival.

Ants begin their initial exploration of the region near their nest when they are looking for food. Ants leave a pheromone chemical path on the ground as they move. They frequently choose routes with high amounts of pheromones when deciding where to go.

The amount of pheromone an ant deposits on the earth during its return journey is influenced by the quantity and nature of the food. Other ants will be directed to the food supply by the pheromone trails. The ability of ants to determine the shortest routes between their colony and food sources is known as stigmergy (Blum, 2005).

ACO algorithms take advantage of this trait of actual ant colonies to resolve issues like discontinuous optimization. ACO algorithms may pertain to various classes of approximate algorithms. ACO algorithms are among the most effective subsets of swarm intelligence from the viewpoint of artificial intelligence.

(Fang et al., 2011) proposed a multi-objective strategy based on an ant colony optimization (ACO) algorithm to solve the evacuation routing problem using the analysis of space-time paths in a hierarchical directed network. The evacuation routes in a stadium were visualized as a hierarchically directed network with destination-oriented links, which has the benefit of getting users to a safe location rapidly. By using destination-oriented heuristic information, the method could calculate an evacuation strategy without engaging in blind searching.

An improved quantum ant colony algorithm (QACA) for exhaustive optimization of the evacuation path that people can use to move from dangerous areas to safe areas was developed by (Liu et al., 2016). Due to the quantum representation and pheromone updating, the QACA was able to discover a suitable solution more quickly and with stronger robustness than an ACO (ant colony optimization) based method while using fewer individuals.

The evacuation routes on conventional evacuation diagrams are fixed, which may lead to an inefficient evacuation because they do not account for the real-time influence of fire products on the routes in the case of a fire. (Xu et al., 2022) suggested an improved ant colony optimization algorithm (IACO) to find the best escape path in a supermarket building with unfavorable fire conditions under the combined effects of temperature and fire products. (Xu et al., 2022).

ACO has many advantages and some disadvantages (Meij, 2020). The advantages of ACO's are:

- One simulation can examine multiple paths.
- The solution will converge to the optimal solution.
- It is easy to adjust to network changes, such as new drifts in the mine.

Some disadvantages of ACO's are:

- After each iteration, there may be a distinct probability distribution.
- Theoretical research could be challenging.
- Dependent random choice sequences.
- It is unclear how long convergence will take to occur.
- Optimality cannot be guaranteed.

CHAPTER 3 : MINE EVACUATION MODELING

3.1 Mixed-Integer Programming

The first 50 years of Mixed-Integer / Integer Programming led to a stable paradigm for problem solving that is both dependable and efficient. The general Mixed-Integer Linear Program (MIP) is of the format:

min $\{c^T x\text{: } Ax \geq b,\ x \geq 0,\ x_j \in Z\ \forall j \in I\}$

where no assumptions are made regarding the specific structure of the matrix A. The algorithmic method depends on the iterative solution of the Linear Programming (LP) relaxation:

min $\{c^T x\text{: } Ax \geq b,\ x \geq 0\}$

which is the same as the general form above but without the integrality constraint on the x variables in the set I. the optimal solution is denoted as x^*. These constraints are dropped because MIP is NP-hard whereas LP is polynomially solvable and can be solved effectively in practice using general-purpose methods (Jünger et al., 2010). The branch-and bound algorithm and the cutting plane techniques are used to solve MIP / IP problems.

The branch-and-bound algorithm divides the solution space repeatedly into sub-IPs that share the same theoretical complexity as the originating IP in its simplest form. For IP solvers, the branching typically yields two children by using the rounding of the LP relaxation solution of a fractional variable, let's say x_j, which is bound as:

$x_j \leq \lfloor x_j^* \rfloor$ or $x_j \geq \lfloor x_j^* \rfloor + 1$

The branches are referred to as the left and right children respectively. The integrality constraint on the variables x_j, $\forall j \in I$, is relaxed on each of the sub-IPs, and the LP relaxation is solved. Additionally, the LP relaxation problem is solved at each node to determine whether it is worthwhile to further partition the node. If the LP relaxation value is already greater than the incumbent, the node can be safely fathomed because none of its children will produce a solution that is superior to the incumbent. If a node's LP reduction is infeasible, it is also fathomed (Jünger et al., 2010).

Gomory's cutting plane method finds the convex hull of its integer solutions and allows for the solution of any IP without the need for branching. To accomplish that, the separation problem must be solved iteratively. Cutting planes, also known as cuts, are any inequality that solves the separation problem and tightens the LP relaxation for better approximation of the convex hull (Jünger et al., 2010).

The demand for effective evacuation plans is rising as awareness of how vulnerable remote areas are to natural disasters increases. Isolated places, like islands, frequently have characteristics that make standard evacuation procedures, like using a private car, impractical. (Krutein & Goodchild, 2022) developed the Isolated Community Evacuation Problem (ICEP) and a corresponding mixed-integer programming formulation to solve this problem. The ICEP reduces the evacuation time of an isolated community by carefully coordinating the movement of a fleet of disparate recovery resources available.

The location of shelters in a hurricane-prone area can have a significant impact on the highway network clearance time, or the amount of time it takes for evacuees to travel from their starting locations to safe areas. Using a specific location allocation model, (Sherali & Carter, 1991) developed both a planning and an operational computer-based tool using mixed-integer programming. The model provided an evacuation plan that reduces the overall congestion-related evacuation time by choosing a set of candidate shelters from a given set of admissible alternatives in a way that is practical for the resources at hand.

Intersections are where regional evacuation travel is most frequently delayed. One method for cutting down on these disruptions is lane-based routing. (Cova & Johnson, 2003) conducted a study using a network flow model for locating the best lane-based escape routing schemes in a complicated road network. The model was used to create routing plans that balance merging against overall car travel-distance while avoiding traffic conflicts at intersections. A mixed-integer programming solver was used to find the best routing schemes for an example road network in Salt Lake City, Utah.

This thesis work makes use of an integer programming approach to solve the evacuation problem by optimizing the routing of available mine vehicles and the miners. The mathematical formulation is described in the next section.

3.2 Mathematical Formulation

The mathematical formulation (IP) contains a set of origin nodes (where miners are located), a set of destination nodes (where safe havens are located), a set of travel modes (foot or vehicle), a set of routes that vehicles can access, and a set of arcs that connect a miner to various destination nodes.

The number of miners at the origin nodes, the capacity of the safe havens (refuge chambers and shafts), the capacity of the routes, the number of vehicles on hand at the time of evacuation, and the travel time between an origin and destination node with a specific mode of travel are some of the mine-specific parameters required by the model.

Table 1 Sets required for the model.

Sets	
Symbol	**Definition**
I	origins
J	destinations
N	nodes (origins, destinations, transhipment)
M	modes of transport (1= fast (via vehicle), 2 = slow (on foot))
R	routes
A	set of arcs (i, j), i.e., feasible I x J combinations
A_r	arcs (i, j) that are on route r

Table 2 Mine specific parameters required for the model.

Parameters		
Symbol	**Definition**	**Units**
s_i	evacuees at node i	number of people
d_j	capacity of refuge site j	number of people
K	capacity of a vehicle	number of people
u_{ij}	capacity of route between i to j	number of people
c_{ijm}	cost of arc (i, j) via mode m	minutes

Table 3 Decision variables to be derived from solving the problem.

Variables		
Symbol	**Definition**	**Units**
x_{ijm}	miners traversing (i, j) via mode m	number of people
v_r	# of vehicles executing route r	number of vehicles

$$\min \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} c_{ijm} \, . \, x_{ijm} \tag{1}$$

$$subject\ to \sum_{i \in I} \sum_{m \in M} x_{ikm} + s_k = d_k + \sum_{j \in J} \sum_{m \in M} x_{kjm} \quad \forall k \in N \tag{2}$$

$$x_{ij1} \leq K \, . \, v_r \quad \forall r \in R, (i,j) \in A_r \tag{3}$$

$$K \, . \, v_r + x_{ij2} \leq u_{ij} \quad \forall (i,j) \in A_r, r \in R \tag{4}$$

$$x_{ijm}, v_r \geq 0 \ and\ integer \quad \forall (i,j) \in A, r \in R \tag{5}$$

3.2.1 Model Description

The objective function (1) minimizes travel time for all evacuees; the model assumes that vehicle cost is sunk and therefore does not incur an additional cost for use. Constraints (2) ensure flow balance at each generic node k. These are sufficiently general to include origins from which miners are fleeing, transhipment nodes (where there is no supply of or demand for miners), and refuge chambers. In the former case, s is positive; in the latter case, d is positive. For transhipment nodes, there are no positive constants in the constraint. Constraint (3) enforces capacity of the vehicles. Constraint (4) enforces capacity along any given arc.

3.2.2 Model Assumptions

The model considers a situation in which the vehicle routes can be enumerated, from where a vehicle starts until where it ends. At that point, a passenger might be at a refuge (including outside the mine), or he/she might be part of the way there and need to walk the rest of the way. The routes within a mine are regularly updated as lateral development progresses. It is assumed that the enumerated routes are the only routes available for the vehicles to traverse at the time of the evacuation. The model assumes that the capacity of a vehicle is fixed for all vehicles, and that each vehicle drives at the same speed. This can be relaxed and does not change the structure of the model though more indices will be required to designate the vehicle type and which sort of vehicle a passenger travels in, if applicable.

The model also assumes that along a route, people will get into a vehicle, perhaps at various points, but that if a person gets out, another will not get in. This is because, if the person gets out, then he/she is at a safe location or must walk to it. There would therefore be no point in another person getting in. Another assumption of the model is that all miners are homogeneous, and no special preference is given to any one miner. The final assumption of the model is that the evacuation problem is a single-period problem in that an emergency occurs and all miners must get to a refuge as quickly as possible.

3.3 Optimization Framework

The mathematical model was scripted using the Python 3 programming language. Python was chosen because it is a general-purpose programming language with dozens of libraries available for optimization. The Pyomo modeling framework was used for this thesis.

Python Optimization Modeling Objects (Pyomo) enables the formulation and analysis of mathematical models. Commercial algebraic modeling languages (AMLs) like AIMMS, AMPL, and GAMS are frequently linked to this feature. Pyomo uses a rich set of modeling and analysis capabilities and offers access to these capabilities within Python (Hart et al., 2017).

The specification of a model that is transmitted to a solver software program is necessary for the computational analysis of an optimization model. The process of writing input files, running a solver, and extracting results from a solver is laborious and prone to error without a language to describe optimization models. Complex, real-world applications that are challenging to debug when errors arise exacerbate this difficulty. However, only a small number of the input forms used by solvers are regarded as standards. As a result, adding more solvers to the analysis of a particular optimization model adds complexity (Hart et al., 2017). In addition, without high-level languages for expressing models, model verification is very challenging.

With a framework that encourages flexibility, extensibility, portability, and maintainability, Pyomo provides a platform for defining optimization models that incorporates key concepts found in contemporary AMLs. Pyomo adds objects for modeling optimization to Python. These objects can be used to define optimization models and convert them into several formats that external algorithms can use.

Pyomo enables the definition of optimization models using an object-oriented design. The basic stages in a straightforward modeling procedure are:

- Create a model and define its components.
- Initiate the model.
- Apply the solver.
- Examine the solver's output.

These stages could be repeated while using different data or altering the model's constraints (Pyomo, 2020). Pyomo is capable of robustly modeling large constraint matrices such as MIP / IP models. It also has integrated support for automatic differentiation of complex nonlinear models (Sandia National Laboratories, 2016). It includes many useful modules and is highly stable and well-supported. Pyomo has support for a wide range of solvers including CPLEX, Gurobi, GLPK, SCIP, CBC and Xpress.

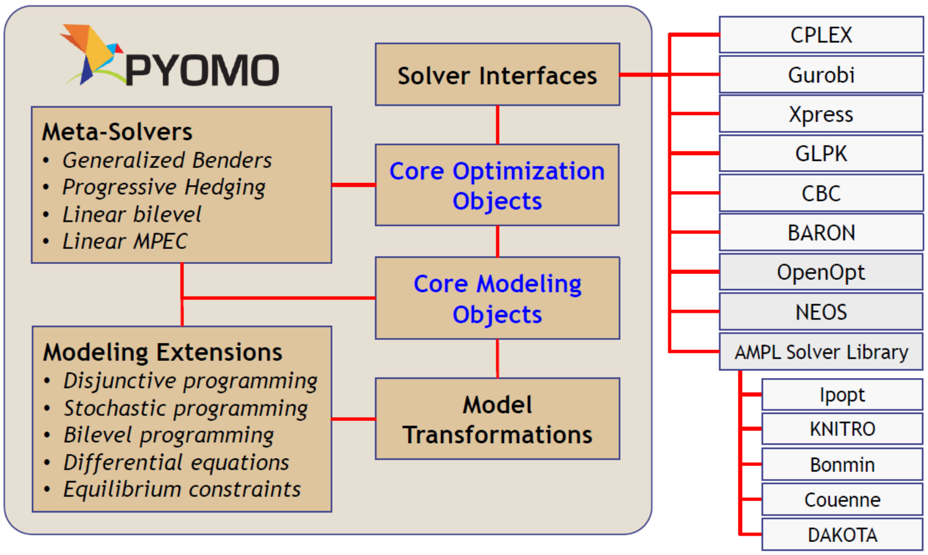

Figure 12 Pyomo at a Glance (Sandia National Laboratories, 2016).

3.4 Case Study

The Turquoise Ridge Complex is operated by Nevada Gold Mines LLC (Nevada Gold Mines), which is based in Humboldt County, Nevada, in the United States. Barrick Gold Corporation (Barrick) and Newmont Corporation (Newmont) are partners in the joint enterprise. Barrick holds 61.5% of the shares, with Newmont holding the final 38.5%.

Under the terms of the joint venture, the Turquoise Ridge Mine owned by Barrick and the Twin Creeks Complex owned by Newmont were merged to form the Turquoise Ridge

Complex. The Turquoise Ridge Underground, Vista Underground, and Turquoise Ridge Surface make up the combined mining complex (Lynn Bolin et al., 2020).

The Turquoise Ridge Complex is in the Potosi Mining District, about 64 kilometers northeast of Winnemucca, Nevada. Non-refractory ore is handled at the Juniper oxide mill or stacked on heap leach pads, while refractory ore is processed at the Sage autoclave. Turquoise Ridge Surface, on what was formerly Newmont's Twin Creeks property, houses all processing equipment.

Turquoise Ridge Underground is presently hoisting 2,700 tonnes of ore per day, which is anticipated to increase once the Third Shaft, which is currently under construction, is completed. The Vista Underground is a portal and ramp accessed vein-style stopping mine with about two years of mine life left that produces about 1,000 tonnes of ore per day. Turquoise Ridge Surface has been in operation for more than 30 years, with the current reserve mine life expected to last until 2030 at a rate of roughly 71,000 tonnes per day. Turquoise Ridge Surface generates oxide heap leach, oxide mill, and sulphide ore, whereas Vista Underground produces sulphide ore.

Figure 13 Turquoise Ridge Mine, Credit: National Mining Association.

In 1883, mining for copper, lead, and silver started on the Turquoise Ridge Underground property. Tungsten was found in 1916 and was mined intermittently until 1957. The current Getchell mine site was found with gold in 1933, and Getchell Mine Inc. operated the property from 1934 to 1945, producing a total of 788,875 ounces of gold. From 1960 to 2009, the Getchell mine operated sporadically, with underground mining, open pit mining, and heap leaching of dumps.

Turquoise Ridge Underground is located near the northeast edge of the Osgood Mountains in the Basin and Range province. The Getchell Fault, one of the region's most notable structural features, usually strikes north-south to north-northwest and dips approximately 50° to the northeast near the mine site. The mineralization in the Turquoise Ridge North Zone closely resembles the orientation of the Getchell Fault (Lynn Bolin et al., 2020).

The Turquoise Ridge deposit is a standard Carlin-type deposit, with sediment-hosted, structurally, and stratigraphically controlled replacement deposits containing disseminated micron-sized gold. The gold is found in arsenic-rich rims that develop on pyrite, primarily in decalcified, carbonaceous rocks. All gold-bearing zones at Turquoise Ridge are close to granodiorite dikes from the Osgood stock. The geometry of mineralization is heavily influenced by lithology and structure. To the north, mineralized domains have strike lengths surpassing 304 m and typical thicknesses ranging from 61 m to 152 m. Down dip distances of more than 304 m are not uncommon. Because the mineralized domains and bedding are primarily stratigraphically controlled, they hit north-northwest and dip east (between 25° and 45°) (Lynn Bolin et al., 2020).

Turquoise Ridge Underground is accessible via two shafts and an interior ramp system, and it employs underhand drift and fill mining techniques with cemented rockfill. Turquoise Ridge Underground also uses automated mining and sill benching as mining techniques. Turquoise Ridge Underground presently operates two road headers. Turquoise Ridge Underground's ground conditions are poor, and the Rock Mass Rating (RMR) in ore headings may be less than 20, or very poor.

The development of adequate stoping areas and the transition from top-cut development to undercut stoping are key challenges in achieving production levels and costs. To reach and optimize higher production levels, infrastructure development in the North Zone must be completed (Lynn Bolin et al., 2020).

3.5 Steps of the Algorithm

An AutoCAD drawing interchange (.dxf) file of the Turquoise Ridge Mine was obtained from previous studies of the mine. The drift ('airlines') data was extracted from the AutoCAD file into a .xlsx format to be used for scripting. Four mine shaft accesses and four refuge chambers were chosen for modeling purposes with a refuge chamber stationed within a 30-minute walking distance from the proposed active working areas.

Two refuge chambers were located closer to the bottom levels of the mine to accommodate miners working at those levels. The remaining chambers were located closer to the upper levels. Miners were randomly distributed on all levels to simulate an actual working environment in a single shift. The number of people in the mine was varied to simulate a night shift, a morning shift, and a special case shift. The layout of the TR mine is shown in Figure 14 and Figure 15 below.

Four different scenarios were tested in this thesis work. Three simulations involving 100, 200 and 300 miners were tested for all four scenarios. Firstly, a MCNF problem in which all the miners are required to evacuate by foot and where all the miners are assumed to have the same stamina levels at the time of evacuation. The number of refuge chambers and shaft accesses were kept constant and at the same locations for all the different scenarios.

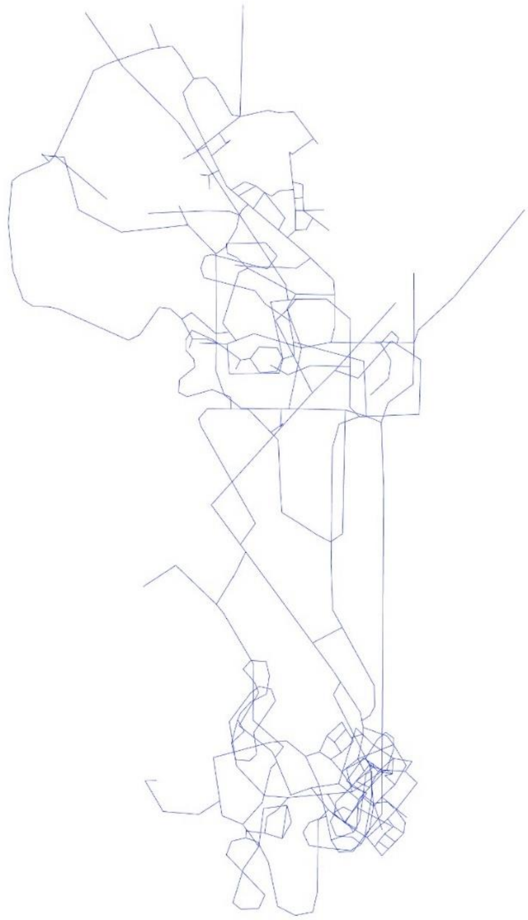

Figure 14 A Plan View of The TR Mine Drift Network.

The three simulations were then tested on a MCNF problem in which the miners are required to evacuate by foot, but miners were given stamina ratings to prioritise distressed miners during the evacuation. Another set of simulations were tested using the IP formulation discussed in this thesis. Three routes were enumerated, along which the available mine vehicles can traverse during the evacuation. No stamina ratings were applied to the miners for this set.

The final set of simulations were tested using the IP formulation but with stamina ratings applied to each miner to vary the stamina levels of the miners during the evacuation process.

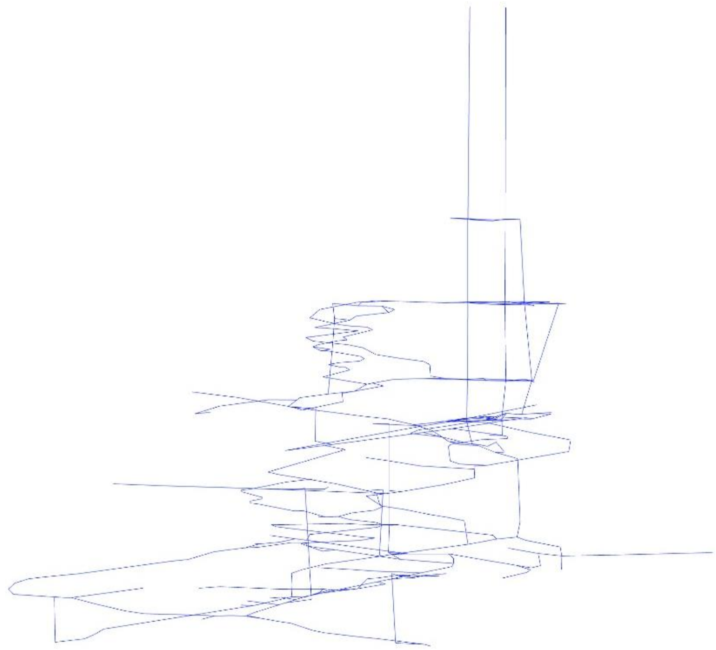

Figure 15 Front View of The TR Mine Drift Network.

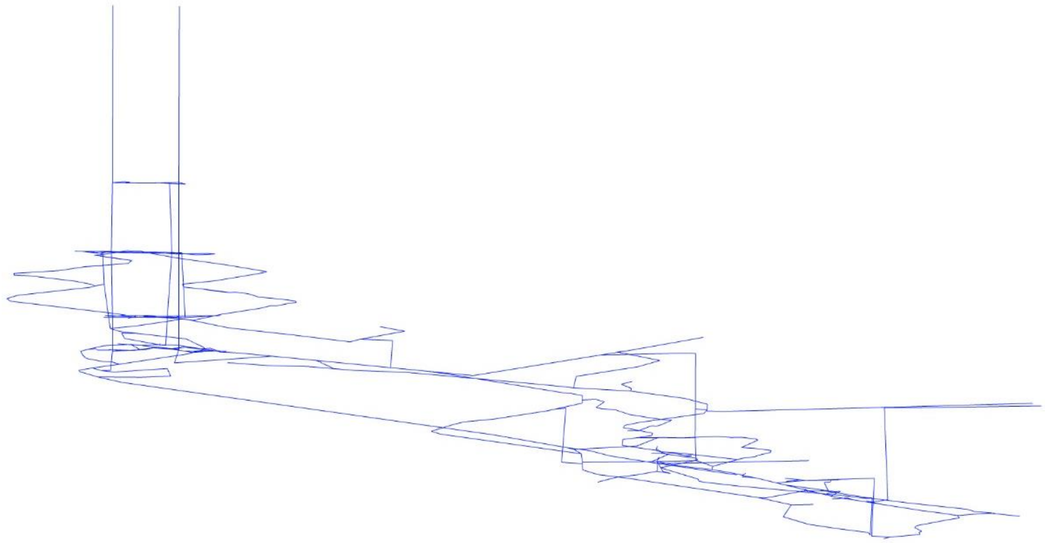

Figure 16 Side View of The TR Mine Drift Network.

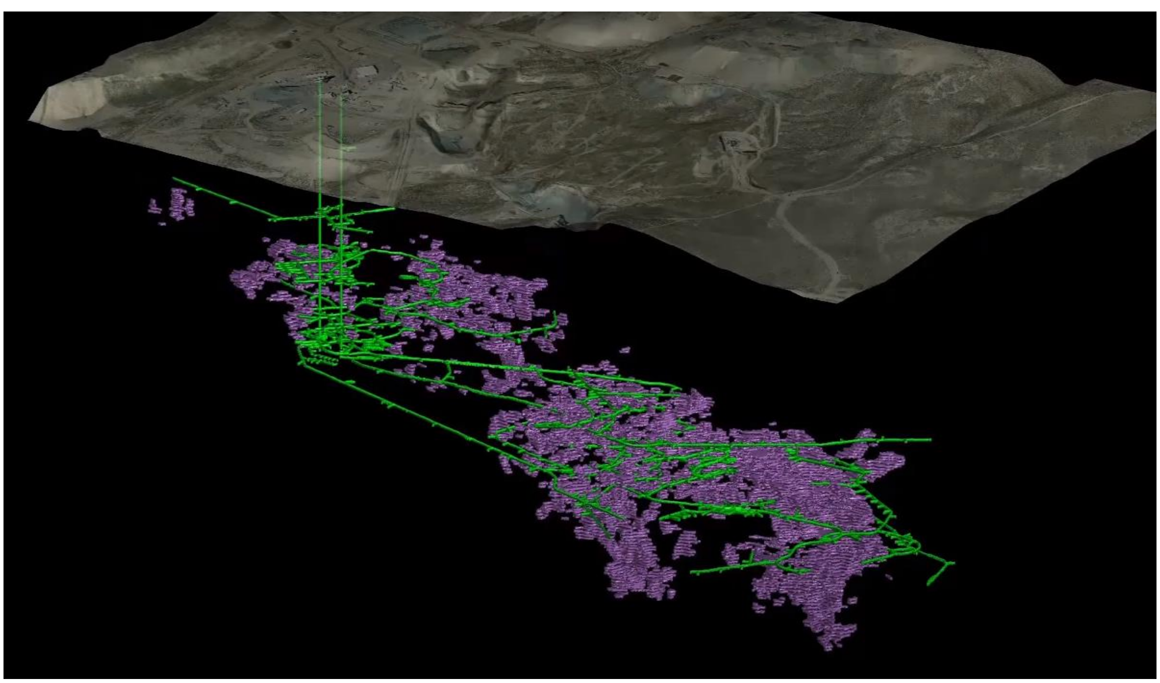

Figure 17 Drift Network with Mined-Out Stopes. Credit: Barrick Gold Corporation.

3.5.1 Basic Steps

The basic steps involved in the development of the model are shown in the flowchart below:

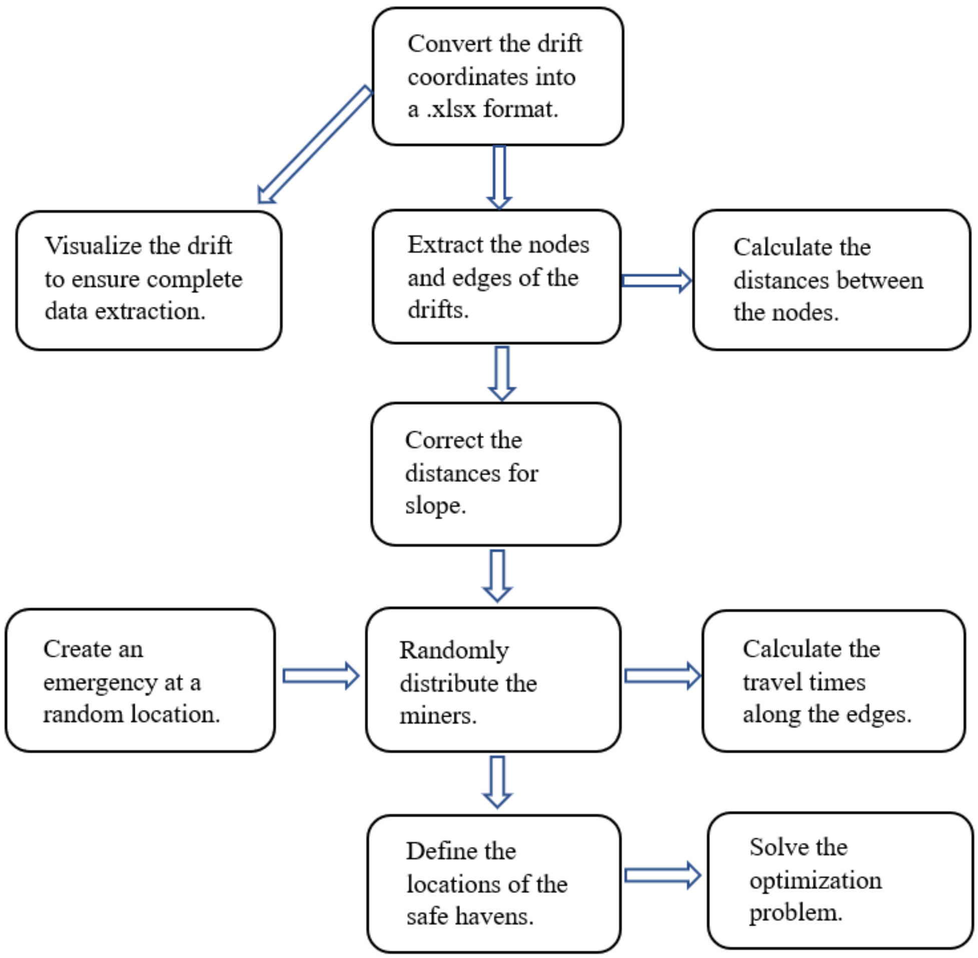

Figure 18 Flowchart Showing the Basic Steps of The Model Generation Process.

The drift data was extracted using a separate python script with the help of the 'ezdxf' python library. The drift data was obtained from the 'airlines' layer of the .dxf file. One unit of distance in the .dxf file equalled one meter.

The model was built upon the initial work of (Meij, 2020), who developed an integer program for the MCNF evacuation problem where miners are evacuated by foot and the objective was to minimize the total distance travelled by all miners during the evacuation.

The *'define_nodes'* function in the script was used to extract the drift nodes from the .xlsx file. The *'define_edges'* function then generates the feasible node combinations for the drift edges within the network. The function works by iterating through the end nodes and appending nodes which have not yet been accounted for in the list of nodes after the initial sweep of the start nodes of an edge. Integer indexes were assigned to each node for use in the model. This was done to avoid the use of floating-point numbers within the variable and parameter generation processes.

The distances along the edges were then calculated. Varying elevations of the nodes within the drift network required a correction of the distances by the slope of the edges between the nodes. The correction factor, according to (Meij, 2020), is defined below:

$$k = \frac{m * g * v * sin\theta}{P} + cos\theta$$

Where:

- k is the correction factor.
- m is the mass of a miner.
- g is the gravitational constant (9.81m/s^2).
- v is the walking velocity (1.35m/s).
- θ is the slope angle of the edge.
- P is the walking power of a miner (200W).

The corrections were applied to inclines (upward dipping slopes). Downward dipping edges were kept at the original lengths. This thesis assumes the mine already has an effective indoor positioning system where the real-life location coordinates of each individual and vehicle can be obtained. The application of these systems within the mine is beyond the scope of the thesis.

For the first model involving foot evacuation with no stamina ratings, the nodes and edges were extracted as described above. The corrected distances for the edges were then divided by the average walking speed, which was taken to be 1.35m/s, to find the time it takes to traverse the edge on foot. These times represented the cost associated with utilizing the various edges during evacuation.

The random distribution of the miners was achieved via the ‘random’ module. A random edge within the network is selected for each miner. The miner is then positioned at any location within the selected edge. A temporary node is created to represent the miner, and temporary edges are created to connect the miner to the closest nodes within the drift network. The exact locations and edge weights for all the miners are then extracted and stored in a list.

Different trigger events, as discussed in Chapter 2.3 above, will require evacuation of the mine. For this thesis, a fire emergency is simulated at a random location within the mine network. A random edge within the drift network is selected as the potential location of the fire. The actual fire can be located anywhere along this edge. The exact location of the fire is represented by a node. Edges within the vicinity of the fire emergency are removed from the drift network to prevent miners from accessing the potentially dangerous areas during evacuation.

The locations of the shafts and refuge chambers were then defined. The safe havens were represented by nodes, and the indexes of these nodes were extracted and stored in a list. These represent the final destinations of the miners during the evacuation. The distribution of the refuge chambers and the shaft nodes are shown in Figure 19 and Figure 20 below. The shafts were assigned a net demand (capacity) of 1000 miners since they serve as primary egress and many miners can be evacuated from the mine upon arriving at the shaft collars. The refuge chambers were assumed to have a capacity of 30 miners, in line with the specifications of the MineSAFE Essential Design Cost Effective Refuge Chamber and considering the size of the mine and the number of people within the mine.

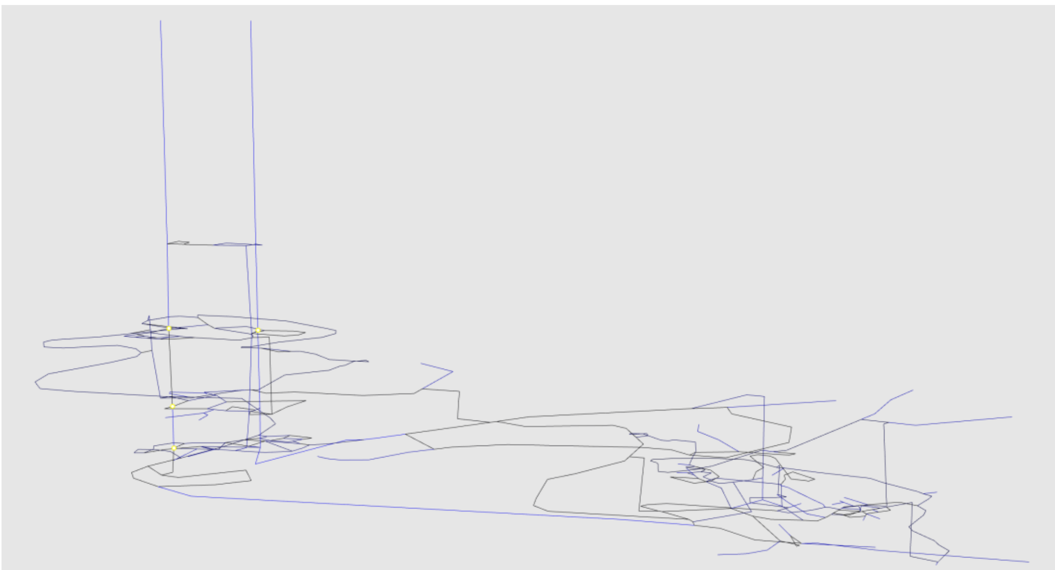

Figure 19 Shaft Access Nodes Shown as Yellow-Colored Points.

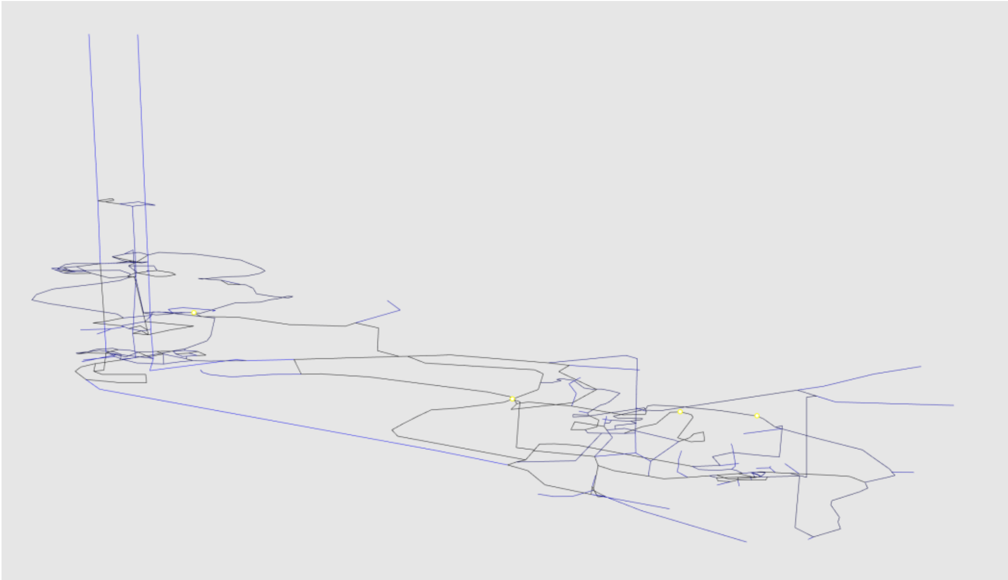

Figure 20 Refuge Chamber Nodes Shown as Yellow-Colored Points (Side View).

Figure 21 Refuge Chamber Nodes Shown as Yellow-Colored Points (Plan View).

A concrete model for the problem was then scripted using the ‘ConcreteModel’ function available in the Pyomo library. The sets, parameters and decision variables were then defined. The GUROBI solver was then called using the ‘SolverFactory’ module to solve the evacuation instance. The results from the solved model were then extracted and analysed. The results are discussed beginning from Chapter 4.1 of this document.

The same process was used for the models in which the stamina of the miners were accounted for. However, with these models, stamina ratings of 0.8 and 1.0 were assigned to the miners randomly to simulate varying levels of fitness at the time of evacuation. A miner with a stamina rating of 1.0 is considered fit, and hence no adjustments are made for the edges along which he/she travels. However, a miner with a stamina rating of 0.8 is assumed to be less fit, hence the edge costs are adjusted by dividing the edge length by the stamina rating. This step artificially lengthens the edge length for the miner with the intention of the solver prioritizing the miner during the evacuation.

The IP models discussed in this thesis follows this format. However, each edge is assigned two weights. The first weight is assigned to a miner who traverses a given edge by foot, while the second weight is assigned to a miner who traverses the edge via vehicle. The routes along which the vehicles can traverse were enumerated beforehand. Three distinct routes were enumerated for the purpose of the study. Two routes connected the bottom levels of the mine to the upper levels and the shafts whiles one route connected the upper levels to the shafts. The nodes along the three routes are shown in Figure 22, Figure 23 and Figure 24 below.

Figure 22 Nodes Along Route 0 (Shown as Yellow Points).

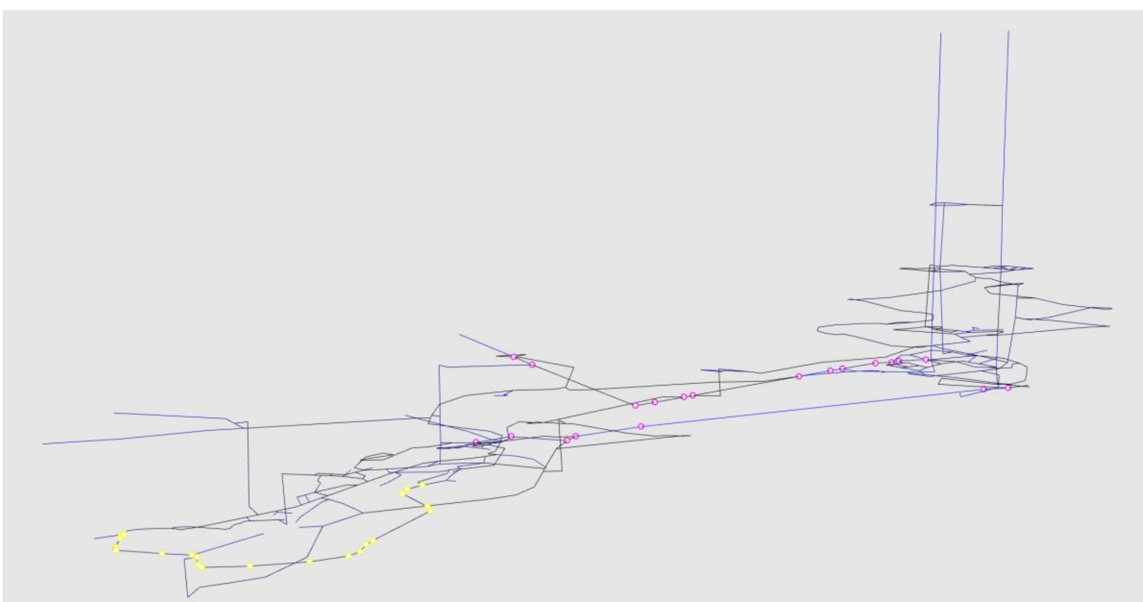

Figure 23 Nodes Along Route 1 (Shown as Yellow Points).

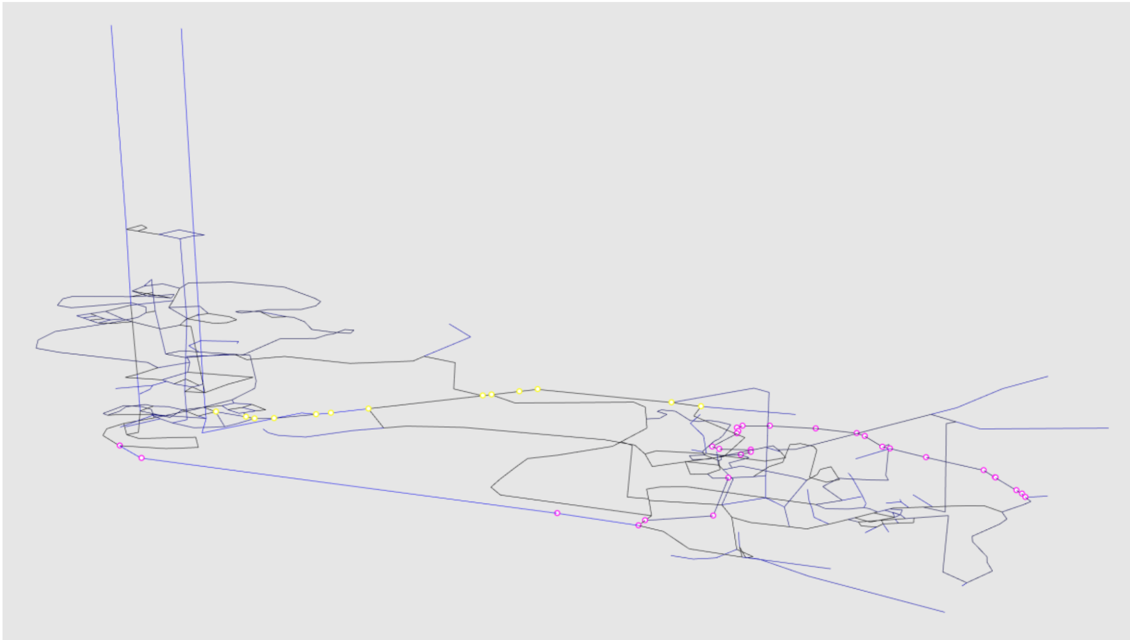

Figure 24 Nodes Along Route 2 (Shown as Yellow Points).

3.5.2 Timing of the algorithms.

The four scripts were timed with the help of the 'timeit' library in python. The start of the timer was set right before the generation of the components of the model. The timer ends immediately after an optimal solution is found. This was done to compare the running times of the various algorithms to better understand the influence of the various factors and scenarios. The start and the end positions of the timer may be altered depending on the period within which a reader may be interested in and the components under consideration. The reader should be aware of the factors influencing the running times to better understand the results presented, beginning from Chapter 4.1.

3.5.3 Description of the models.

A standard MCNF model was used as a benchmark for comparison of the results obtained from the IP formulation. The structure of the MCNF model is described below:

Table 4 Sets Required for The Benchmark MCNF Model.

Sets	
Symbol	**Definition**
ORIGINS	origins
DESTINATIONS	destinations
NODES	nodes (origins, destinations, transhipment)
ARCS	set of arcs *(i, j)*, i.e., feasible *I* x *J* combinations

Table 5 Parameters Required for The Benchmark MCNF Model.

Parameters		
Symbol	**Definition**	**Units**
$netDemand_i$	net demand at node *i*	number of people
$cost_{ij}$	travel-time for arc (*i, j*)	minutes

Table 6 Decision Variables for The Benchmark MCNF Model.

Variables		
Symbol	**Definition**	**Units**
x_{ij}	evacuees traversing arc *(i, j)*	number of people

$$min \sum_{(i,j)\in Arcs} cost_{ij} * x_{ij} \tag{1}$$

$$subject\ to \sum_{(k,i)\in Arcs} x_{ki} - \sum_{(i,j)\in Arcs} x_{ij} = netdemand_i \quad \forall\ i\ \in NODES \tag{2}$$

$$x_{ij} \geq 0 \quad \forall\ (i,j) \in ARCS \tag{3}$$

The objective function (1) minimizes the travel time for all evacuees. Constraints (2) ensure flow balance at each generic node i. These are sufficiently general to include origins from which miners are fleeing, transshipment nodes (where there is no supply of or demand for miners), and refuge chambers. Constraint (3) ensures the non-negativity constraints for the decision variables.

This formulation serves as the backbone for the first two models involving evacuation solely by foot. The results are presented in Chapter 4.1 and Chapter 4.2. The running times and the total evacuation costs are also discussed. Also, the distribution of the miners to the safe havens, that is, the refuge chambers and the shafts, is analyzed.

CHAPTER 4 : RESULTS

This chapter presents an overview of the results obtained from the four different scenarios with three simulations of miner distributions (number of miners) each. The four scenarios are:

- Scenario 1: This scenario involves evacuating miners solely by foot and without the application of stamina ratings to the miners.
- Scenario 2: This scenario involves evacuating miners by foot and adjusting the edge lengths to account for the stamina ratings of the miners.
- Scenario 3: This scenario involves evacuating miners via a combination of foot and vehicle modes (IP) without the application of stamina ratings.
- Scenario 4: This scenario involves evacuating miners via a combination of foot and vehicle modes (IP) and with the application of stamina ratings for the miners.

Three simulations involving 100, 200 and 300 miners were tested for each scenario. The locations of the refuge chambers and shaft accesses were unchanged for all four scenarios. A single fire emergency was used for all the scenarios. The routes enumerated were kept the same for scenarios 3 and 4. A total of 12 different simulations were run for this thesis.

The distribution of the miners to the various safe havens will first be reviewed and presented. Four refuge chambers, situated at nodes 156, 198, 305 and 348 were utilized with four shaft accesses located at nodes 28, 69, 73 and 74. The total evacuation cost, which is a function of the travel times will then be presented. The total evacuation cost is the cumulative travel time for all miners during the evacuation. Minimizing the cumulative travel time enables comparisons to be drawn with the benchmark Minimum Cost Network Flow (MCNF) formulation. Finally, the solver run times will be analysed and comparisons will be drawn between the scenarios.

4.1 Scenario 1

This scenario, as described above involves miner evacuation by foot with no stamina ratings applied. No corrections were applied to the edge lengths besides the slope corrections.

4.1.1 Division of Miners Among Safe Havens

Table 7 shows the distribution of miners to the refuge chambers and shaft accesses for the three different simulations of the number of miners present at the time of the evacuation.

Table 7 Distribution of Miners to Safe Havens (Scenario 1).

Safe Haven	**100**	**200**	**300**
Shaft 28	15	30	113
Shaft 69	9	22	29
Shaft 73	6	12	16
Shaft 74	11	17	22
Chamber 156	16	30	30
Chamber 198	6	29	30
Chamber 305	20	30	30
Chamber 348	17	30	30
Total	**100**	**200**	**300**

From the distribution table, it can be observed that as the number of miners increased from 100 to 200, the refuge chambers were prioritized and filled before miners were sent out to the shaft accesses. This minimizes the movement of miners to ensure that an optimal evacuation time is achieved.

For the simulation with 100 miners, the variability in the number of miners within the refuge chambers is due to the proximity of the miners to the various refuge chambers. The miners closest to the shaft accesses were sent there and not to refuge chambers even though the chambers were not filled.

4.1.2 Evacuation Cost

The evacuation cost, which is a function of the travel times for all the miners during the evacuation is presented in Figure 25 below.

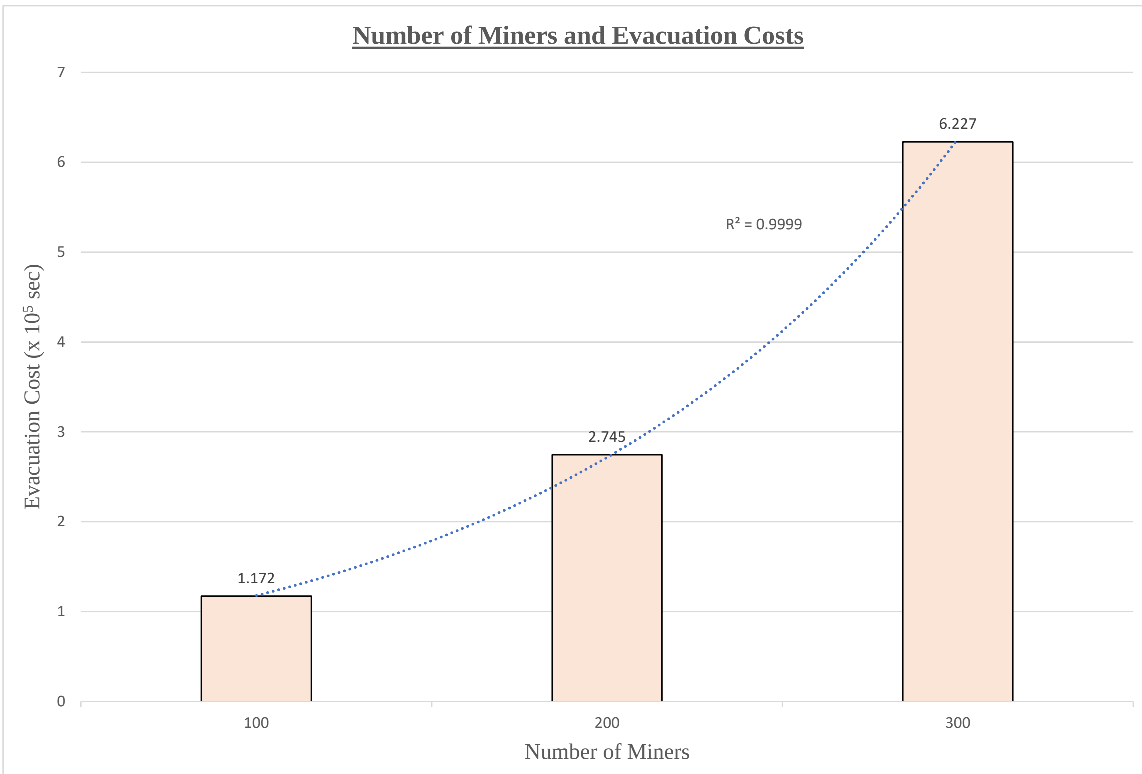

Figure 25 Number of Miners and The Evacuation Costs (Scenario 1).

The evacuation cost grew exponentially as the number of miners increased. This result augers well with those obtained by (Meij, 2020) in his simulations. The more miners present in the mine, the longer it will take to get every miner to a safe haven. It is expected, for a mine of this size, that miners at the bottom levels travel several kilometers to the shafts if the refuge chambers cannot accommodate them at the time of evacuation.

4.1.3 Running Times

A comparison of the time taken to create all the model components and find an optimal solution to the problem for the various simulations is shown in Figure 26 below.

Figure 26 Number of Miners and The Solver Run Times (Scenario 1).

The solver times increased linearly with increasing number of miners. All the simulations took less than three seconds to return an optimal solution. This means that, within three seconds, the optimal routing of each miner can be obtained for evacuation purposes.

4.2 Scenario 2

This scenario involved running the simulations on a model in which the miners evacuate by foot, with stamina ratings applied to each miner. The stamina ratings are applied to the edges to increase the weights of the edges along which the weaker miners travel. The edge weights are kept the same for fit miners.

4.2.1 Division of Miners Among Safe Havens

Table 8 below shows the distribution of miners to the refuge chambers and shaft accesses for the three different simulations of the number of miners present at the time of the evacuation.

Table 8 Distribution of Miners to Safe Havens (Scenario 2).

Safe Haven	**100**	**200**	**300**
Shaft 28	20	30	113
Shaft 69	8	22	29
Shaft 73	2	12	16
Shaft 74	5	17	22
Chamber 156	20	30	30
Chamber 198	6	29	30
Chamber 305	24	30	30
Chamber 348	15	30	30
Total	**100**	**200**	**300**

For the simulation with 100 miners, the distribution of miners changed, showing the influence of the stamina ratings on the optimized solution. However, for 200 and 300 miners, the distribution of miners among the safe havens remained unchanged. This is due to the filling up of the refuge chambers to capacity, resulting in the remaining miners being sent directly to the shafts. Miners with lower stamina ratings were prioritized for filling up the refuge chambers while fit miners were sent to the shafts.

4.2.2 Evacuation Cost

The evacuation cost, which is a function of the travel times for all the miners during the evacuation is presented in Figure 27 below.

Figure 27 Number of Miners and The Evacuation Costs (Scenario 2).

The evacuation costs in this scenario exceeded those without stamina ratings for all three simulations. The presence of larger weights on some edges due to the weaker miners increased the cost of traversing those edges resulting in higher total evacuation costs.

This demonstrates the assertion made concerning the distribution of miners for the 200 and 300 miners simulations. Even though the number of miners sent to each safe haven remained the same, the total evacuation costs increased due to the presence of weaker miners.

4.2.3 Running Times

A comparison of the time taken to create all the model components and find an optimal solution to the problem for the three simulations in this scenario is shown in Figure 28 below.

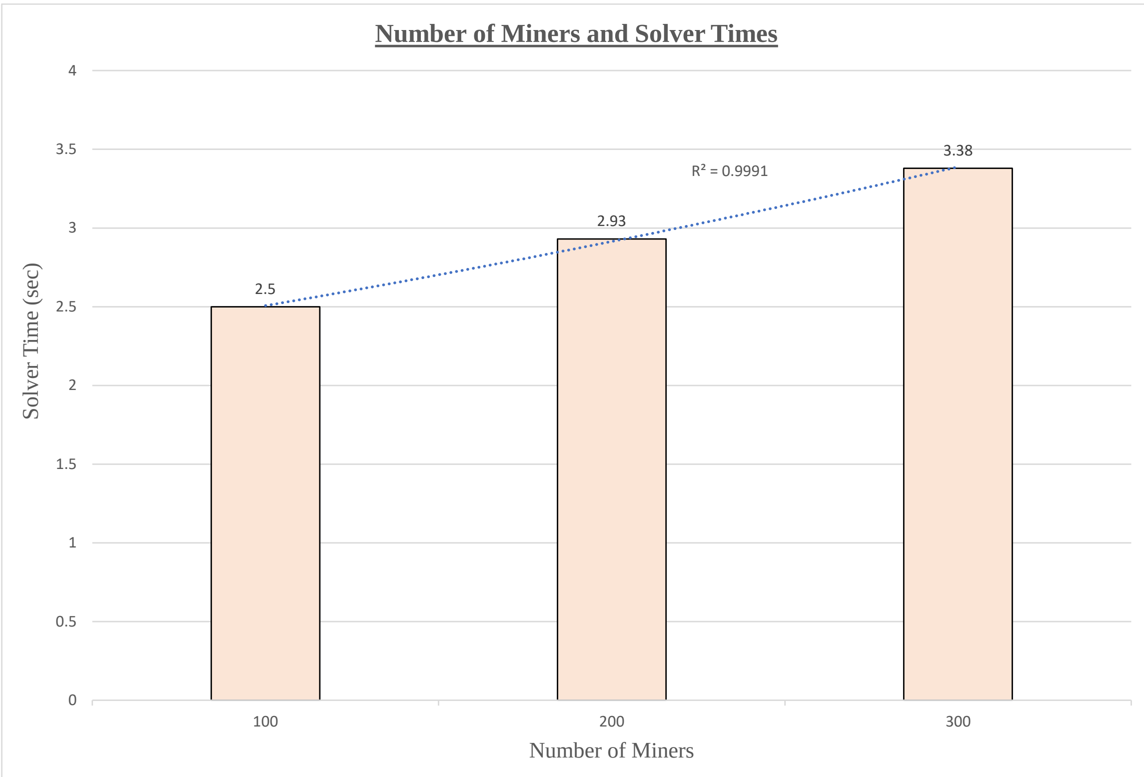

Figure 28 Number of Miners and The Solver Run Times (Scenario 2).

The solver run times increased linearly with increasing number of miners as before. However, the times were higher for all three simulations. This is due to the increased number of edges accounting for the different stamina ratings. The increased number of edges resulted in an increase in the number of decision variables and constraints, hence increasing the time required to arrive at an optimal solution.

4.3 Scenario 3

This scenario implements the IP formulation of the thesis and considers both foot and vehicle modes of evacuation. Three different routes were enumerated for the mine along which the vehicles can traverse. No stamina ratings were applied for the miners. Both the vehicle capacities and the number of available vehicles were kept constant.

4.3.1 Division of Miners Among Safe Havens

Table 9 below shows the distribution of the miners to the refuge chambers and shaft accesses for the three different simulations.

Table 9 Distribution of Miners to Safe Havens (Scenario 3).

Safe Haven	**100**	**200**	**300**
Shaft 28	18	37	113
Shaft 69	9	22	29
Shaft 73	6	12	16
Shaft 74	10	17	22
Chamber 156	17	30	30
Chamber 198	6	22	30
Chamber 305	20	30	30
Chamber 348	14	30	30
Number of vehicles	5	5	5
Vehicle capacity	4	4	4
Total # of miners	**100**	**200**	**300**

The five vehicles aided with the evacuation of miners to both the refuge chambers and the shaft accesses. The starting and ending points of the routes were selected such that a vehicle drops off the miners either at a safe haven or a short distance from the safe haven, from which they can walk. For the simulation involving 100 miners, the optimal solution assigned one vehicle to route 0, three to route 1 and one to route 2. The same vehicle distribution was suggested for the simulation involving 200 miners. For 300 miners, two vehicles were assigned to route 0, one vehicle to route 1 and two vehicles to route 2.

The distribution of miners among the safe havens was different from the distributions obtained in scenarios 1 and 2 for both 100 and 200 miners. However, for 300 miners, the distribution of the miners remained the same.

4.3.2 Evacuation Cost

The evacuation cost, which is a function of the travel times for all the miners during the evacuation in scenario 3 is presented in Figure 29 below.

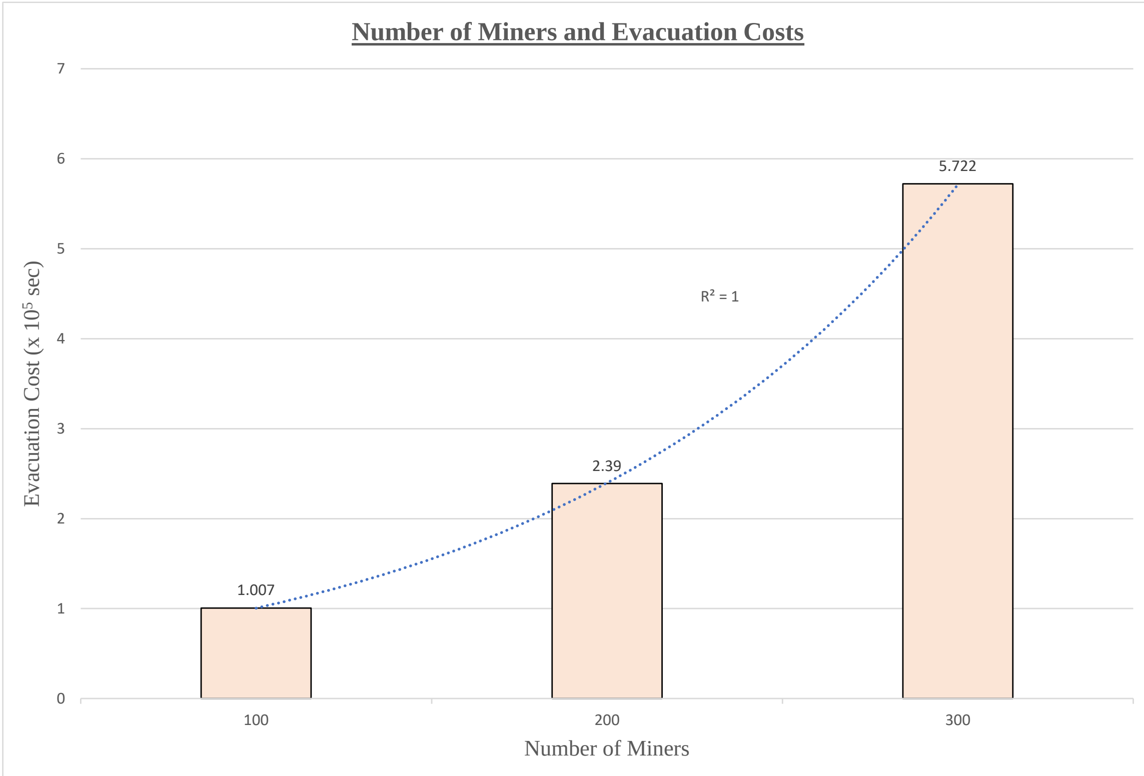

Figure 29 Number of Miners and The Evacuation Costs (Scenario 3).

The evacuation costs increased exponentially with increasing number of miners. However, the costs were significantly lower than those obtained from evacuating solely by foot (scenarios 1 and 2), especially for an increasing number of miners (300 miners). Though the distribution of miners to the safe havens remained the same for 300 miners, the significant decrease in evacuation time demonstrated the impact of the vehicles during the evacuation.

4.3.3 Running Times

A comparison of the time taken to create all the model components and find an optimal solution to the problem for the various simulations is shown in Figure 30 below.

Figure 30 Number of Miners and The Solver Run Times (Scenario 3).

The solver run times for all three simulations did not differ significantly from those obtained in scenario 2 (with stamina ratings). However, they were higher than those obtained from scenario 1. This is because of the additional decision variables and constraints catering for the number of vehicles and their routes. An optimal solution was still reached within four seconds for all three simulations.

4.4 Scenario 4

The final scenario involved implementing the IP formulation in conjunction with stamina ratings for the miners. The same routes used in scenario 3 were used in this scenario. The number of vehicles and their capacities were also maintained as before.

4.4.1 Division of Miners Among Safe Havens

Table 10 below shows the distribution of the miners to the refuge chambers and shaft accesses for the three different simulations at the time of the evacuation.

Table 10 Distribution of Miners to Safe Havens (Scenario 4).

Safe Haven	**100**	**200**	**300**
Shaft 28	20	50	121
Shaft 69	8	14	22
Shaft 73	2	10	18
Shaft 74	5	11	19
Chamber 156	20	30	30
Chamber 198	6	25	30
Chamber 305	26	30	30
Chamber 348	13	30	30
Number of vehicles	5	5	5
Vehicle capacity	4	4	4
Total # of miners	**100**	**200**	**300**

The distribution of the miners to the safe havens was different for all three simulations in comparison to the distributions in scenario 3. The effect of the stamina ratings of the miners on the distribution was evident. For 100 miners, all five vehicles were assigned to route 1. In the case of 200 miners, two vehicles were assigned to route 0, one vehicle to route 1 and two vehicles to route 2. The simulation involving 300 miners had a vehicle distribution like the case with 200 miners.

4.4.2 Evacuation Cost

The evacuation cost, which is a function of the travel times for all the miners during the evacuation is presented in Figure 31 below.

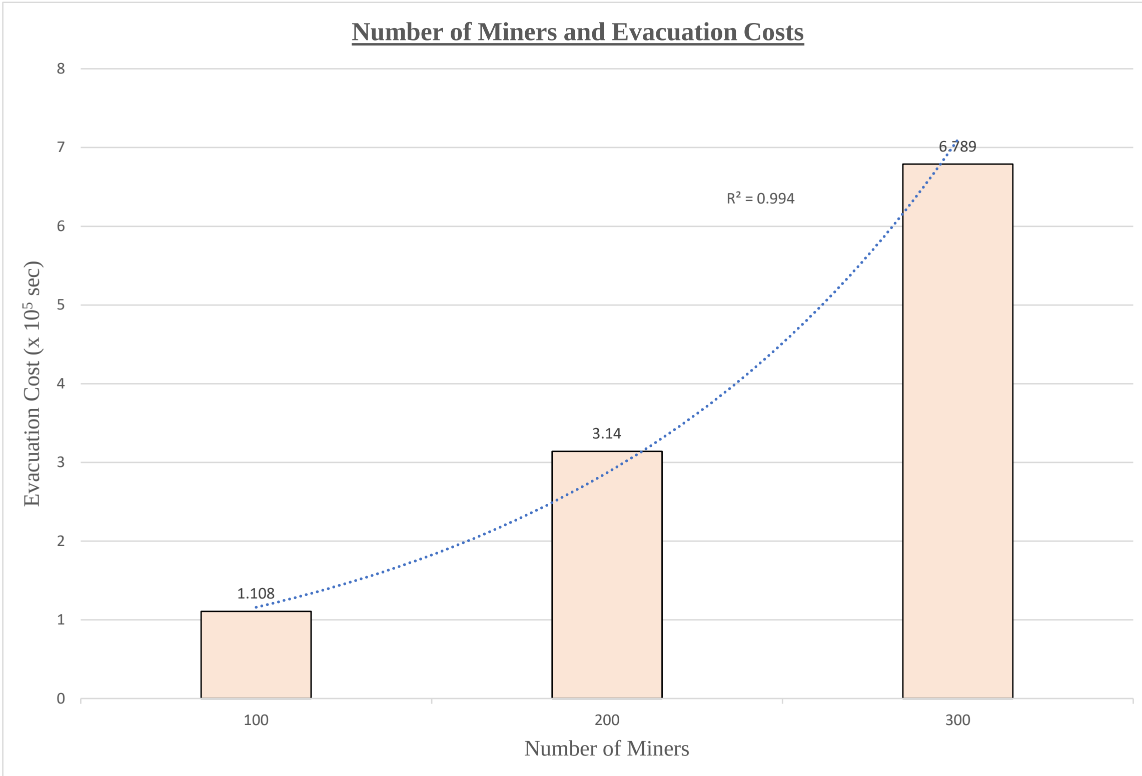

Figure 31 Number of Miners and The Evacuation Costs (Scenario 4).

The evacuation costs for all three simulations were higher than those from scenario 3 (without stamina ratings). The presence of longer edges, due to weaker miners, increased the evacuation costs. The evacuation costs increased exponentially, like the first three scenarios.

4.4.3 Running Times

A comparison of the time taken to create all the model components and find an optimal solution to the problem for all three scenarios is shown in Figure 32 below.

Figure 32 Number of Miners and The Solver Run Times (Scenario 4).

The solver run times for all three simulations were about 1.5 times higher than those obtained in scenario 3 (without stamina ratings). This is because of the additional decision variables and constraints for the weaker miners. An optimal solution was still reached within seven seconds for all three simulations.

4.5 Comparison Between Scenarios 1 and 3

The main objective of this thesis work is to compare the evacuation costs when vehicles are incorporated into the evacuation process (scenario 3), that is the IP formulation, to the evacuation cost of a MCNF (scenario 1) model where miners evacuate solely by foot.

Figure 33 below shows the differences in evacuation costs between the two scenarios for all three simulations.

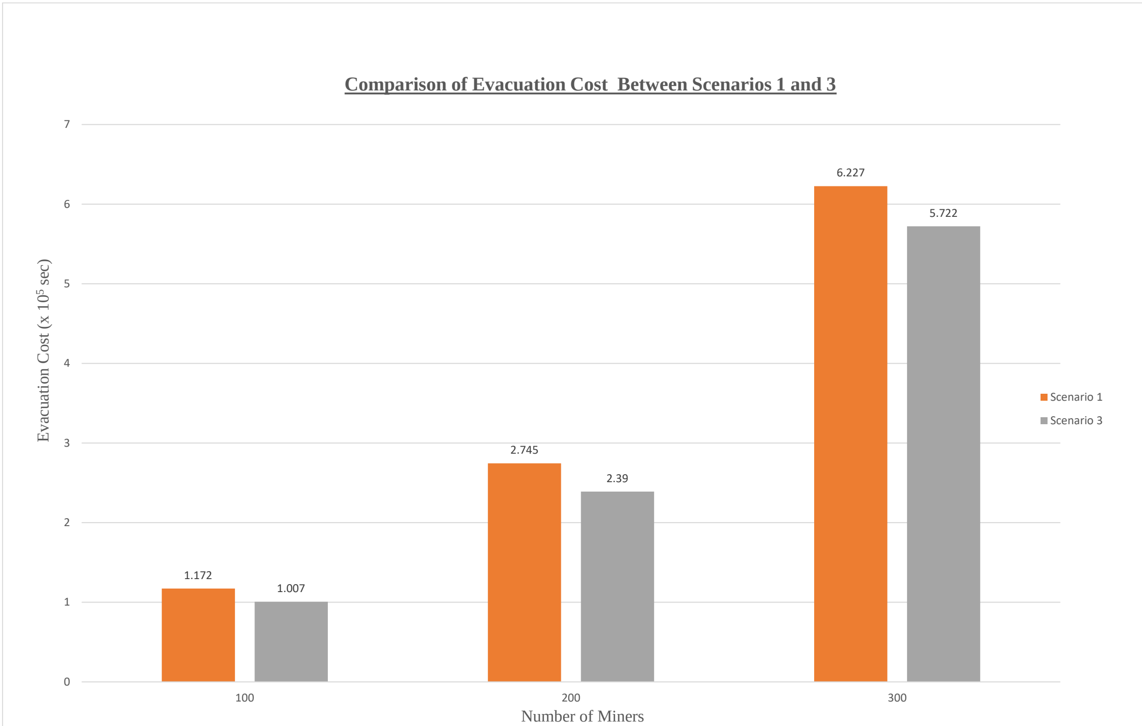

Figure 33 Comparison of Evacuation Cost Between Scenarios 1 and 3.

The evacuation costs for all three simulations in scenario 3, where vehicles were incorporated, were lower than the evacuation costs for evacuation solely by foot. The cost savings grew significantly with increasing number of miners. Figure 34 below shows the increase in evacuation cost savings with increasing number of miners when vehicles are optimally routed, and miners can evacuate using a combination of walking and vehicle modes.

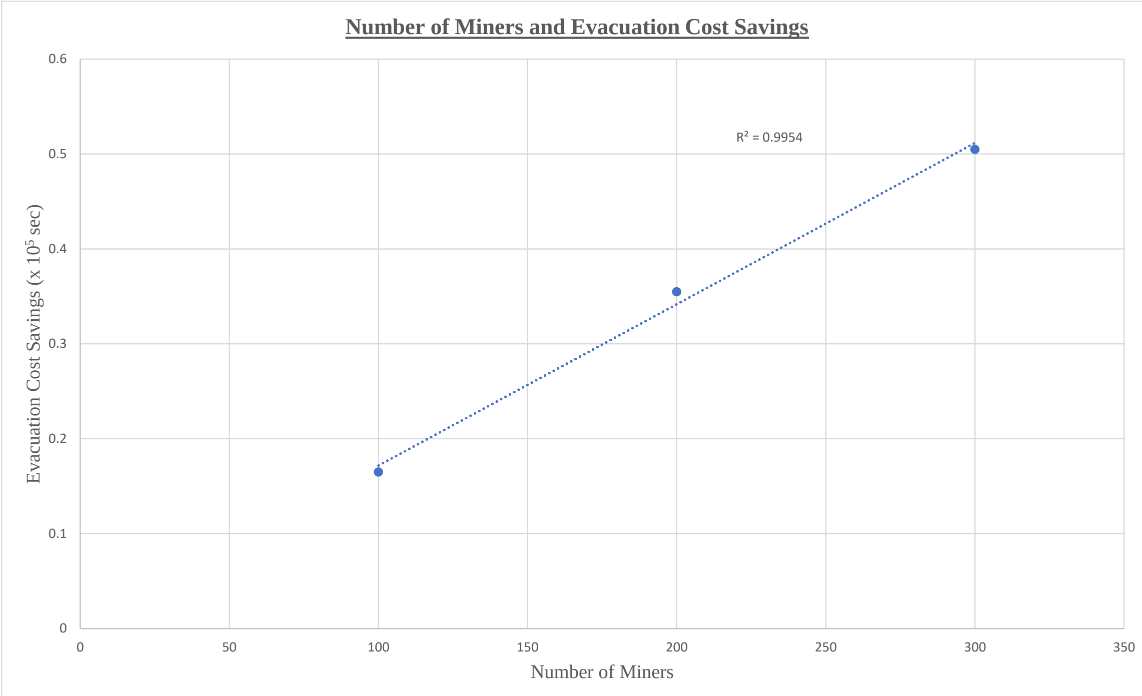

Figure 34 Number of Miners and Evacuation Cost Savings.

The evacuation cost savings increased linearly with an increase in the number of miners found underground at the time of evacuation.

The conclusions from this research and some proposed future work for implementing the IP formulation are discussed in the next chapter.

CHAPTER 5 : CONCLUSION AND DISCUSSION

An integer program was developed for this thesis to minimize the total evacuation time by incorporating available mine vehicles. The algorithm was implemented using the Turquoise Ridge Mine, an underground mine located in Nevada and owned by Nevada Gold Mines. Four different scripts, representing four scenarios, were developed. For each scenario, three different simulations of the number of miners present at the time of evacuation were run to determine the evacuation costs and the running times (computational efficiency) of the algorithm.

Shortest path algorithms such as Dijkstra's algorithm and Floyd-Warshall algorithm have been used to tackle the evacuation problem in the past. These algorithms were predominantly used to calculate the shortest paths each miner should take to reach a safe haven. The objective was to minimize the total distance travelled by all the miners during the evacuation. Ant colony algorithms and some genetic algorithms have also been used to tackle this problem, especially for large scale evacuations during natural disasters.

A MCNF model was developed by (Meij, 2020) with the objective of minimizing the total distance travelled during a mine evacuation process. Meij developed two scripts, the first being an optimization model where all miners evacuate by foot, and the edge weights were the distances between the connected nodes. The second script included the use of stamina categories, to rank the miners according to their stamina at the time of evacuation. Both models sought to minimize the total distance travelled from a dangerous area within the mine to a safe haven.

Four different algorithms were developed for this thesis work. In contrast to Meij's work, the IP formulation developed for this thesis had the objective of minimizing the total evacuation time, and not the total distance travelled. The first algorithm considered a case in which all the miners are required to evacuate solely by foot. The second algorithm included stamina ratings for each miner to differentiate between strong and weak miners at the time of evacuation. The third algorithm considered incorporating available mine vehicles at the time of evacuation. This algorithm is the main algorithm for this thesis work. The final algorithm involved the addition of stamina ratings to the IP model described in the third algorithm.

The goal of this thesis work was to determine if incorporating the available mine vehicles into the evacuation process can significantly minimize the total evacuation time. This was achieved by comparing scenario 1 (evacuation solely by foot), and scenario 3 (evacuating using a combination of foot and vehicle modes). Scenarios 2 and 4 were developed to study the impact of the miners' stamina on the total evacuation time. However, these scenarios were not the primary objective of this thesis work.

The travel times were used as the edge weights in this thesis work. These times were obtained by dividing the distance between the nodes (length of edges) by the travel speed. For foot evacuation, an average walking speed of 1.35 m/s was used. A speed of 8.35 m/s was used as the average driving speed of the vehicles during the evacuation. Five vehicles were used for the scenarios involving vehicles. This number was chosen to represent a lower bound on the number of vehicles available in a mine of this size. Three routes were enumerated for the mine. These routes were enumerated such that miners on all levels have a chance of joining a vehicle at some point during the evacuation. The random seed function in python was used to keep the random distribution of the miners constant for every run of the script to ensure that the results of the optimization can be replicated.

The evacuation costs increased exponentially with increasing number of miners for all the four scenarios. However, comparing scenarios 1 and 3, as shown in Figure 33 above, the evacuation costs were lower in all three simulations for scenario 3. Figure 34 shows that as the number of miners increased, the savings in evacuation time increased linearly when the vehicles were incorporated.

This shows that, incorporating mine vehicles in the evacuation process drastically minimizes the total evacuation time. The impact of the vehicles becomes paramount as the number of people that need to be evacuated increases. As underground mines continue to expand and get deeper, more miners may be required to work on the different mine levels and to keep up with the production requirements. Also, advancements of development headings will increase the distances the miners are required to cover during an emergency. The mine vehicles will go a long way in minimizing the total time required to evacuate the miners through optimal routing and higher travel speeds.

The scenarios in this thesis were formulated as single-period problems where an emergency occurs, and all the miners must get to a safe haven as quickly as possible. The total evacuations costs can be further minimized by re-running the script at regular intervals to simulate the movement of the vehicles from a start point to an end point on a given route and getting back to the starting points to pick up more miners along the routes.

The addition of stamina ratings in scenarios 2 and 4, increased the evacuation costs. However, the cost savings ratios were preserved. For future work, more research should be conducted in stamina ratings by determining the factors such as heart rates which will influence the ratings applied to the individual miners. A combination of different health parameters that can be quantified, may be incorporated into a function that determines the rating to be applied for each miner at the time of evacuation.

Also, the IP model may be introduced into software that run on smart devices in future research. This will enable real-time implementation of the algorithm through miner location-tracking and allow for further modifications of the algorithm to improve performance. The system may then be tested in underground mines which have effective indoor positioning systems to validate its performance and to seek more inputs that may be required for the specific mine sites.

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SOURCE CODES

The algorithms (scripts) used in this thesis work can be found using the links below in GitHub.

- Algorithm for mine evacuation without vehicles nor stamina ratings.
- Algorithm for mine evacuation without vehicles but with stamina ratings.
- Algorithm for mine evacuation with vehicles but no stamina ratings.
- Algorithm for mine evacuation with vehicles and stamina ratings.