DEVELOPMENT OF A NEW METHODOLOGY FOR PATH OPTIMIZATION OF UNDERGROUND MINE HAUL ROADS USING EVOLUTIONARY ALGORITHMS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

AHMET GÜNEŞ YARDIMCI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
MINING ENGINEERING

MARCH 2018

Approval of the thesis:

DEVELOPMENT OF A NEW METHODOLOGY FOR PATH OPTIMIZATION OF UNDERGROUND MINE HAUL ROADS USING EVOLUTIONARY ALGORITHMS

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ABSTRACT

DEVELOPMENT OF A NEW METHODOLOGY FOR PATH OPTIMIZATION OF UNDERGROUND MINE HAUL ROADS USING EVOLUTIONARY ALGORITHMS

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March 2018, 129 pages

The main haul road serves as an access route for men, equipment, transportation of extracted ore and ventilation air in underground mines. Initial capital investment and operating cost parameters are affected by the haul road path. However, the most common method to design a main haul road is to rely on the provisions of skilled mine design experts. Contrary to the simple underground mine layouts, determination of the optimum path without violating navigability constraints in complex underground networks may exceed the limit of human intelligence. Obviously, a new methodology is required to obtain the shortest mine haul road that satisfy the minimum turning radius and maximum gradient constraints. It is also useful to avoid some structural defect zones (like faults, joints) or any kind of undesired regions. In addition to the path length minimization, rock mass quality should also be optimized for increasing safety and decreasing tunnel support costs. This study aims to provide an algorithmic solution to one of the major design problems in underground mine planning. In the first stage, the shortest path optimization is adapted to this specific mining problem. Conventional methods are investigated and an improved solution mechanism is established using evolutionary algorithms. In the second stage, path length and the rock mass quality covering the haul road are optimized by a multi objective optimization. Developed algorithms are verified on simple benchmark problems. Finally, algorithmic designs are compared to the designs of human experts on actively operating underground mines. Advantages of evolutionary algorithms are shown.

Keywords: Haul Road Design, Path planning, Optimization, Evolutionary Algorithms

ÖZ

YERALTI MADENLERİNDE ANA NAKLİYE YOLU GÜZERGÂHININ OPTİMİZE EDİLMESİ MAKSADIYLA EVRİMLEŞEN ALGORİTMALARA DAYALI YENİ BİR METODOLOJİ GELİŞTİRİLMESİ

Yardımcı, Ahmet Güneş
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Tez Yöneticisi: Prof. Dr. Celal Karpuz

Mart 2018, 129 sayfa

Yeraltı madenlerinde ana nakliye yolu, personel, ekipmanlar, üretilen cevher ve hava için erişim güzergâhı olarak görev yapar. Ana nakliye yolu güzergâhı, ilk yatırım maliyeti ve işletme maliyeti parametrelerini kontrol etmektedir. Önemine rağmen bir ana nakliye yolu tasarımı yapmanın en yaygın yolu deneyimli maden tasarım uzmanlarının öngörülerine güvenmektir. Basit yeraltı maden planlarının aksine karmaşık yeraltı madeni planlarında seyir edebilirlik kısıtlamalarını ihlal etmeyen optimum güzergahın belirlenmesi insanın düşünsel kapasitesini aşabilmektedir. Açıkça bellidir ki en küçük dönüş yarıçapı ve en büyük yol eğimi kısıtlamalarını sağlayan ve en kısa ana nakliye yolu güzergahını belirlemede kullanılacak yeni bir metodolojiye ihtiyaç vardır. Ayrıca, yapısal olarak bozuk bölgelerden (fay, eklem gibi) veya herhangi bir istenmeyen bölgeden kaçınmak faydalı olabilir. Güzergah uzunluğu minimizasyonuna ek olarak, güvenliği artırmak ve tünel tahkimat maliyetlerini düşürmek maksadıyla kaya kütlesi kalitesi de optimize edilmelidir. Bu çalışma, yeraltı maden planlamasındaki önemli bir tasarım sorununa algoritmik bir çözüm getirmeyi amaçlamaktadır. İlk aşamada, en kısa yol optimizasyonu bu spesifik madencilik problemine uyarlanmıştır. Geleneksel yöntemler incelenmiş ve evrimleşen algoritmalar kullanılarak iyileştirilmiş bir çözüm mekanizması geliştirilmiştir. İkinci

aşamada güzergah mesafesi ve nakliye yolunu çevreleyen kaya kütle kalitesi çok amaçlı optimizasyon yöntemiyle optimize edilmiştir. Geliştirilen algoritmalar basit kıyaslama problemleri ile kontrol edilmiştir. Son olarak, algoritmik tasarımlar ile insan uzmanların halihazırda aktif olarak işleyen yeraltı madenleri için hazırladığı tasarımlar kıyaslanmıştır. Evrimleşen algoritmaların faydaları gösterilmiştir.

Anahtar Kelimeler: Nakliye Yolu Tasarımı, Rota Planlama, Optimizasyon, Evrimsel Algoritma

This dissertation is dedicated to my beloved family and my love

ACKNOWLEDGMENTS

First of all, I would like to thank my supervisor Professor Dr. Celal Karpuz for being a tremendous mentor. His encouraging attitude to work on novel research topics has been the main inspiration of this study.

I would like to express my sincere thanks to Prof. Dr. Kemal Leblebicioglu for his invaluable guidance. His insightful academic advices and continuous support has always been a motivation for me.

I would like to give my special thanks to Assoc. Prof. Dr. Mehmet Ali Hindistan and Assoc. Prof. Dr. Hasan Öztürk for their brilliant comments and suggestions during the thesis advisory meetings.

I would also like to thank my thesis defense committee members, Prof. Dr. A. Erhan Tercan, Assoc. Prof. Dr. Mehmet Ali Hindistan, Assoc. Prof. Dr. Hasan Öztürk and Asst. Prof. Dr. Mustafa Erkayaoğlu for letting my defense be an enjoyable moment, and for their wonderful comments and suggestions, thanks to you.

Asst. Prof. Dr. Mustafa Erkayaoğlu has never hesitate to provide his kind support and guidance. I appreciate his tremendously generous attitude for sharing his knowledge and providing the data required in the case studies. Thank you.

I would like to thank my friends and colleagues Onur Gölbaşı and Doğukan Güner for their precious supports and encouragement.

I am also thankful to my family. Words cannot express how grateful I am to my mother İlfer Yardımcı, my father Erol Engin Yardımcı and my sister Merve Yağmur Yardımcı. I am lucky to have such a great family.

Last but not least, I would like to give my special thanks to the woman, who own my heart. Ceren, your smile makes me happy and your love fulfills me.

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CHAPTER 1

INTRODUCTION

The demand for raw materials increased worldwide due to the improvements in industry. Since the last century, shallow ore bodies have been a major source of raw material with the advantage of low production cost and operational simplicity. Although today's technology allows for ore extraction from deeper open pit mines, physical and economical conditions limit the feasible depth. Apparently, deep ore bodies extracted by underground mining methods will play a more dominant role in the future by supplying required raw materials to the society.

There are two common methods to access deeply lying underground orebodies and to transport the extracted material. The first one is a vertical shaft, which connects the topographical surface to the underground production levels by a vertical excavation. Vertical shafts have the advantage of connecting production levels with the shortest path. Although the amount of excavation is decreased, a vertical shaft is still difficult to excavate. In addition, the ore production rate is limited by the capacity of the shaft. The alternative method connects the underground production levels by a system of declines and helical ramps with a gentle slope. This method allows more mechanization to be implemented. Compared to the vertical shafts, bulk production increases ore production rates. Therefore, decline/ramp system is the first choice of any mine design expert, where it is applicable.

In decline/ramp system, ore and waste rock transportation shares the vast majority of operating cost in an underground mine. The fuel consumption of haul trucks is one of the long term cost items. Another one is the excavation cost. Not only the monetary cost but also the time required to complete the excavation is also critical. All of these cost items are directly related to the haul road length, which makes it a critical parameter to be optimized.

Decline/ramp is a permanent opening in which safety is a vital asset. In order to reduce support cost, rock mass hosting the haul road needs to be optimized.

Briefly, an ideal underground mine haul road is expected to connect the topographical surface to the underground production levels with the optimum path. Optimality is defined in terms of the path length and the host rock mass quality.

Optimization is still a primary research topic among the mining society. Decrease in commodity prices has revealed the importance of initial and operational cost minimization and profit maximization. Compared to the extensive research on open pit mine optimization, there are limited attempts for underground mines. Brazil et.al. [1] asserts that the complex topology of underground mines contributes to the limited interest of researchers. Optimization in open pit mines majorly focuses on the production and scheduling. Recently, some researchers have studied stope optimization in underground mines. However, there is limited work on the optimization of underground mine topology. As an early attempt, Lee [2] investigated underground network optimization. Later, Brazil et al. [3] proposed a decline optimization tool. Underground mine haul roads are constrained by the navigability limitations (minimum turning radius and maximum gradient) of the underground mining equipment. Gradient constrained paths for underground haul roads have long been investigated by researchers [4].

In this study, a new methodology is proposed for the underground mine haul road design. Compared to the previous research, our solution mechanism makes use of evolutionary algorithms in order to minimize the path length. This novelty provides the computational efficiency. Another research outcome is special mutation operators those are developed for avoiding undesired regions or strictly passing inside the desired regions. In this way, the road is kept safely away from buffer zones, discontinuities, or aquifers. In addition, the road can be planned strictly inside the region of interest. None of the previous studies consider the rock mass quality while searching for a suitable path. In this study, we make multi objective optimization for to determine the minimum length road that is driven inside the maximum possible rock mass quality. Finally, the developed methodology is embedded onto a software.

1.1 Problem Statement

Conventional approaches in underground mine design are still not transformed by the fast paced technological advances of the information age. Although Computer Aided Design (CAD) has replaced the traditional routines, design is still practiced by engineers. CAD saves the time required to complete a design task and it has operational benefits. However, it is not capable of testing the design optimality. Excluding the limited research on optimum stope dimensioning, underground mine design is still a challenging human task. For instance, main haul roads are manually designed by skilled mine design specialists. The output is most likely to be a subjective design controlled by the operator's judgment and experience. For a simple underground mine layout, optimum design would not be hard to guess for a human operator. However, complex layouts might challenge the human cognitive capacity.

Recently, there have been some pioneering studies on the haul road optimization algorithms. The common method is to connect the user defined nodes by a continuous path that does not violate the kinematical constraints of the mobilized vehicles. This approach is adapted from the robotics or Unmanned Air Vehicle (UAV) path planning solutions. Despite the fundamental concepts, mining has its unique requirements, which are not considered by the current solutions. Haul road length dominantly controls the development cost. Another cost factor is the host rock mass quality. The haul road should be excavated inside a high quality rock mass in order to decrease the supporting cost. This is also beneficial for having a safe and reliable long term opening. To summarize, the shortest haul road path needs to pass inside a good quality rock mass. Multi objective optimization is required to optimize the path length and the rock mass quality at the same time. Until now, heuristic methods and single objective optimization have been investigated by different researchers. Some researchers optimized multiple cost items in a single objective function just by using weighting factors. None of these approaches could achieve the global optimality. In addition, there has been no suggestion about considering the host rock mass quality in optimization. Finally, most of the algorithms proposed until now suffer from long processing times and powerful computational system requirements.

1.2 Objectives of the Study

This study aims to develop an efficient and reliable path planning algorithm to determine the optimum underground mine haul road in terms of length and rock mass quality. Optimality is implemented in terms of cost minimization. Generally, the shortest path is the most commonly desired goal in underground mine design and this problem is implemented by a single objective function.

Low quality rock zones may be inhibited inside a rock mass. Avoiding such undesirable zones potentially decreases cost of supporting and increases safety. In addition, road (opening) development progresses faster in better ground conditions. It is more appropriate to implement as a multi objective optimization problem. Cost items are the path length and the host rock mass quality. Although both of the items are desired to be optimized, they do not have an equal weight of importance. In other words, tradeoff between the path length and rock mass quality does not have a rate of unity. Path length is always more critical than the rock mass quality because low quality rock zones can be passed by heavy supporting for the sake of cost. However, any increase in the path length affects the operating cost throughout the whole mine life. Therefore, the objective function is established as a summation of the weighted cost items.

In multi objective optimization, cost items might have opposite effects on the cost. This study aims to calculate the tradeoff between the cost items and come up with a least cost solution. Although, global optimality cannot be achieved for both of the cost items rock mass quality optimization is a useful contribution for the optimization of underground mine haul roads.

In the optimization process, navigability is defined by the kinematic constraints; minimum turning radius and maximum gradient. Undesired regions (such as heavily faulted zones, jointed rock mass, aquifers, etc.) are avoided by local corrections.

This research aims to explore the advantages of intelligent algorithms in haul road path planning. Dynamic Programming and heuristic solutions are compared to evolutionary algorithms. Human-like thinking is integrated into the genetic algorithm by modified mutation operators.

Below, objective of this study are summarized;

- To replace the conventional methods of underground mine haul road design by a computationally efficient algorithm for
- To optimize the path length of the haul road
- To optimize the rock mass quality of the hosting rock mass
- To take the advantage of intelligent algorithms in optimization
- To develop special mutation operators for undesired region avoidance
- To develop a user-friendly software

1.3 Research Methodology

The research strategy of this thesis focuses on the methods of developing an efficient path-planning algorithm for underground mine access roads. Firstly, alternative mathematical models are explored for simulating the motion of an underground mining vehicle. Dubins car model suits well for the purpose. Later, problem variables, inputs, assumptions, and outputs are established.

In this study, two different objectives are optimized. The first objective is to determine the shortest path connecting the surface portal to the underground production levels (also called as main nodes). The first solution method is based on Dubins curves. This method proves that the path length changes by the node directions. In addition, determining the optimum path among the complete solution space takes a long time (even impossible for a large set of main nodes) using trial and error method. The second method is optimization by Dynamic Programming. This method is capable of calculating the global optimum in a more efficient way. However, solution for a large set of decision variables still takes long time. The objective function is established to minimize the path length. In other words, it is a single objective optimization. Third solution is optimization by an evolutionary algorithm. Genetic algorithm sacrifices the global optimality; however, makes an appealing improvement in the computational efficiency. This method also makes use of a single objective function that minimizes the path length. The kinematic model remains the same; however, the path between each two main nodes is defined by four decision variables. Violating undesired regions such as aquifers and shear zones is penalized by the objective function. On the contrary, passing along the desired regions is awarded. Local corrections are carried out in order to avoid or catch special regions. The path is enforced to avoid the undesired regions by obstacle avoidance algorithms while the desired regions are traversed in the same manner. In Dynamic Programming, semi-algebraic methods manipulate the path sections for those special regions. However; in genetic algorithm, heuristics are added by special mutation operators.

The second objective is to determine the least cost path for underground mine access roads. The cost of rock mass quality that the path is driven inside is also integrated into the objective function in addition to the cost of path length. The rock mass quality is defined by a geotechnical block model. Multi objective optimization is carried out. In the objective function, path length and rock mass quality does not take the same importance weight. The major concern is always the path length. Effect of rock mass quality on the optimum path is investigated by different weightings. Dubins curves, Dynamic Programming, and Genetic Algorithm solvers are adapted to the multi objective optimization.

For the purpose of verification, a simple mine layout is used. It is assumed that if the algorithm works on a simple verification problem, it is prone to be successful in more complicated problems. After verification, the shortest path algorithm is verified on real underground mine access roads. Performance of the algorithm is compared to the manual design of human operators. In addition, output of the Dynamic Programming is compared to the Genetic Algorithm. The least cost path problem is investigated on hypothetical cases. The effect of the rock mass quality cost is checked by altering the weightings in the objective function.

The optimization algorithm is implemented in MATLAB. A graphical user interface (GUI) is prepared for the ease of regenerating the case studies. The GUI is capable of importing data from the widely used mine planning software. It also allows manual data entry. The optimized path can be exported to the commonly used file formats in mine planning software. The problem inputs and outputs can be seen throughout the plot screen. The result summary is reported in a message history screen.

To summarize the research methodology;

- Haul road optimization is carried out for single and multiple objectives
- The single objective optimization minimizes the road length
- Dubins car model is selected to represent the kinematics of the mobilized underground mining equipment.
- Dynamic Programming is used to determine the optimum Dubins curves.
- Genetic Algorithm is implemented as an efficient method.
- Special mutation operators are developed for making heuristic corrections on the path.
- Multi objective optimization is carried out by the Genetic Algorithm
- Rock mass quality is defined in terms of a Geotechnical block model.
- Pareto front is created and optimal path is determined by a weighted objective function.

1.4 Outline of Thesis

This dissertation is organized into seven chapters. Overview of each chapter is given in the below paragraphs,

Chapter 1 makes a brief introduction by presenting the problems associated with the underground mine haul road design. Later on, research objectives and methodology outlines the key concepts used in this study together with the novel contributions to the literature of underground mine haul road design.

Chapter 2 outlines the background of this dissertation. Underground mining, mine planning, alternative underground mine access types, path planning, Operations Research in mining, Dubins path, Dynamic Programming, and evolutionary algorithms are presented.

In Chapter 3, previous research on optimization in mining and optimization of underground mine access are presented.
Chapter 4, presents an overview of the optimization problem. Mathematical model of the motion of a mobilized underground mining equipment is defined. Later, underground mine access optimization as a shortest path problem is investigated with a single objective function. Path length minimization on curvature-constrained paths is investigated with Exhaustive Search, Heuristic Algorithm and Dynamic Programming. Finally, Genetic algorithm is used to solve the same problem. The algorithms are verified on simple problems. Real underground mine haul roads are compared with the algorithmic designs.

In Chapter 5, underground mine access optimization is transformed into a least cost estimation problem. The objective function contains the path length and the host rock mass quality. Multi objective optimization with weighted cost items is applied in order to determine a least cost path.

The dissertation ends with main outcomes of this study and some recommendations for future researches are presented in Chapter 6.

1.5 Research Contributions

This study makes some novel contributions to one of the neglected topics in mine planning. Conventionally, underground mine access design is carried out by human experts. This study proposes an algorithm to determine the optimum path. Although skilled experts can make proper designs for simple mine layouts, complex mines are harder to interpret for the human operators. Optimization ensures the best solution is reached. Path planning applications of robotics and aeronautics are reviewed and the most appropriate solution for mining is implemented. By this way, one of the most fundamental design procedures in underground mining is automated.

This study compares exact optimizers with intelligent algorithms. Although Dynamic Programming provides the global optimum, computational efficiency is provided by the intelligent algorithms. It is observed that sacrificing the global optimum is feasible when the sub optimal solution is close to.

Another contribution is the heuristic correction on the path in order to avoid the undesired regions or catch the desired regions. In Dynamic Programming, semi-algebraic methods are proposed for this purpose. Genetic algorithm performs this type of path manipulation by some special mutation operators. The main contributions of this study are these proposed mutation operators.

Summary of the original contributions of this study are listed below;

- A Genetic Algorithm is proposed for underground mine haul road design, which can replace the manual design of human experts.
- Custom mutation operator is developed for avoiding undesired zones like discontinuity zones or aquifers.
- Custom mutation operator is developed for keeping the path inside a region of interest.

- Rock mass quality of the hosting rock is optimized together with the road length.

Below is the list of publications based on this Ph.D. study:

1 A. G. Yardimci and C. Karpuz, " Development of a New Methodology for Underground Mine Haul Road Design Using Evolutionary Algorithms" Journal, 2018. (Under Review)

2 A.G. Yardimci and C. Karpuz, “Optimized Path Planning in Underground Mine Ramp Design Using Genetic Algorithm,” in 26th International Symposium on Mine Planning & Equipment Selection, MPES2017, Luleå/Sweden, 08/2017

3 A.G. Yardimci and C. Karpuz, “Optimization of Underground Haul Roads Using an Evolutionary Algorithm,” in 25th International Mining Congress and Exhibition of Turkey, IMCET 2017, Antalya/Turkey, 04/2017

4 A.G. Yardimci and C. Karpuz, “Shortest Path Estimation Considering Kinematical Constraints of Main Haulage Roads in Underground Mines: A Heuristic Algorithm,” in 6th International Conference on Computer Applications in the Minerals Industries, CAMI2016, Istanbul/ Turkey, 10/2016

CHAPTER 2

BACKGROUND

This chapter provides background information about the fundamental concepts of the research. Firstly; underground mining, mine planning and underground mine access subjects are outlined. Later, literature related to the path planning and previous researches are reviewed. Finally, Dubins path, dynamic programming and evolutionary algorithms are briefly described.

2.1 Underground Mining

Mining is an engineering activity performed to reveal the economically valuable minerals of the Earth's crust and supply them for the benefit of the mankind. An ideal mining method should provide a profitable job in safe working conditions. Besides numerous control variables, depth of the orebody has a dominant influence in mining method selection. Underground mining is an ore extraction method for deeply underlying orebodies. Mining cost is higher compared to surface mining. However, greater selectivity decreases the amount of waste rock extraction.

In underground mining, orebody is accessed via a vertical shaft or a ramp. Although vertical shaft connects the production levels with the shortest path, a ramp offers a better alternative by higher production rates. In addition, ramp allows for fully mechanized operation. The orebody is connected to these surface access by drifts and haul roads. The basic cycle of an underground mine begins by extracting ore with the selected mining method. Later, the ore is transported by haulage equipment (truck, locomotive or conveyor belt) to the vertical shaft or ramp. If the surface access is a vertical shaft, the ore is hoisted inside the mine cars by a crane. However, if the surface access is provided by a ramp, haulage equipment delivers the run of mine to the surface. In some cases, run of mine top size might be reduced by primary crushing. Later, the crushed material is transported to the surface. Typical layouts of open pit and underground mines can be seen in Figure 1.

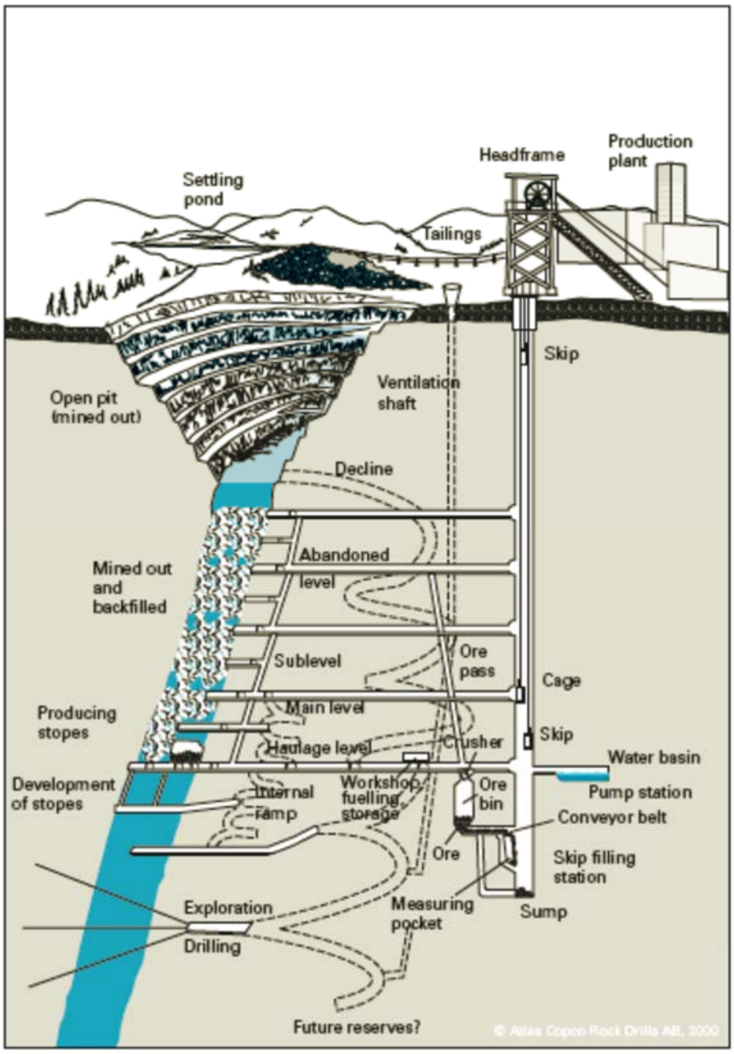


Figure 1 A typical open pit and underground mine layout [5]

Underground metal mining method selection is controlled by the type of the deposit, geometry of the orebody, geology, and geotechnical properties. Based on the supporting mechanism, underground mining methods are classified into three groups. Naturally supported methods are room and pillar, stope and pillar, shrinkage and sublevel stoping. Although extensive roof bolting and localized support measures are taken, these methods require no artificial pillars. Either undisturbed rock pillars or stopes filled by fragmented rock supports the walls. Artificially supported methods are cut and fill stoping and square set stoping. Although operational safety is increased, supporting cost and slow-paced development are the major disadvantages. Caving methods have economic merits due to bulk underground ore production with less blasting and excavation. Longwall stoping is a popular underground coal mining method while sublevel caving and block caving methods are more popular in underground metal mines.

Mine planning is an essential stage of mine management and should be followed continuously regardless of the selected mining method.

2.2 Mine Planning

Mine planning starts from the early stages of orebody exploration and continues throughout the mine life. The scope of the feasibility studies mainly focus on the production and even includes the rehabilitation plan right after the orebody exploitation is completed. Geological modelling and resource/reserve estimation form the basis of any further planning tasks. Mining method selection outlines the mine design guidelines. Production scheduling arranges the cash flow. Although each mine has different characteristics, the basic operations listed in Figure 2 are most commonly applicable.

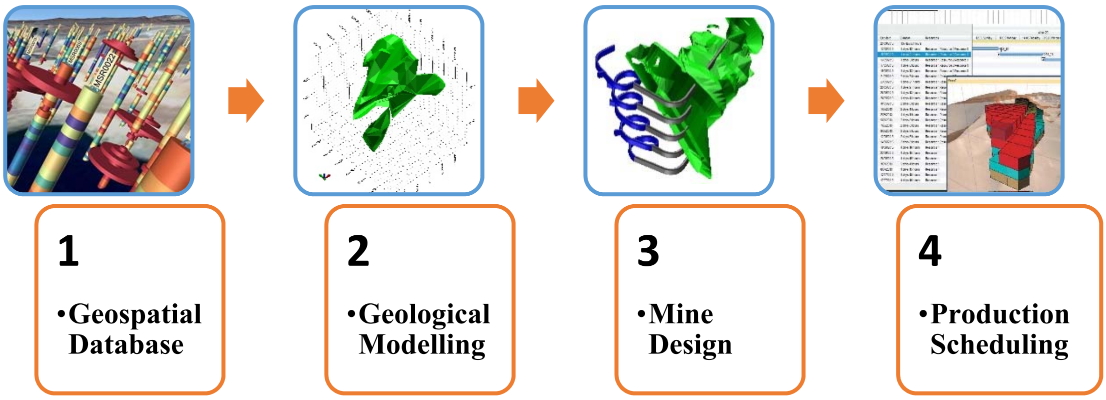


Figure 2 Basic workflow of mine planning [6]

Mine planning requires huge amount of data from different sources. The plan should be improved by fresh data and investigated for multiple scenarios. In addition, geological complexities should be included for the sake of accuracy. Conventional methods of interpreting such a complex input would lead to static and inaccurate mine plans. However, dynamic models would be more beneficial in order to adapt to continuously changing operation conditions. Although first versions of the mine planning softwares go back to 80s, invention of powerful computers improved the popularity of them by the late 90s. Today, orebody modelling, reserve estimation, grade control, mine layout design, and production scheduling are carried out extensively by computational methods. Orebody modelling can be implemented by explicit and implicit methods. Computer Aided Design (CAD) is used for the mine layout design. 3D wire meshing allows for realistic topographical mapping in the virtual environment. Short term and long term production scheduling can be organized to maximize the Net Present Value (NPV).

The development of transportation roads has a major share of development cost in underground mining and is crucial for Net Present Value (NPV) calculations.

2.3 Underground Mine Access

Mine access is the main transportation road connecting the surface to the underground orebody. Development of mine access starts in the early stages. A network of production openings is connected to the mine access. Throughout the mine life, extracted ore and waste rock are transported to the surface via the mine access. Therefore, this road is required to be capable of handling heavy traffic under reliable geotechnical conditions.

Site-specific conditions determine the mine access type and design specifications. Some of the vital considerations are characteristics of orebody deposit, life of mine, amount of reserve, production rate, mining method, extent of mechanization, opening dimensions, kinematical constraints of mobilized equipment, and ventilation network.

As indicated by Tatiya [7] underground mine access types are:

- Adit
- Incline
- Decline/Ramp
- Shafts (Inclined / Vertical)

In Figure 3, underground mine access types are presented.

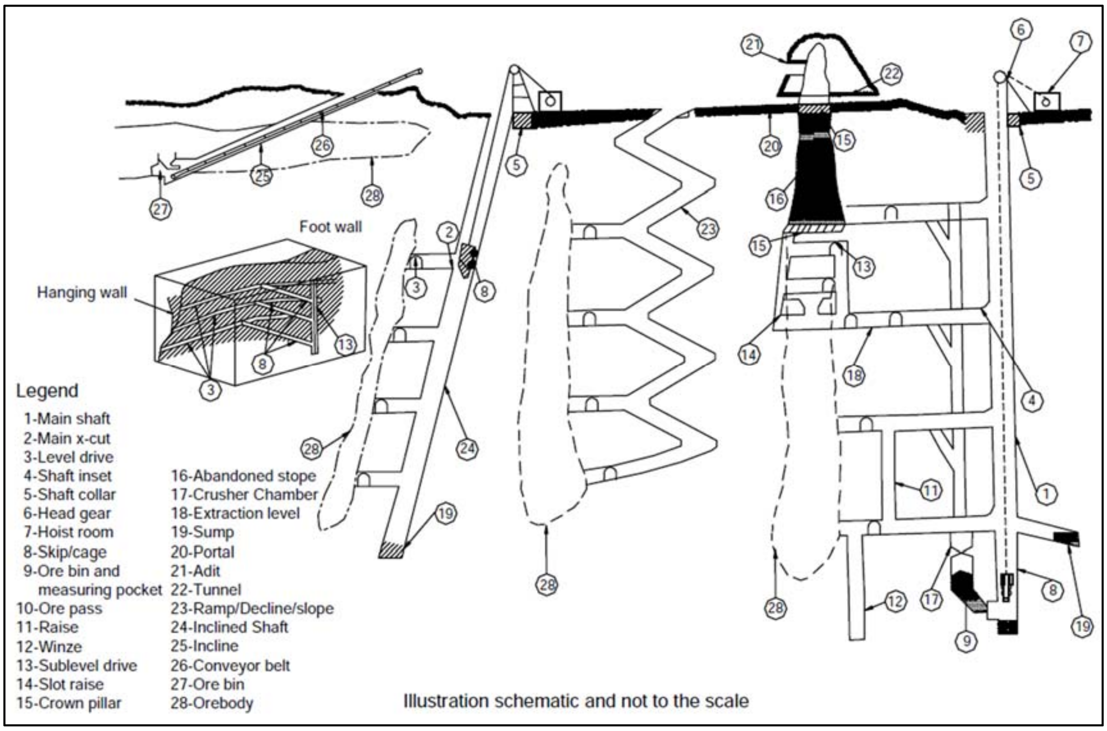


Figure 3 Underground mine access types [7]

An adit provides access to the underground via an almost horizontal opening, where the deposit extends above the valley. Compared to the alternatives, development cost is significantly low and driving rate is the fastest.

Incline is an access road with a slope up to 20°. It is suitable for flat dipping orebodies. Maximum depth of excavation does not exceed 150 m [7]. Development rate is faster compared to the decline and shafts but slower than the adit. Development cost is low.

Decline is a helical path with a gradient of up to 8°. Maximum feasible depth for a decline is 250 m. Curved path allows travelling to lower levels in a restricted area. Maximum turning radius for the curved parts are determined by the mobilized equipment specs, which is generally 15 – 40 m. Driving rate is faster than shafts but slower than the adit and incline. Complex excavation plans increase the construction cost; however, there is a remarkable advantage compared to the shafts.

Shafts can be driven either vertical or inclined with a slope down to 70°. Maximum feasible path is no more than 100 m [7]. Although it is the shortest path to transport the extracted ore out of the mine, it restricts production capacity. Degree of mechanization is limited. Driving a shaft is the slowest way to develop an underground mine access. In addition, it is the can be associated to the highest cost compared to any of the other methods.

All underground mine access types can be considered as part of a shortest path problem in mining. Therefore, path planning should be performed to find the most feasible way to connect the start and end nodes.

2.4 Path Planning

Path planning aims to generate a feasible path between a start and a target node by avoiding obstacles. A path is feasible if all the nodes are connected without violating the kinematic constraints. Kinematic constraints arise from the technical limitations of the moving object. For instance, the turn of a mine car is restricted by a minimum turning radius. In addition, the capacity of a car to climb up or down a slope is limited by the maximum gradient. Path planning has been extensively used on robotics, aviation, and computer games.

There are two common types of path planning algorithms. The first approach, which is online path planning, is capable of predicting the optimum path based on the live information gathered during the vehicle's movement. This approach is most widely used in robotics and aeronautics, where the environment is dynamic. Sensors attached on the vehicle detect unknown or changing environment and an autopilot system decides the optimum path simultaneous to the movement. A sample application is proposed by unmanned air vehicle (UAV) researchers [8] by an evolutionary algorithm that makes online planning and maximizes the information collected in a mission with multiple unmanned aerial vehicles. The second approach is offline path planning. In this approach, the environment is already recognized and the path is planned prior to the travel of the vehicle. This method is not dynamic and the vehicle moves exactly on the predicted path. In this study, we used offline path planning based on the static environment of the problem solution space. Problem inputs are recognized prior to the travel of the vehicle. Reif and Wang [9] have shown that this problem is NP-hard, which means that there is no existing polynomial time algorithm to date that can solve this problem. However, discretization techniques are proven to work well for these kind of problems.

Discretization creates a configuration space to simplify the problem. This concept was introduced in the late 70s as a result of the kinematic constraints on moving objects. A set of parameters that define the position and orientation of the mine car in a plane is defined as the configuration. Commonly, reducing the robot down to a point and increasing the size of the obstacles is the method of building a configuration space.

Path planning is an essential part of analyzing the short and/or safest travel of moving objects, especially in limited space such as underground mines. Different methods of Operational Research have been implemented to problems of mining engineering.

2.5 Operational Research

Operations research focuses on the analytical solutions of complex engineering and management problems. It aims to improve decision-making mechanism by providing knowledge by using some computational tools; optimum values of the decision variables are explored. These tools originate from various disciplines like mathematics, statistics, economics and engineering.

The history of Operations Research goes back to the early stages of WWII. British and American armies were looking for effective methods of allocating military resources to different operations. Therefore, they established a scientific research group. After the war, the booming industry interested on this new field, which had proven its success. Operations Research problems require high computational capacity. Although scientists developed new solution techniques, those handful calculations took long time for human operators. Invention of electronic computers led to faster calculations by a capacity increase of arithmetic calculations of thousands of times.

Implementing an Operations Research method starts by defining the mathematical model of the problem. Formulation consists of parameters, decision variables, objective function, and constraints. The coefficients in the objective function, constraints and exponents in nonlinear formulations are provided by the parameters. The mathematical model determines the decision variables. The objective function calculates a cost to be minimized or maximized considering the constraints. Constraints are limits of the decision variables such as the upper and lower limits.

Optimization is commonly used in mining. Pit optimization techniques are used to determine the excavation boundary in open pit mines with the maximum Net Present Value. Recently, there are some studies on the optimization of stope dimensions in underground mines. Some of the commonly used optimization methods in mining are linear programming, integer programming, nonlinear programming, dynamic programming and network theory.

Linear programming is a constrained optimization method with a linear objective function and linear constraints. Simplex method and interior point method are commonly used solution algorithms for Linear Programming.

Integer programming is almost similar to the Linear Programming. Difference lies in the decision variable, which must be any value greater than or equal to 0 and also an integer. Binary situations like 1 or 0 can be modelled with Integer Programming. Solution of Integer programs are not as easy as the Linear programs. Branch and bound algorithm makes systematic enumeration for the solution.

Nonlinear Programming investigates any nonlinearity in the objective function or the constraints. Decision variables can be any discrete value that is greater than zero. Although the problem can be solved more easily by linearization of the constraints, it may cause loss of accuracy. Unconstrained nonlinear programs can be solved by the steepest decent and Newton's method. Penalty and barrier algorithms solve constrained nonlinear programs.

A model with integer decision variables is called a pure integer program. A Mixed Integer Program consists of integer and continuous variables together. If there are nonlinear constraints, then it is a mixed integer nonlinear program.

Mathematical problems are classified based on their level of complexity. P problems can be solved by polynomial time algorithms. n^p is the maximum solution time for these problems, where n is the input size and p is a constant. NP problems cannot be solved efficiently in polynomial time but any solution can be verified. NP stands for 'Nondeterministic polynomial time'. NP-hard problems are harder than any NP problem. If a polynomial time algorithm can solve an NP-complete problem, then there is a polynomial time algorithm for every NP-complete problem.

Simulation is used to investigate uncertainties and different scenarios in complex mining related problems. Open pit haul fleet selection and production scheduling are either simulated or optimization techniques are applied. Heuristic methods can be used when the explicit expression of the problem is difficult or the solution is time consuming. Optimization algorithms can be fed by a heuristic initial solution to obtain a faster convergence. An example to this is the shortest path optimization that can be applied to underground mining equipment. A well-known concept in path optimization is the Dubins path.

2.6 Dubins Path

A particle mass in the space is free to move in any direction, which is equal to its degree of freedom. In these conditions, the shortest way of travelling from an initial point to a terminal point is a straight path. This type of behavior can be performed by a holonomic platform. Unlikely, a simple car can drive forward and backward but not on its sideways. As a natural consequence, parallel parking is a challenging task due to the complex maneuvers. Driver must steer the front wheels for a turning motion. Later, straight movements in forward and backward directions are required to fit the car in the parking lot. Such restricted motion capability makes the car nonholonomic. Underground mining vehicles are also nonholonomic. As the number of maneuvers increase, total length of travel also does. Apparently, it is challenging to determine the shortest path for a curved route.

Lester Dubins [10] proposed that three motion primitives are sufficient to traverse the shortest curved path. While the 'Straight' action moves the car on a straight path, 'Left' and 'Right' actions turn the car on the assigned direction as sharply as possible. Motion primitives are denoted by their initial capitals. A sequence of three motion primitives is called as a 'word'. Each word is a potential shortest path. Dubins declared that the shortest path is one of the six potential words:

$$\{RSL, LSR, RLR, LRL, RSR, LSL\}$$

where;

R = Right

S = Straight

L = Left

These are called the Dubins curves. Motion primitives can be classified based on the qualitative similarities. If ‘Left’ and ‘Right’ actions are symbolized by ‘C’, that is the initial of ‘Curve’ the Dubins curves are reduced to only two words:

$$\{CCC, CSC\}$$

Kirszenblat [11] presented physical interpretations of Dubins curves. On a perforated table, a string winds around thick disks and both ends of the string carries an equal weight. String under tension follows the shortest path and the curved sections are dominated by the radius of the disks.

Figure 4 presents an overview of Dubins curves on a sample 2 dimensional curvature constrained path. The LHD follows an RSR path, which connects an initial point with (x_i,y_i) coordinates to a terminal point with (x_t,y_t) coordinates. Minimum turning radius is symbolized by tr_{min}.

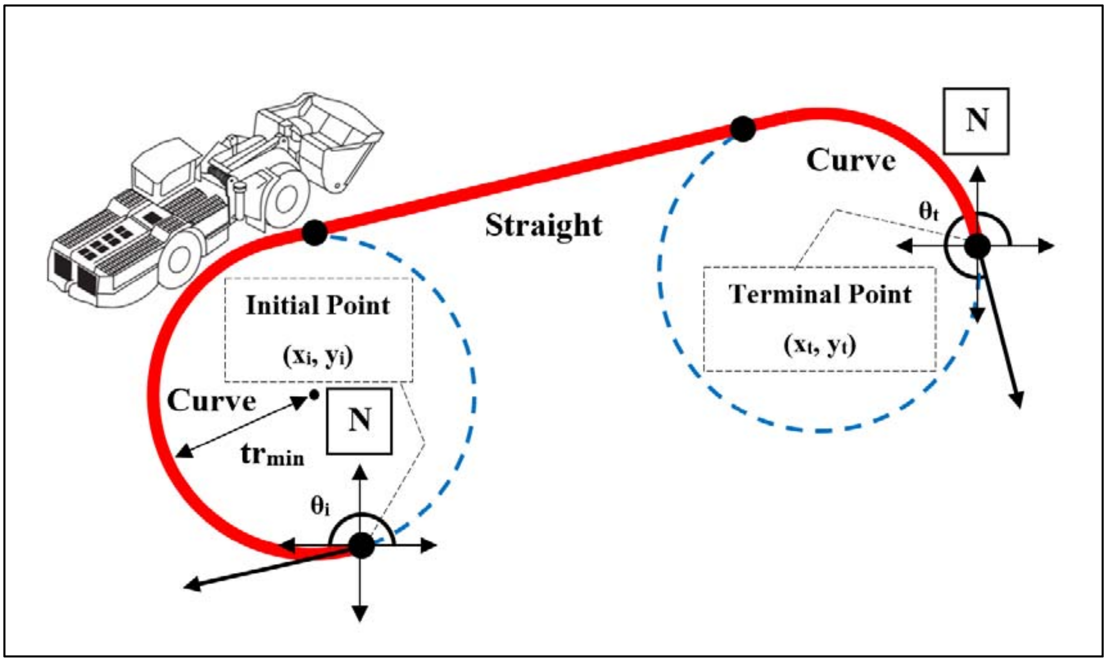


Figure 4 Overview of an RSR type 2D Dubins curve

The LHD starts motion with a heading angle of θ_i and arrives at the terminal point at a heading angle of θ_t. Starting from the initial point, heading angle of the car changes at a constant rate on an arc shaped path until the outer tangent point of the circle with a radius of tr_{min}. This curved section is denoted by ‘C’. Later, the heading angle kept constant up to the outer tangent point of the second circle and the straight motion is symbolized by ‘S’. Finally, the heading angle changes again at a constant rate until the LHD reaches the terminal point. ‘C’ denotes the final section. Similarly, LSL path connect the outer tangent points of the circles. However, RSL and LSR paths are connected by the inner tangent points.

Figure 5 presents a sample for 2D Dubins curves between an initial point located at (0,0) and a terminal point at (50,50) coordinates. Initially the path is driven with a heading angle of 10° and the terminal point heading angle is requested to be 240°. Curvatures have a turning radius of 15 m. Among the six Dubins curves, the shortest path comes out to be an LSR path with a length of 119 m.

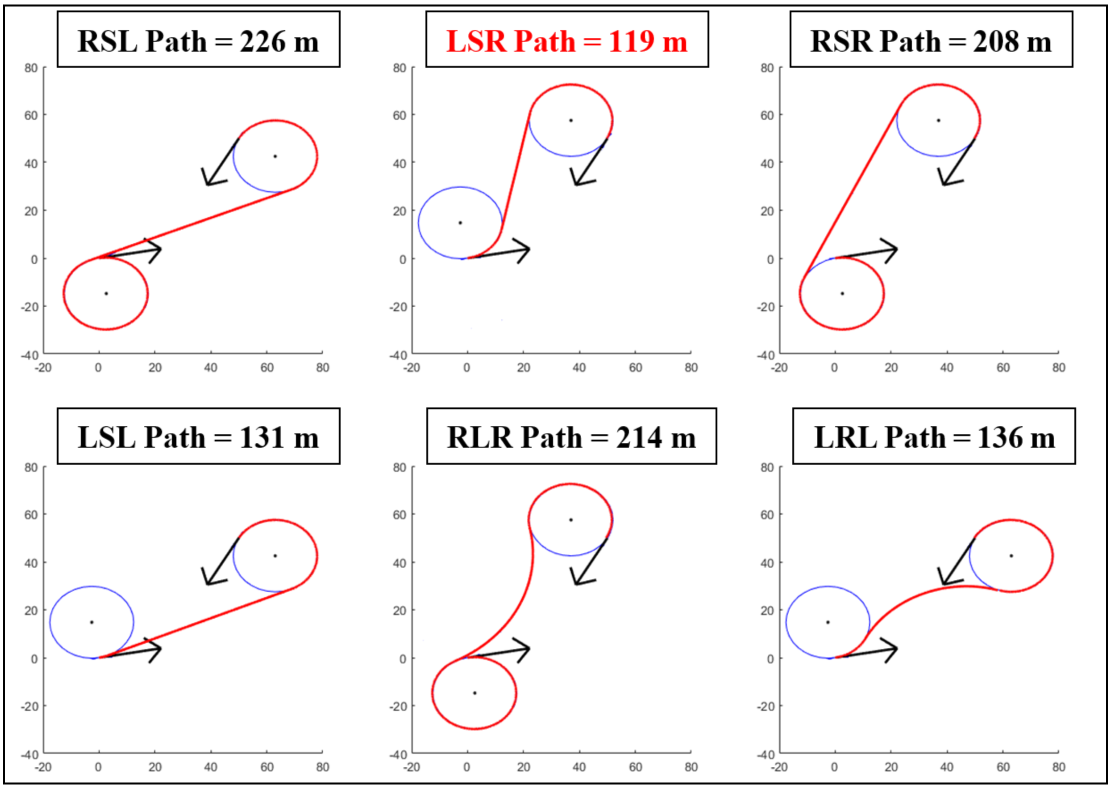


Figure 5 Sample view of six alternative Dubins Paths in 2D space between two nodes

Dubins curves have a wide range of use in robotics and aeronautics. Plane autopilot systems control the avionics based on the output of the route planning algorithms. Dubins curves determine the optimum route between waypoints. Because planes are not appropriate for sharp maneuvers, physical constraints of the plane should be considered. Underground mining vehicles have very similar physical restrictions.

Dubins [10] and Boissonnat et al. [12] proved that the shortest curvature constrained path on a 2D space is formed of three motion primitives. Sussman [13] showed that in a 3 dimensional problem space, the shortest path can be either a helix, a CSC path, a CCC path or a degenerated form of a Dubins path. An underground mine ramp is a 3 dimensional structure. Apparently, the original concept should be modified to work in the 3D environment. The optimization problem in 3D environment might require a computationally efficient optimization solver, such as Dynamic Programming.

2.7 Dynamic Programming

Dynamic programming (DP) is an optimization solver with the benefit of computational efficiency. Explicit enumeration guarantees the global optimum by checking each potential solution. However, solution takes longer time due to solving sub problems repeatedly. DP simply breaks down the problem into simpler sub problems. Each sub problem is solved only once and called from a look up list when it is needed. By this way, the number of computations are reduced. The advantage is more apparent when the input size escalates the number of repeating sub problems exponentially.

A simple illustration for the solution mechanism of DP can be seen in Figure 6 for a travelling salesman problem. In this characteristic problem, each of the nodes denoted by a capital letter is a city and called as states. There are four groups of cities that are called stages. A salesman plans to start from city A and arrive at city H by travelling the shortest path. Initially, DP generates a distance matrix showing the distance between each paired cities and later determines the shortest route that visits at least one city in each stage. The search can possibly flow in forward direction (from city A to city H) or in the backward direction (from city H to city A). In this study, backward induction is preferred.

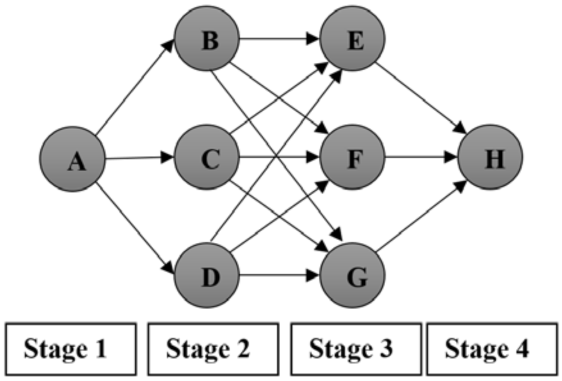


Figure 6 Sample solution tree for DP

Commonly, DP problems have the following characteristics:

1. The problem can be divided into ‘stages’ with a ‘decision’ required at each stage.
2. Each stage has a number of ‘states’ associated with it.
3. The decision at one stage transforms one state into a state in the next stage.
4. Given the current state, the optimal decision for each of the remaining states does not depend on the previous states or decisions.
5. A recursive relationship identifies the optimal decision for a stage, given that the next stage has already been solved.
6. The final stage must be solvable by itself.

Complexity of a problem is directly related to the number of states and stages. DP would be inefficient for a crowded solution space. Intelligent algorithms perform better by sacrificing the global optimality. However, sub optimal solutions would be more useful where the global optimum does not make a significant difference. Evolutionary algorithms are alternative methods to DP in solving complex problems.

2.8 Evolutionary Algorithms

Evolutionary algorithm (EA) is the most general name to define computer-based problem solving systems that use computational models of evolutionary processes as the main concept in their design and implementation. There are various evolutionary algorithms. Most commonly knowns are:

- Genetic algorithm
- Evolutionary programming
- Evolution strategies
- Classifier system
- Genetic programming

All of them are based on the same concept that simulates the 'evolution' of 'individual' structures via processes of 'selection', 'mutation', and 'reproduction'.

EAs improve a 'population', by evolving the weak parts that are determined by 'selection' rules. Evolving is achieved by "search operators", (or genetic operators), such as 'recombination' or 'mutation'. 'Individual' in the population is measured by its 'fitness' in the 'environment'. 'Reproduction' focuses on highly fit individuals. Recombination and mutation provide perturbation to those individuals. The algorithms basically imitate the biological process to determine better off springs. This study focused on implementing these problem solving techniques for shortest path optimization while avoiding certain regions in underground mining.

2.9 Rock Mass Classification Systems

Rock mass quality can be quantified by classifications systems. This section makes a brief investigation about these kinds of systems.

2.9.1 Overview of Geomechanical Classification Systems

Rock engineers aim to design safe and economical underground and surface rock structures. Common tools are analytical, observational, and empirical methods. Analytical methods investigate stresses and deformations around openings by closed form solutions, numerical models, analog simulations and physical models. Observational methods keep track of in-situ ground stresses and deformations while the excavation is in progress. Calibrating the numerical model with field measurements provide a reliable validation tool. Empirical methods suggest quantitative relations derived from statistical data for the purpose of solving certain rock stability problems. Rock mass classification is one of the empirical methods that relies on case histories and requires periodical update.

Rock mass quality is an important aspect that needs to be well defined before constructing a rock structure. Classification systems are practical tools for engineers to characterize the rock mass even with limited input data. Qualitative assessments can be easily converted to quantitative descriptions to represent the rock mass properties. It is also an advantage to establish a common ground for the experts of different disciplines.

Bieniawski [14] defines the most fundamental functions of rock mass classification systems:

a. Dominant parameters that determine the behavior of rock mass should be identified.
b. Rock masses of different quality should be divided into classes.
c. Generated rock mass classes should provide information about their characteristics.
d. Types of rocks encountered in different sites should be related to each other.
e. Quantitative data representing rock mass properties and guidelines to assess that data should be provided for engineering design.
f. An effective way of communication should be established for the members of geotechnical design groups coming from different backgrounds.

Classification systems should not replace analytical - numerical methods, field observations or engineering judgment but they are just useful tools in the preliminary stage of design which is going to be the basis of further advanced analysis techniques leading to the ultimate solution of the design problem.

2.9.2 Historical Background of Rock Mass Classification Systems

Researchers have developed numerous rock mass classification systems either for general use or specific purposes.

Terzaghi [15] was the first researcher to classify rock masses in terms of their geotechnical characteristics for engineering design purposes. He proposed support systems by considering underground opening dimensions according to the nine rock classes defined by himself.

Lauffer [16] system highlights the relation of active span and stand up time for support design for the first time. It has significant effect on development of recent classification systems, however it lacks of usefulness due to lack of a rating system.

Deere et al. [17] established a quantitative index called Rock Quality Designation (RQD). Proportion of length of drillhole core samples obtained from diamond drilling and greater than 100 mm to the total length of drilling is defined as the RQD index. Although it is a fast and easy way to investigate the rock quality, it does not consider geological or groundwater conditions but only focuses on fractures.

Wickham et. al. [18] proposed Rock Structure Rating (RSR). It is a quantitative classification method and it provides support system suggestions. Although this system relies on case histories of small tunnels supported by steel sets it was the pioneer of referencing to shotcrete support. RSR score is the summation of three parameters geology, geometry, and groundwater effect parameters, which are denoted by A, B, and C initials.

Barton et. al. [19] introduced Q-system that can predict rock mass characteristics and tunnel support requirements. Q index has a logarithmic scale between 0.001 -1000 and it is based on six parameters.

Recently, Aydan et. al. [20] introduced a novel rock mass rating system named as Rock Mass Quality Rating (RMQR). Estimation of rock mass properties from intact rock properties and rock classification systems is a widely used method. In spite of its usefulness, this method is known to have some drawbacks. RMQR suggests a new methodology to estimate the rock mass geomechanical properties.

The most widely used classification systems are Rock Mass Rating (RMR) and Q-system. In this study, rock mass covering the haul road is optimized by depending on the RMR scores. In the following section, it will be explained in more detail.

2.9.3 Rock Mass Rating (RMR)

Bieniawski [21] developed a popular rock mass classification system that is called Geomechanics Classification or Rock Mass Rating (RMR). The system has been modified several times by adjusting the rating parameters and interval boundaries. In addition, it is adapted for specific purposes. For instance, Unal [22] proposed an empirical relation to predict rock load intensity that causes roof collapse in coal mines. Romana [23] developed an enhanced version of the basic RMR by adding four geometrical parameters in order to predict slope failure modes. It is mostly used in tunneling, foundations, and slopes. Moreover, there are application in coal mining, rippability, and boreability.

Singh and Goel [24] summarizes some of the significant modifications in the core prediction mechanism. In 1974, the number of RMR parameters were reduced from 8 to 6. In 1975, ratings of parameters were adjusted and support recommendations were reduced. In 1976, rating intervals of parameters were modified. In 1979, ISRM (1978) rock mass descriptions were adopted. The final revision came in 1989. Due to changing class boundaries and ratings throughout the time, same rock mass can take different RMR scores; thus, it is vital to state the RMR version while working on RMR scores.

In its basic version, RMR has five parameters, which are;

a. Uniaxial compressive strength (UCS) of intact rock material
b. Rock quality designation (RQD)
c. Spacing of discontinuities (JS)
d. Condition of discontinuities (JC)
e. Groundwater conditions (GW)

RMR basic parameters are summed up to rate the rock quality as shown in Equation (2).

$$RMR_{basic} = UCS + RQD + JS + JC + GW \tag{2}$$

Some adjustment factors can be added to the basic RMR score for use in special conditions. Some of these factors are orientation and blasting adjustment.

The resultant score can be used to interpret the rock quality class, stand up time for underground openings, and rock mass mechanical parameters.

2.9.4 Common Problems of Classification Systems

Classifications systems are known to have some drawbacks. Daftaribesheli et. al. [25] reports them to be sharp class boundaries, assigning same numerical scores for upper and lower class boundaries, ambiguity in converting linguistic terms to numerical values, and presence of uncertainties as a result of the complex nature of rock. Problem of the same scores for upper and lower limits in RMR has been studied by Tomás et al. [26]. They recommend the use of continuous rating just as Sen and Sadagah [27]. Although continuous rating works for parameters defined by numerical intervals, linguistic parameters pursue to constitute a problem. Rock quality score may be misleaded by these drawbacks. Basarir and Saiang [28] created two hypothetical rock masses of different properties and proved that it is possible to obtain the same RMR score. They proposed fuzzy RMR as a solution. Yardimci and Karpuz [29] proved that the RMR score estimation is affected by the mentioned drawbacks on weak rocks. They proposed a Fuzzy RMR system to overcome the problem.

CHAPTER 3

PREVIOUS WORK

3.1 Optimization in Mining

Optimization has been used in mining since the 1960s. Initial attempts were on the production scheduling of open pit mines [30]. However, it didn't take so long to see underground mining applications. As a result of depleting orebodies and falling commodity prices, optimization has become more important today, like it has never been before. Researchers study on novel applications of optimization in underground mining.

Erdogan et. al. [31] studied the applicability of some of the stope boundary optimization algorithms. They aimed to maximize the economic profit by selecting the best possible layout. Their application considers the operational, geotechnical and physical constraints. A real underground mine operation is examined by four algorithms, which are namely, Floating Stope, Maximum Value Neighborhood, and two special applications that are developed by Sens and Topal [32], Sandanayake [33], and Topal [34]. Results of the algorithms are compared using the dimensions of an actual underground mine stope.

Gilani and Sattarvand [35] presented a new non-linear heuristic approach to model variable slope angles in open pit optimization. They used a fixed slope angle together with special block configurations. They report that these configurations suffer from creating the higher or lower angles than desired. Later, they used the cone template based methods with variable slope angles and improved the solution quality.

Salama et.al. [36] compared operating costs of a mine at different production levels for diesel and electric trucks, shaft and belt conveyor haulage systems. Their study considered different scenarios with forecasted energy prices. They intended to search for alternative sequencing techniques as mine depth increases. Discrete event simulation and mixed integer programming (MIP) were used to optimize the mine plans. They revealed that energy cost increases across each haulage method at both current and future energy prices by increasing depth. In addition, their study proves that discrete event simulation and MIP is a useful combination for a better decision making mechanism.

Nehring et.al. [37] studied production schedule optimization for underground mines. A classical MIP model was established for production scheduling of a sublevel stoping operation. A new model formulation was proposed to significantly reduce solution times. Case studies were carried out to check the performance of the proposed model.

In mine ventilation, solving ventilation networks of natural air splitting is a classical problem. Commonly the problem is formulated similar to the Kirchhoff's voltage and current laws. The solution is obtained by an iterative technique, which is known as the Hardy Cross method. Ueng and Wang [38], proved that the problem can be solved as an unconstrained optimization (minimization) problem..

Kaiyan et.al. [39] established a nonlinear multi-objective optimization mathematical model with constraints for highly difficult semi-controlled splitting problem. The optimization is based on the theory of mine ventilation networks. They proposed a new algorithm, that combines the improved differential evaluation and the critical path method (CPM). It has been observed that the global optimal solution is obtained more efficiently. A computer program was developed and it is capable of solving large-scale generalized ventilation network optimization problems.

Bakhtavar et.al. [40] studied the optimal transition depth from open-pit to underground. They established a model based on block economic values of open-pit and underground methods together with the Net Present Value (NPV). Later, they calculated the optimal transition depth based on NPV.

3.2 Underground Mine Access Optimization

Underground mine access optimization is a relatively niche subject. Although some researchers have proposed premature solutions, they need to be improved.

Brazil and Thomas [41] have realized the potential of optimization and strategic planning of underground mines. They adapted network optimization on underground mine optimization. Aim of the study was to design a connected system of declines, ramps, drives, and possibly shafts. By this way, capital development and haulage costs over the lifetime of a mine can be minimized. Mathematical model of this problem was established as a variation of the Steiner problem. Navigability constraints and obstacle avoidance were included. They established a fundamental model, and advanced by more complicated and generalized models. These models add extra costs and constraints to the fundamental model.

Kirszenblat et.al. [42] presented an exact 3D algorithm for the construction of the shortest curvature-constrained path interconnecting a given set of directed points. Minimum Dubins network is an underground mining related optimization problem. They aimed to construct a navigable network of tunnels for trucks with the least cost. They claimed that the Dubins network problem is similar to the Steiner tree problem; however, there is a curvature constraint and the terminals are directed. They proposed a minimum curvature-constrained Steiner point algorithm by fixing two terminals and varying the third.

Brazil et.al. [1] studied underground networks and improved underground access road optimization. Research outcomes are two software tools called as PUNO and DOT. These softwares make use of principles from geometric optimization. They used these tools on ore deposits at the Prominent Hill mine in South Australia and the Leeville old mine in Nevada. Comparing the software and human designs, it is concluded that the software makes better and faster design.

Later, Brazil et.al. [3] improved the DOT by modelling the decline as a mathematical network that meets the operational constraints and costs of a real mine. Geometric methods were used for constrained path optimization. The improved algorithm effectively uses the geometric properties of gradient and turning circle constrained paths. By this way, efficiency of the procedure for designing optimal declines has been increased. The new version of DOT, which is DOTTMover, contains the mentioned improvements.

Chang et. al. [43] studied the minimum cost curvature-constrained path between two directed points. In addition, they investigated the cost effect of geological characteristics on the tunnel development [44]. Their research generalizes the outcomes of the Dubins paths. To summarize, they claim that optimal paths are of the same forms as Dubins paths if the reciprocal of the directional-cost function is strictly polarly convex. However, there exists an optimal Dubins path if the strict polar convexity is relaxed to weak polar convexity. The results apply to the optimization of underground mine networks.

Brazil et.al. [45] focused on optimizing the development and haulage costs of accessing to and from the ore zones. In addition to the previous work on ramps, shafts were also investigated. They modelled this optimization problem as a weighted network.

Zoran et. al. [46] developed a genetic algorithm to interconnect multiple orebodies with a decline. They modeled a spatial network with nonlinear constrained objective function representing the cost of mine development and ore haulage. Later, they minimized the cost.
Research on optimizing underground haul roads is still in progress and can be defined specifically by using certain input and output parameters.

CHAPTER 4

THE SHORTEST UNDERGROUND MINE ACCESS ROAD BY SINGLE OBJECTIVE OPTIMIZATION

This chapter presents the implementation of commonly used optimization techniques for determining the shortest underground mine haul road.

First of all, a mathematically proven method for the shortest curved path connecting an initial node to a terminal node is presented. This method guarantees the path with minimal length by the prescribed travel directions in each node. However, changing node travel directions has the potential to improve optimality. Brute force algorithms investigate each node for each possible travel direction. Global optimality is chased for the sake of computational efficiency. Search is conducted at least between two nodes. As the number of nodes increase, optimization takes more time. Heuristic algorithms are presented as an alternative. This approach implements some extra limitations to reduce the solution space. Although computation is faster, the result is a local optimum. Dynamic Programming, is proposed as an efficient alternative to chase the global optimality. The basic mechanism relies on the mathematically proven method that was presented before; however, search is carried out between at least two nodes and more.

Finally, Genetic Algorithm (GA) is implemented to determine the near global optimum path. Global optimality is sacrificed for the sake of computational efficiency. In addition, local corrections are made on the path for avoiding undesired regions or catching desired regions. Heuristics are added by special mutation operators.

In order to check validity, the algorithms are implemented on validation problems. Later, they are compared by their computational efficiency and degree of optimality. Advantages of the proposed Genetic Algorithm are noticed.

4.1 Presentation of the Essentials of Underground Mine Haul Road Optimization Problem

In this section, the underground haul road optimization problem is presented. Assumption, inputs and outputs are introduced. A suitable mathematical model for simulating the motion of mobilized underground mining vehicles is proposed.

4.1.1 Overview of the Problem: Assumptions, Inputs and Outputs

In this section, an overview of the underground mine access optimization problem is presented. Basic layout of the problem geometry is presented in Figure 7. The path presented by a green line connects the surface portal of an underground mine to the crosscut entry points of the sublevels. The path is a navigable and curvature constrained route.

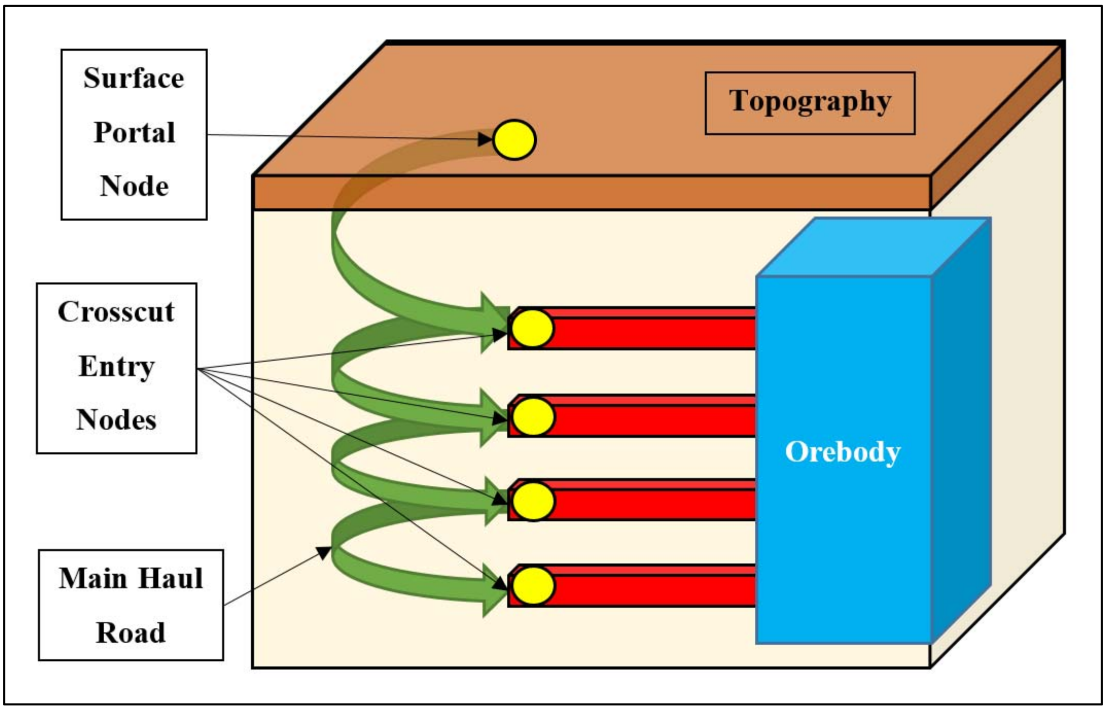


Figure 7 Basic layout of the underground mine haul road optimization problem

The path progresses from the upper elevations to the lower elevations. Visiting sequence of the nodes is certain. In this way, there is no need to solve a Travelling Salesman Problem (TSP). To briefly explain, TSP is necessary where there are multiple nodes to travel and visiting sequence is not certain.
Assumptions of the algorithm, inputs and expected outputs are listed below.

Assumptions:

- The algorithm makes valid shortest path predictions for single orebody problems.
- The portal location and the crosscut entry points (nodes) are defined in terms of x, y, and z coordinates.
- Heading angles for each of the nodes are defined.
- Visiting sequence of the nodes is known.
- Elevation of the nodes decreases gradually.
- The algorithm cannot predict paths climbing up a slope.
- The algorithm is capable of simulating horizontal paths.
- The valid path between two nodes can be one of the followings:
    - A straight section.
    - A Curve-Straight-Curve (CSC) type section
    - A Curve-Curve-Curve (CCC) type section
    - A straight section followed by a helical ramp
    - A helical ramp
- If two main nodes can be connected by a straight path within the allowable limits of gradient, then it is preferred.
- If it is not possible to connect two main nodes by a straight path, the shortest one of the CSC or CCC type section is used.
- If two main nodes can be connected by a CSC or CCC type of path with a smaller gradient than the maximum allowable gradient, than it is used.
- If two main nodes cannot be connected by neither of a straight section, a CSC or CCC type of path with the maximum allowable gradient because of the high elevation difference, then the final portion is connected by a helical path with a

gradient up to the maximum allowable gradient. In case a smaller gradient is possible in this portion, it is used.

- Number of turns in a helical ramp depends on the level difference between two succeeding nodes and the gradient.
- Undesired regions are polygons that are restricted from the fixed elevations on the roof and floor
- The optimum path is located exactly inside the desired region

Givens:

- Node coordinates.
- Undesired regions.
- Desired region.
- Kinematical constraints:
    - Minimum turning radius (m)
    - Maximum gradient (%)
- Rock mass quality block model.

Outputs:

- x, y, z coordinates of the equally spaced nodes on the shortest valid path.

4.1.2 Mathematical Model of an Underground Mining Vehicle

In path planning, location of a moving object needs to be predicted throughout the simulation time. Accurate or simple kinematical models have been proven to work mostly by Unmanned Air Vehicle (UAV) path planning researchers. True motion of a vehicle can be accurately modelled using non-linear fully coupled ordinary differential equations of motion for a vehicle moving along three axes with six degrees of freedom. This approach is also capable to include the forces and moments acting on the vehicle body, which are driven by gravity, propulsion and aerodynamic forces. However, no closed form solutions exist for these complex equations. Therefore, numerical solutions are required for steady state solutions. A more simplistic approach, which is the Dubins vehicle, is an appropriate kinematical model for underground mining equipment. A Dubins vehicle is a bounded speed and no reversing planar vehicle with constriction to move along paths of bounded curvature [47]. The equations for an underground mining equipment modelled as a Dubins vehicle can be seen below:

$$x_i = v_i \cos(\theta_i) \qquad i = 1 \dots n$$
$$y_i = v_i \sin(\theta_i) \qquad i = 1 \dots n$$
$$z_i = -v_i \sin(\psi_i) \qquad i = 1 \dots n$$
$$\theta_i = \frac{u_i v_i}{r_{min}} \qquad i = 1 \dots n$$

where;

$i = node\ number$

$n = maximum\ number\ of\ nodes$

$x_i = x\ coordinate\ of\ the\ i^{th} node$

$y_i = y\ coordinate\ of\ the\ i^{th} node$

$z_i = z\ coordinate\ of\ the\ i^{th} node$

$\theta_i = heading\ angle\ of\ the\ i^{th} node$

$\psi_i = gradient\ of\ the\ i^{th} node$

$u_i = turn\ control$

$v_i = velocity$

$r_{min} = minimum\ turning\ radius$

4.2 The Shortest Path between an Initial Node and a Terminal Node with Fixed Heading Angles

This method establishes the fundamentals for the exhaustive search, heuristic algorithm, and Dynamic Programming. The shortest path connects an initial node to a terminal node. As mentioned before, Lester Dubins [10] proved that the shortest curved path is one of the six alternative paths. Each path is composed of three motion primitives, which are left turn, right turn and straight motion. Kinematical restrictions control the curved sections and gradient of the road. Minimum turning radius and maximum gradient parameters are controlled by the specifications of, mobile underground mining equipment.

4.2.1 Objective Function

Objective of this path planning problem is to minimize the path length between two nodes. Mathematical expression is given below:

$$\boldsymbol{Minimize}\ \{Path\ Length\}$$

Where;

$\theta_i = Heading\ angle\ of the\ nodes$

$\psi_i = Gradient$

$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$

Subject to:

$$0 \le \theta_i \le 2\pi$$
$$0 \le \psi_i \le grad_{max}$$
$$0 \le v_i$$

Given;

$(east_{initial\ node}, north_{initial\ node}, elevation_{initial\ node}, heading\ angle_{initial\ node})$

$(east_{terminal\ node}, north_{terminal\ node}, elevation_{terminal\ node}, heading\ angle_{terminal\ node})$

$tr_{min} = minimum\ turning\ radius$

$grad_{max} = maximum\ graident$

4.2.2 Workflow of the Algorithm

The Dubins car starts to travel on a curved section. Later, the path proceeds either by a straight or a curved section. Finally, the travel ends with a curved section. This study makes use of geometrical rules to calculate curvature constrained paths. Normally, Dubins curves are established in 2D space; however, gradient constraint is integrated to the algorithm. In case maximum gradient is not sufficient to connect to the terminal point, the path makes extra helical travels with the maximum possible gradient. Although a fixed gradient is highly recommended in underground mines, geometry may not allow it in some specific cases. Figure 8 shows the flowsheet of the shortest path algorithm between an initial node and a terminal node.

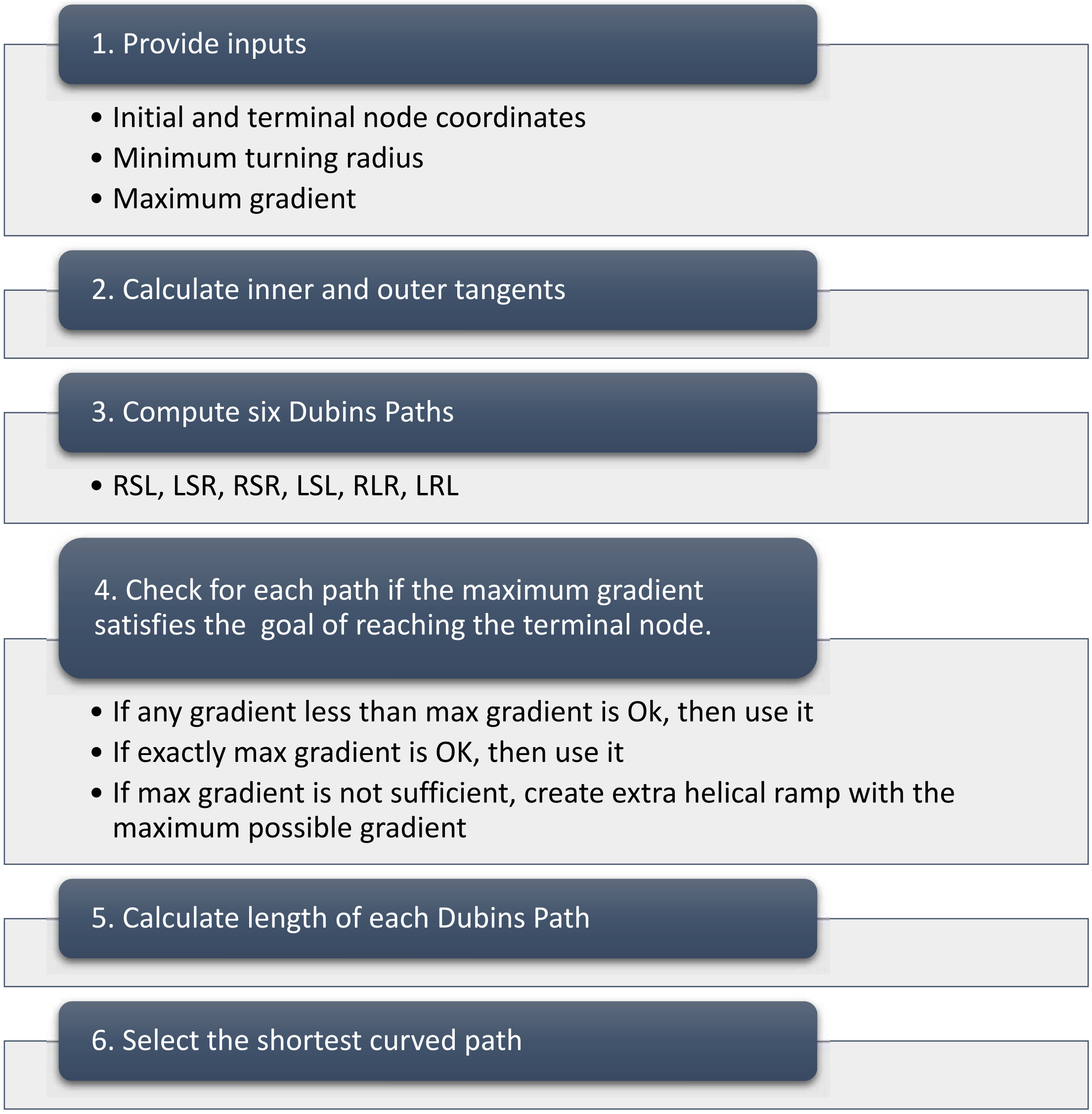


Figure 8 Flowsheet of the shortest path algorithm between an initial node and a terminal node

Initial and final node coordinates and heading angles must be provided. For each node, the algorithm calculates the center points of the perpendicular circles on both sides with a distance of minimum turning radius. In this study, initial node and its perpendicular circles are called the ‘primary section’, the terminal node and its perpendicular circles are called the ‘secondary section’ and the transition zone that connects the primary section to the secondary section is called the ‘middle section’. In order to calculate six Dubins Paths, the algorithm must use one of the perpendicular circles in each section. Figure 9 demonstrates a basic layout described above.

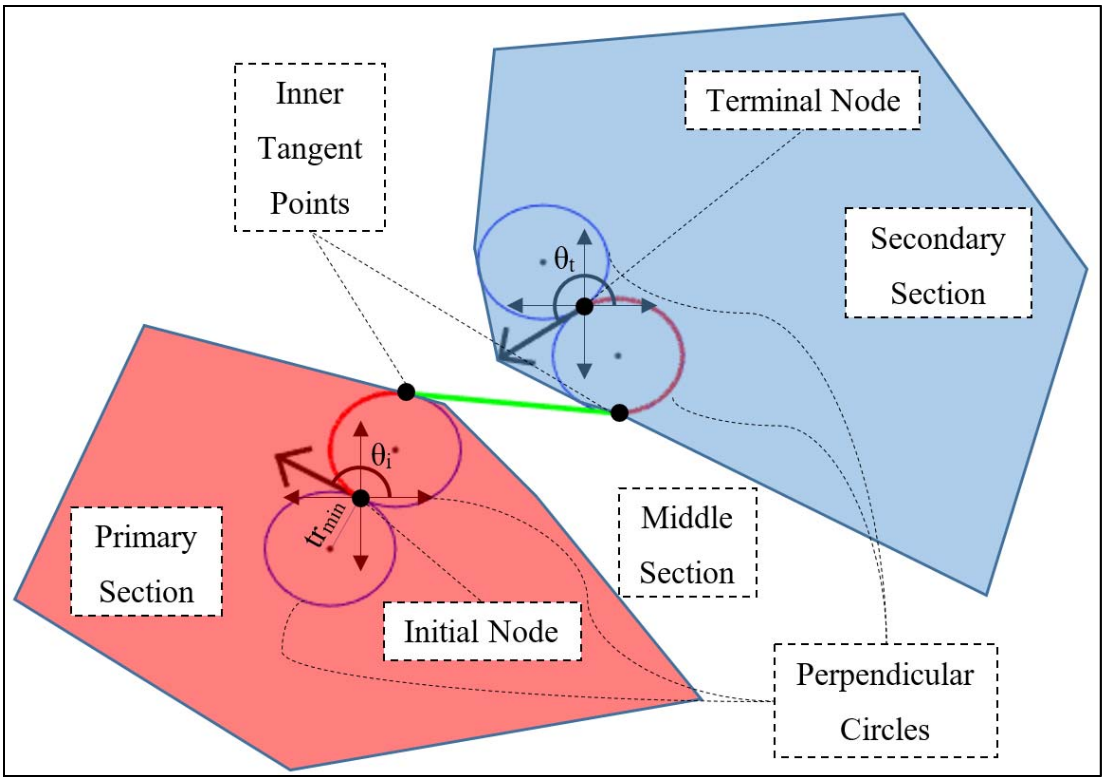
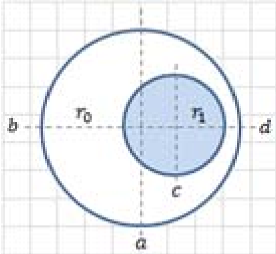
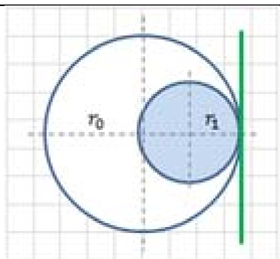
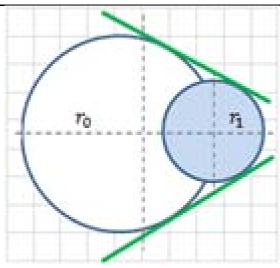
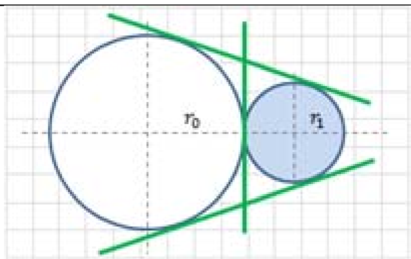
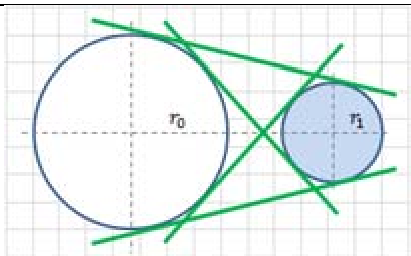


Figure 9 Basic layout of a Dubins Path

The transition zone is restricted either by the inner or outer tangent points between the circles. The algorithm starts by calculating the number of tangent lines. Inner tangent lines are necessary for 'RSL' and 'LSR' type paths while outer tangents are required for 'RSR' and 'LSL' type paths. If the number of tangent lines is equal to '0' or '1', then one of the circles is encapsulated by another. However, this state is valid only for circles with different radius. In this study, curvature is constrained. Therefore, there is no possibility for these two cases. If the number of tangents are '2' or '3' then the circles intersect on either one or two points. In these cases, only 'RSR' and 'LSL' type paths are possible. If the number of tangent lines is '4' then all of the four paths that have a straight middle section are possible. Table 1 shows the number of tangent lines and their conditions.

Table 1 Equations for calculating the number of tangent lines

Illustration	**Number of Tangent Lines**	**Condition**
	0	$D = \sqrt{(c-a)^2 + (d-b)^2}$
	1	$D = \lvert r_0 - r_1 \rvert$
	2	$\lvert r_0 - r_1 \rvert < D < r_0 + r_1$
	3	$D = r_0 + r_1$
	4	$D > r_0 + r_1$

Inner and outer tangent coordinates can be calculated by the equations between (3) and (12).

$$D = \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2} \tag{3}$$

$$L = \sqrt{D^2 + (R_i \pm R_t)^2} \tag{4}$$

$$R_1 = \sqrt{L^2 + {R_t}^2} \tag{5}$$

$$\sigma_1 = \frac{1}{4}\sqrt{(D + R_i + R_1)(D + R_i - R_1)(D - R_i + R_1)(-D + R_i + R_1)} \tag{6}$$

$$x_1 = \frac{x_i + x_t}{2} + \frac{(x_t - x_i)\left({R_i}^2 - {R_1}^2\right)}{2D^2} \pm 2\frac{y_i - y_t}{D^2}\sigma_1 \tag{7}$$

$$y_1 = \frac{y_i + y_t}{2} + \frac{(y_t - y_i)\left({R_i}^2 - {R_1}^2\right)}{2D^2} \pm 2\frac{x_i - x_t}{D^2}\sigma_1 \tag{8}$$

$$R_2 = \sqrt{L^2 + {R_i}^2} \tag{9}$$

$$\sigma_2 = \frac{1}{4}\sqrt{(D + R_t + R_2)(D + R_t - R_2)(D - R_t + R_2)(-D + R_t + R_2)} \tag{10}$$

$$x_2 = \frac{x_t + x_i}{2} + \frac{(x_i - x_t)\left({R_t}^2 - {R_2}^2\right)}{2D^2} \pm 2\frac{y_t - y_i}{D^2}\sigma_2 \tag{11}$$

$$y_2 = \frac{y_t + y_i}{2} + \frac{(y_i - y_t)\left({R_t}^2 - {R_2}^2\right)}{2D^2} \pm 2\frac{x_t - x_i}{D^2}\sigma_2 \tag{12}$$

The mathematical model of the underground mining vehicle runs on a discrete path with equally spaced paces. The heading angle changes with a fixed rate on the primary and secondary sections. If the middle section is of 'straight' type, the heading angle keeps constant. Change in heading angle is controlled by the minimum turning radius (tr_{min}), pace length (v), and calculated by equation (13).

$$D = \cos^{-1}\frac{\left(2{tr_{min}}^2 - v^2\right)}{2{tr_{min}}^2} \tag{13}$$

Pace length is a critical parameter that may disturb the ideal path. To be more specific, if the pace length is a bigger value then the path may deviate from the terminal node. However, the problem has a final node constraint. An appropriate pace length should be selected.

For the curved middle sections, the radius is determined by the distance between the primary and secondary sections. This radius can be at least the minimum turning radius and may be even more.

After calculating all six Dubins Paths, the shortest one is selected. If both of the nodes have equal heading angles and their elevations conform, then the algorithm is capable of computing the shortest path as a straight path. In addition, if the nodes line up on the same vertical track, then the algorithm predicts a helical ramp as the shortest path.

4.2.3 Verification

Dubins path was proven by its success in the shortest curved path calculation. However, its Matlab implementation that is prepared in the scope of this study requires to be tested, whether it works properly in common problems and also for some special cases.

This part presents the verification of the shortest path algorithm between two nodes. The algorithm is tested for five distinct cases that includes all of the general and some special cases:

1. Dubins Path with a gradient less than the maximum gradient
2. Extended Dubins Path with the maximum gradient
3. Straight path
4. Straight path with an extension
5. Helical ramp

Kinematical constraints are same for all the problems and presented in Table 2.

Table 2 Kinematic constraints for the verification problem

Kinematic Constraints	
Minimum Turning Radius (m)	**Maximum Gradient (%)**
15	12

The algorithm is implemented in Matlab. A special Graphical User Interface (GUI) is created for the sake of ease in repeating problems.

<u>Dubins Path with a gradient less than the maximum gradient</u>

The first problem seeks for the shortest path where node elevations are so close that the path gradient can be smaller than the maximum gradient. Their coordinates are presented in Table 3.

Table 3 Node coordinates and heading angles for the first verification problem

Node No:	East (m)	North (m)	Elevation (m)	Heading Angle (°)
1	0	0	100	120
2	100	100	90	225

Table 4 shows the shortest path predicted by the algorithm is an 'RSR' type path and it has a length of 194 m. Apparently, alternative path types have much greater length.

Table 4 Length of the alternative Dubins Paths for the first verification problem

Path Length (m)					
RSL	**LSR**	**RSR**	**LSL**	**RLR**	**LRL**
198	281	194	276	203	287

Figure 10 illustrates the shortest path connecting the initial node to the terminal node, coordinates of which are given in Table 3.

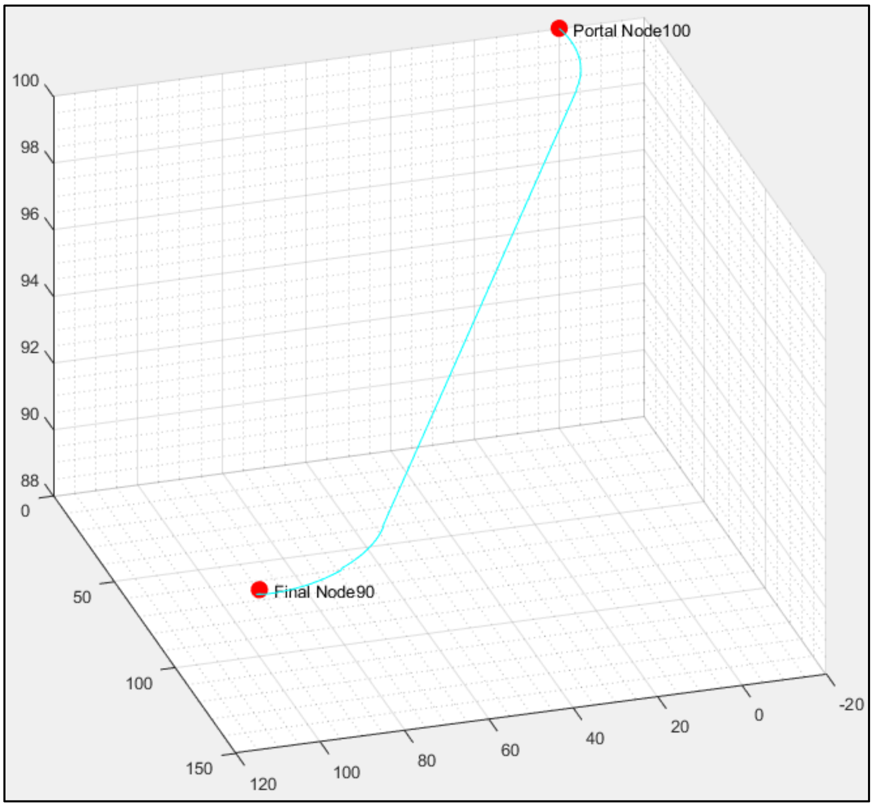


Figure 10 View of the shortest path for the first verification problem

<u>Extended Dubins Path with the maximum gradient</u>

The second problem looks for the shortest path when elevations difference between the nodes is so great that the path cannot reach the terminal node even with the maximum gradient. In such a case, the path is traversed by a typical Dubins Path and later a helical ramp with the possible maximum gradient is used to catch the terminal node. Node coordinates can be seen in Table 5.

Table 5 Node coordinates and heading angles for the second verification problem

Node	East (m)	North (m)	Elevation (m)	Heading Angle (°)
Initial	0	0	100	45
Terminal	100	100	50	225

Table 6 shows the shortest path predicted by the algorithm is an ‘LSL’ type path and it has a length of 475 m. Apparently, alternative path types have much greater length.

Table 6 Length of the alternative Dubins Paths for the second verification problem

Path Length (m)					
RSL	**LSR**	**RSR**	**LSL**	**RLR**	**LRL**
476	477	476	475	476	484

Figure 11 illustrates the shortest path connecting the initial node to the terminal node, coordinates of which are given in Table 5.

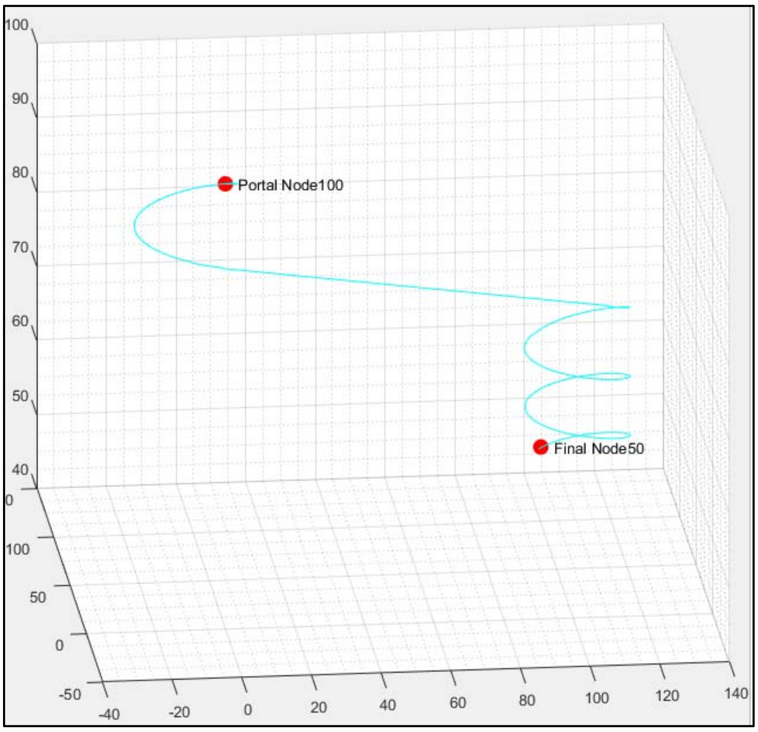


Figure 11 View of the shortest path for the second verification problem

Straight path

The third problem aims to test a special case. It checks the capability of the algorithm whether it can predict the shortest path as a straight path when the nodes have the same heading angles and the elevation difference allows to travel with the maximum gradient or less. Table 7 presents the node coordinates.

Table 7 Node coordinates and heading angles for the third verification problem

Node	East (m)	North (m)	Elevation (m)	Heading Angle (°)
Initial	0	0	100	60
Terminal	100	100	90	60

The algorithm predicts the shortest path as a straight path and it has a length of 141 m. Figure 12 illustrates the shortest path connecting the initial node to the terminal node, coordinates of which are given in Table 7. As it is a straight path, the algorithm is approved.

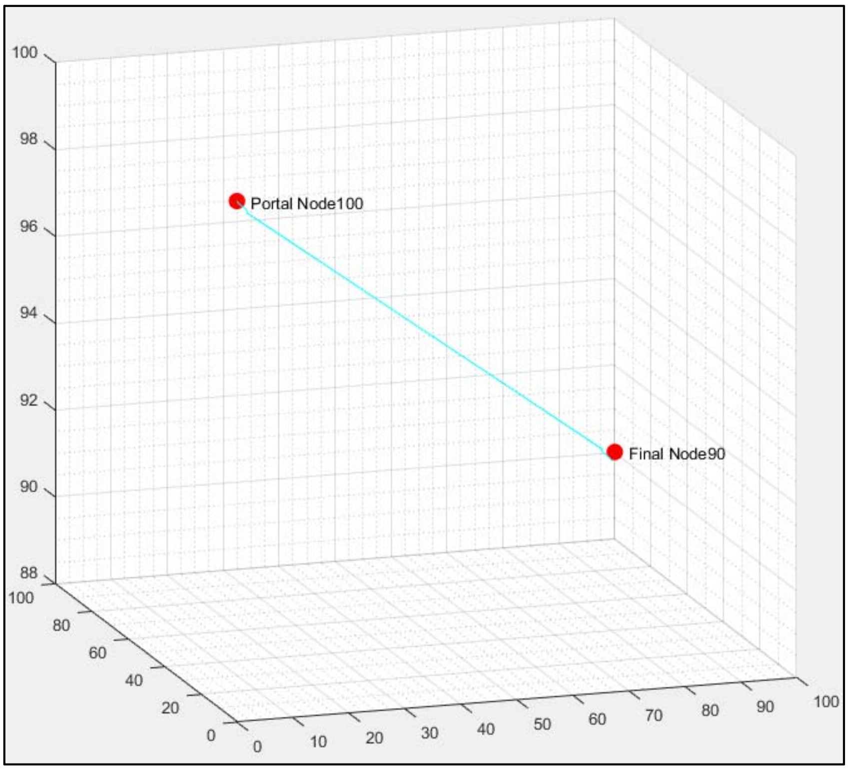


Figure 12 View of the shortest path for the third verification problem

Straight path with an extension

The fourth problem extends the previous problem by checking whether the algorithm can perform the shortest path as a straight path, when the nodes have the same heading angles and the elevation difference is so great that the travel cannot be achieved by the maximum gradient. In this case, the straight path proceeds by a helical ramp with the maximum possible gradient is used. Table 8 presents the node coordinates.

Table 8 Node coordinates and heading angles for the fourth verification problem

Node	East (m)	North (m)	Elevation (m)	Heading Angle (°)
Initial	0	0	100	60
Terminal	100	100	80	60

The algorithm predicts the shortest path as a straight path proceeded by a helical ramp, as it is expected. Figure 13 presents the path, which has a length of 234 m. This approves that the algorithm is successful in predicting straight paths extended by helical ramps.

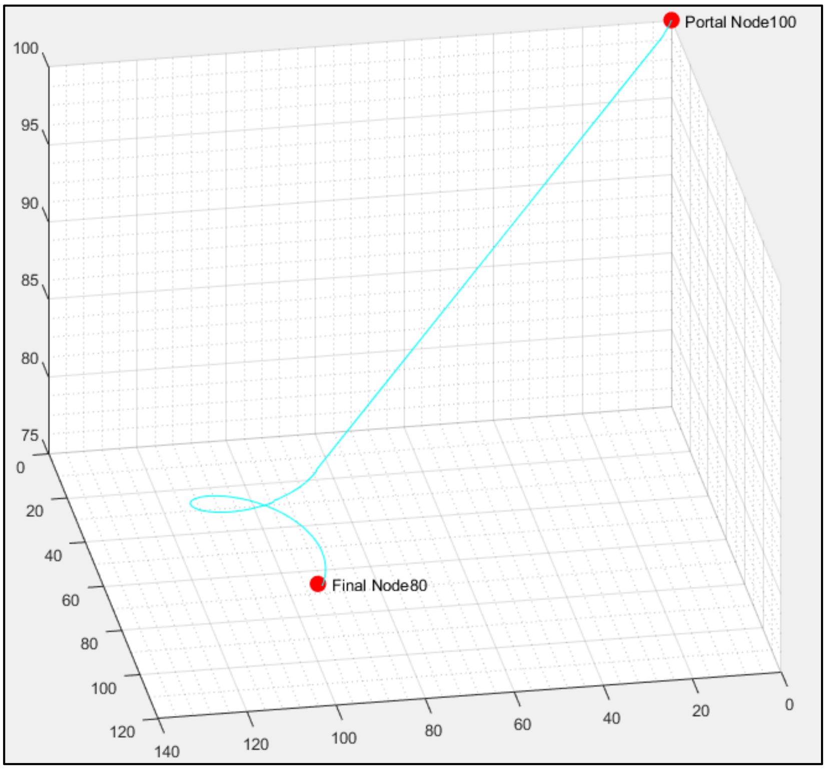


Figure 13 View of the shortest path for the fourth verification problem

__Helical ramp__

The final problem investigates another special case in which the nodes are located on a vertical line. A helical ramp is the expected shortest path in such a kind of situation. Especially, it is the most common layout to be observed in underground mines. Gradient of the ramp is desired to be the maximum allowed value and there may be some local correction in some special cases. Table 9 presents the node coordinates for a simple problem.

Table 9 Node coordinates and heading angles for the fifth verification problem

Node	East (m)	North (m)	Elevation (m)	Heading Angle (°)
Initial	0	0	100	270
Terminal	0	0	80	270

Figure 14 proves that the algorithm is successful in predicting the shortest path as a helical ramp, as it is expected. The path has a length of 190 m.

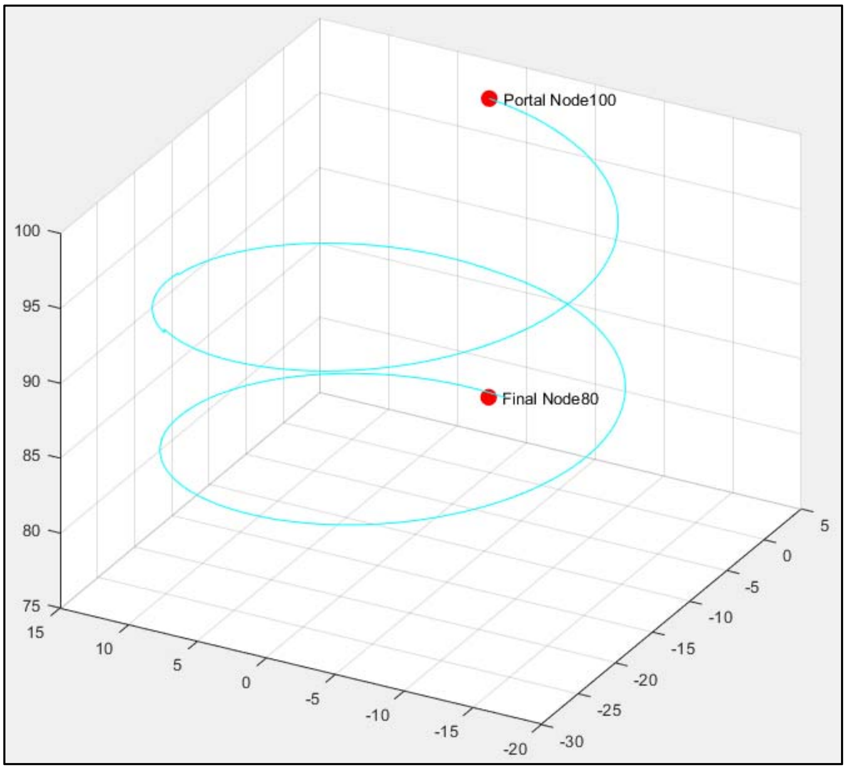


Figure 14 View of the shortest path for the fifth verification problem

Node Heading Angle Sensitivity Analysis

Dubins path determines the shortest path between directed nodes. Changing the heading angle in a node redefines the shortest path length. In order to observe this situation, a sensitivity analysis is carried out on a sample problem configuration. Node coordinates are presented in Table 10. Initial node heading angle is fixed and 45° while the terminal node heading angle is changed by 1° in each step and the shortest Dubins Path is calculated.

Table 10 Node coordinates and heading angles for the fourth verification problem

Node	East (m)	North (m)	Elevation (m)	Heading Angle (°)
Initial	0	0	100	45
Terminal	100	100	0	…

Figure 15 shows the shortest path is obtained when the terminal node heading angle is 341°. The path is a RLR type Dubins Path.

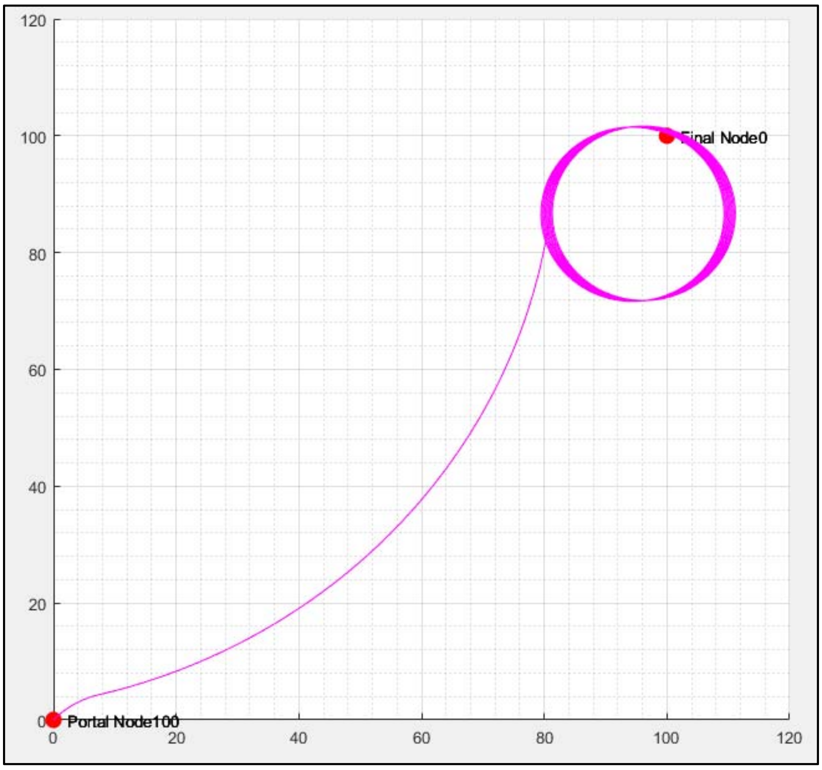


Figure 15 The shortest path for sensitivity analysis

Figure 16 shows the shortest path length by a 1° increase in the terminal node heading angle between an interval of 0° - 360°. Each of the states belong to one of the six Dubins paths. For instance, a 9° terminal node heading angle provides a shortest path of RSL type while, a 120° terminal node heading angle results in an LRL type Dubins Path. This sensitivity analysis apparently shows that the node heading angle governs the Dubins Path type and the path length. Therefore, heading angle becomes one of the most important control variables.

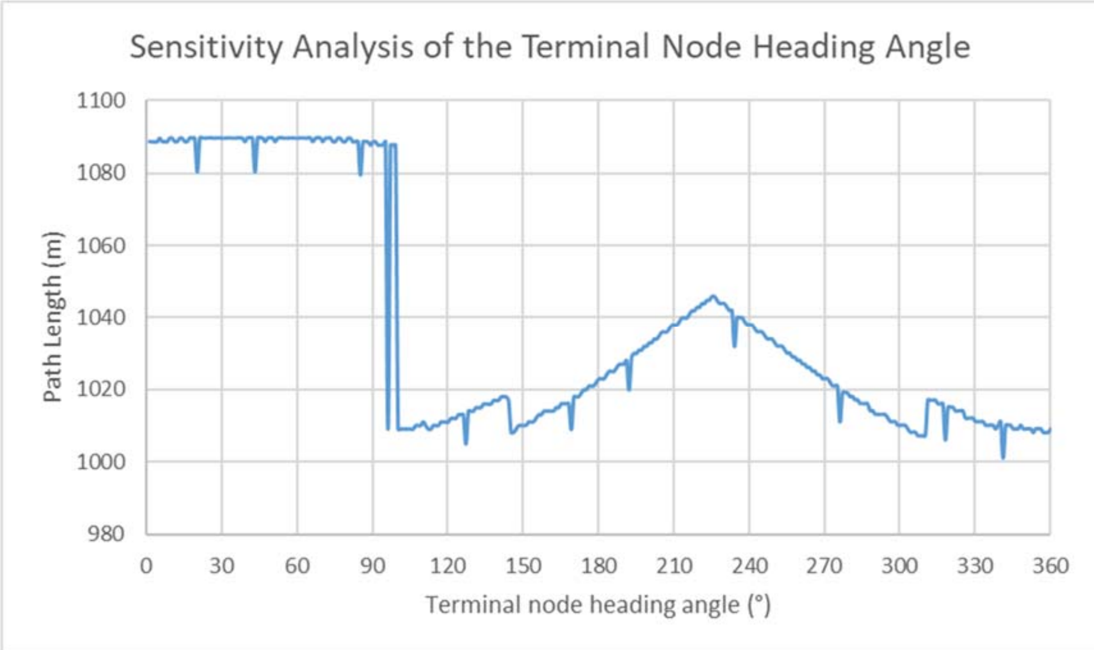


Figure 16 Sensitivity analysis of the terminal node heading angle

4.3 Exhaustive Search

Underground mines have several production levels that are called sublevels, especially for steeply dipping seam type orebodies. Sublevels are accessed via 'crosscuts'. Underground mine access is the road connecting the surface portal to the sublevels. In order to determine the shortest path for this road, the algorithm based on Dubins Path is applied between each node pairs. Optimization of this road requires to repeat the same procedure in each node for a heading angle range of 0°-360°. As the number of nodes increase, the problem transforms into an exponential time problem, which is very hard to solve. However, the result is guaranteed to be the global optimum because all the potential solutions are controlled. To summarize, exhaustive search is an optimization technique that considers all of the possible solutions and provides the global optimum.

4.3.1 Objective Function

Objective of this path planning problem is to minimize the path length between many nodes. Each node pair is connected by any one of the Dubins Paths or special paths. Below is the mathematical expression:

$$\boldsymbol{Minimize}\ \{Path\ Length\}$$

Where;

$\theta_i = Heading\ angle\ of\ the\ nodes$

$\psi_i = Gradient$

$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$

Subject to:

$$0 \leq \theta_i \leq 2\pi$$

$$0 \leq \psi_i \leq grad_{max}$$

$$0 \leq v_i$$

Given;

$(east_i, north_i, elevation_{i^{th}\ node}, heading\ angle_{ie})$

$tr_{min} = minimum\ turning\ radius$

$grad_{max} = maximum\ graident$

4.3.2 Workflow of the Algorithm

Exhaustive search requires coordinates of the surface portal and crosscut entry points. Kinematical constraints are selected to conform to the mining equipment specifications in terms of minimum turning radius (m) and maximum gradient. Search starts by assigning heading angles to each node between an interval of 0 - 360°. Later, six Dubins Paths are calculated for each of the node pairs. All of the possible heading angle combinations are calculated. The shortest path in each combination is selected to represent the ideal path. Apparently, increasing number of main nodes exponentially increases the combinations and more calculation time is required. Finally, the shortest overall path connecting all of the nodes is determined. Workflow of the algorithm can be seen in Figure 17.

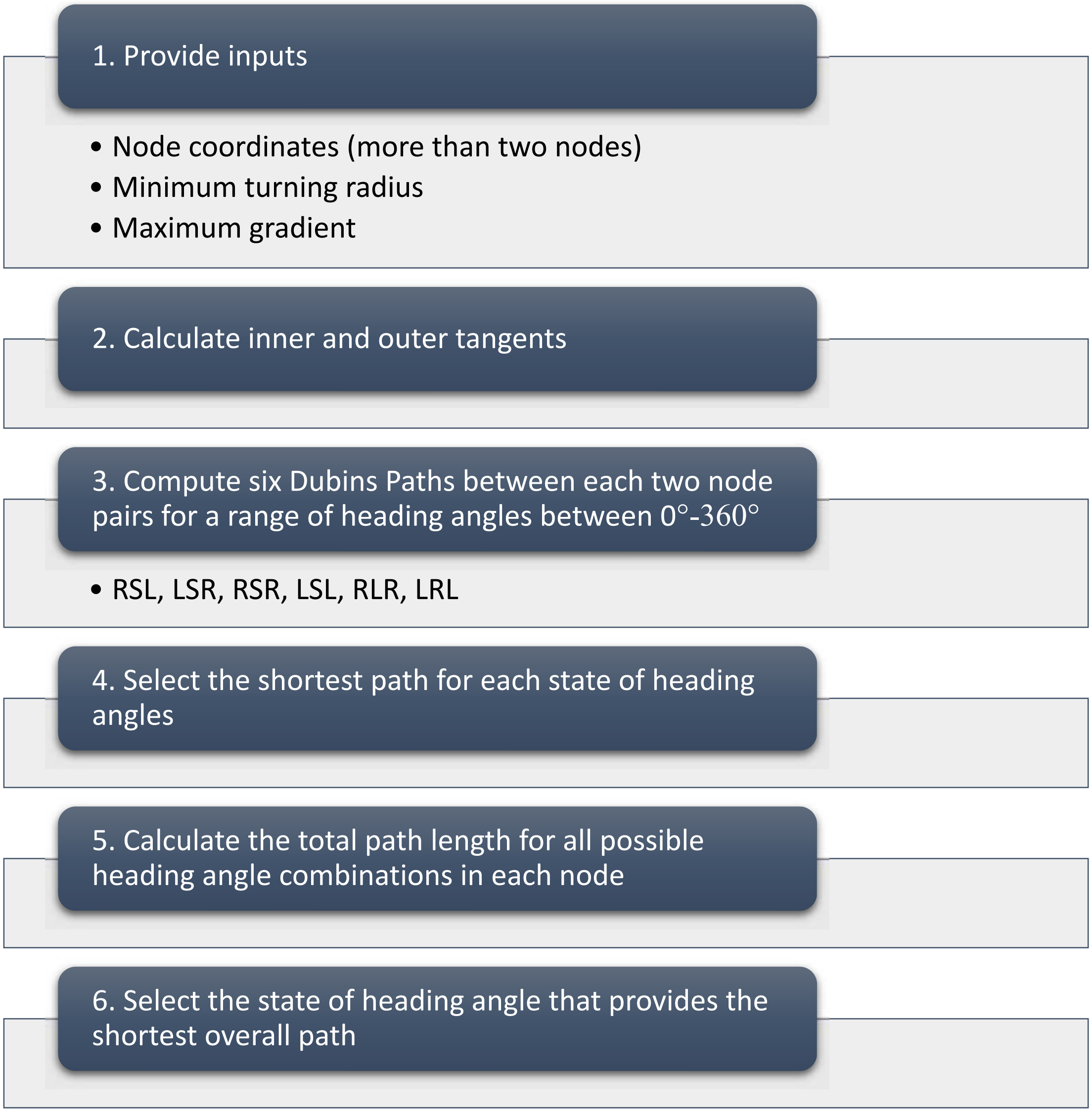


Figure 17 Flowsheet of the exhaustive search for the shortest path in underground mine haul roads

Although exhaustive search makes sure to reach the global optimum, it lacks computational efficiency. Even for a calculation between two nodes there are 360 x 360 heading angle combinations. Considering a simple mine requires tens to hundreds of nodes for a main haul road, it is obvious that a dramatically high computation time is required. Thus, this algorithm needs to be improved.

4.4 Heuristic Algorithm

Heuristic algorithm is a modification of the exhaustive search. Adding some extra constraints decreases the size of solution space. These constraints rely on the expert opinion. By this way, computation requires less time. Underground mine design may be restricted by some undesired rock mass volumes. Mine design experts may prefer to avoid the main haul road from passing those regions. Manipulating the heading angle of nodes can achieve this goal. The heuristic algorithm eludes unnecessary calculations and focuses on the path that traverses on the desired directions.

4.4.1 Objective Function

Objective of this path planning problem is to minimize the path length between many nodes. Each node pair is connected by any one of the Dubins Paths or special paths. Difference from the exhaustive search lies in the solution space. Below is the mathematical expression:

$$\boldsymbol{Minimize}\ \{Path\ Length\}$$

where;

$\theta_i = Heading\ angle\ of\ the\ nodes$

$\psi_i = Gradient$

$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$

Subject to:

$$0 \leq \theta_i \leq 2\pi$$

$$0 \leq \psi_i \leq grad_{max}$$

$$0 \leq v_i$$

Given;

$(east_i, north_i, elevation_i, heading\ angle_i)$

$tr_{min} = minimum\ turning\ radius$

$grad_{max} = maximum\ graident$

$\theta_{i,lower\ boundary} \leq \theta_i \leq \theta_{i,upper\ boundary}$

4.4.2 Workflow of the Algorithm

In exhaustive search, node heading angles are values within an interval of 0 - 360°. In mining practice, the main haul road is most likely to be perpendicular or close to perpendicular to the crosscuts. Heuristic algorithm restricts heading angle intervals for nodes. Normally, complete solution space has 360 x 360 possibilities. However, heuristic algorithm considerably decreases the solution space.

This approach has disadvantages in terms of the degree of optimality. It does not guarantee the global optimum solution because all probable solutions are not evaluated. The solution cannot be claimed to be a near optimum solution because there is a high risk of being trapped inside a local optimum. However, shorter calculation time is a major advantage. Workflow of the algorithm can be seen in Figure 18.

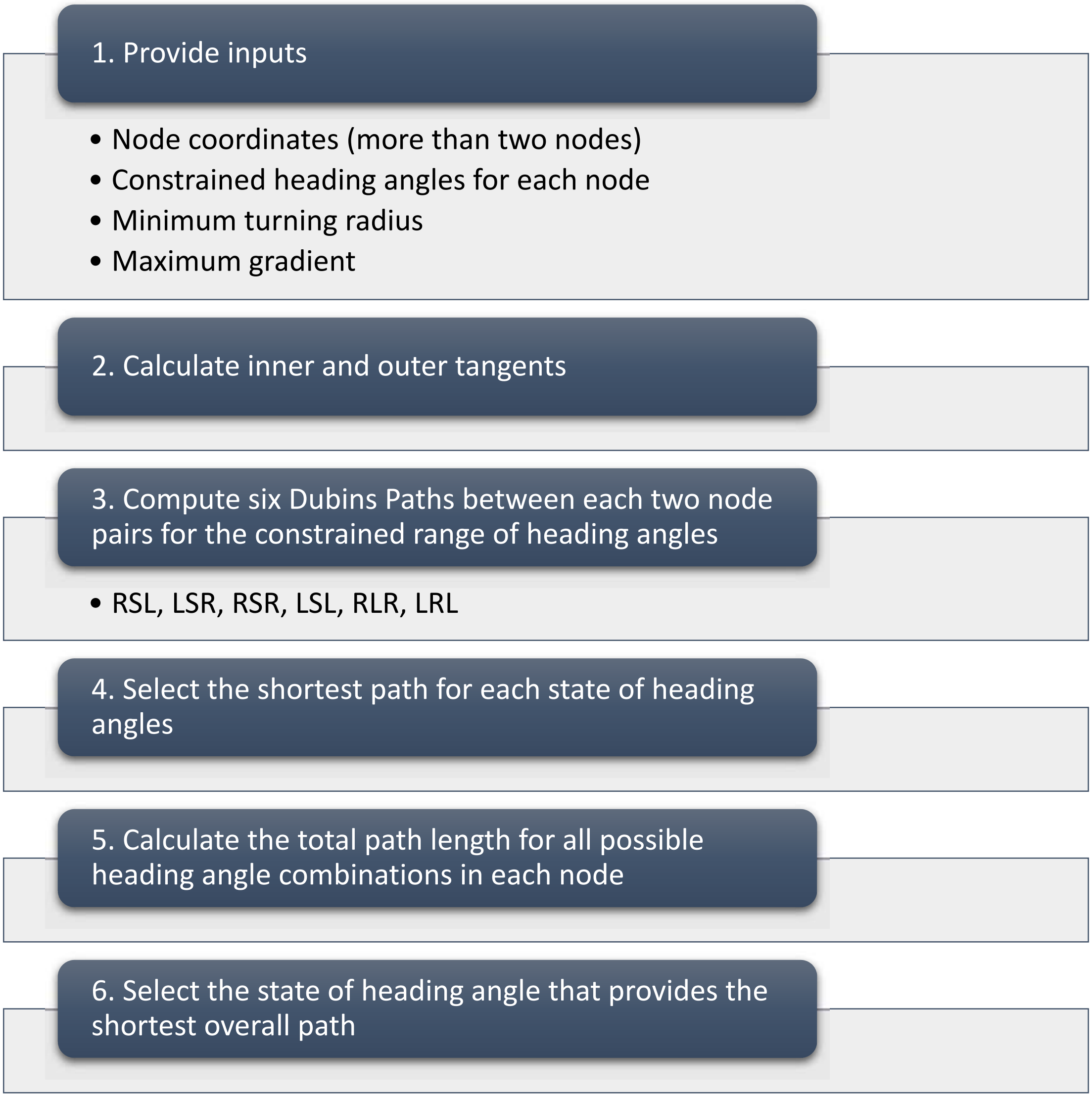


Figure 18 Flowsheet of the heuristic algorithm for the shortest path in underground mine haul roads

4.5 Dynamic Programming (DP)

Until now, all of the presented methods have some advantages and disadvantages. To remind, exhaustive search is presented by its success in computing the global optimum solution. However, computation takes very long time. Heuristic algorithm improves the computation time but the result is not necessarily a global optimum. Apparently, an optimization technique that provides the global or near global solution in a reasonable time is required. Therefore, Dynamic Programming is applied on this path planning problem. Results are observed to match the performance requirements.

4.5.1 Objective Function

Objective of this path planning problem is to minimize the path length between many nodes. Each node pairs are connected by any one of the Dubins Paths or special paths. Below is the mathematical expression:

$$\boldsymbol{Minimize}\ \{Path\ Length\}$$

Where;

$$\theta_i = Heading\ angle\ of\ the\ nodes$$
$$\psi_i = Gradient$$
$$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$$

Subject to:

$$0 \le \theta_i \le 2\pi$$
$$0 \le \psi_i \le grad_{max}$$
$$0 \le v_i$$

Given;

$$(east_i, north_i, elevation_i, heading\ angle_i)$$
$$tr_{min} = minimum\ turning\ radius$$
$$grad_{max} = maximum\ graident$$

4.5.2 Workflow of the DP Optimization

Node coordinates and kinematical constraints are defined. Heading angle combinations are written into a matrix. In this matrix, each column represents a stage and each state denotes a heading angle between 0° - 360°. Later, Dubins Paths are calculated and the shortest one is selected for each state. Length of the shortest path is calculated and written into the matrix. This matrix is called the length matrix. As it can be predicted, increasing number of main nodes increases the number of possible paths and the calculation time. Next, DP starts to evaluate the shortest route starting from the last stage and going through the first stage. In each stage the heading angle combination that gives the shortest path is determined. As progressing backwards, heading angle combination that gives the shortest path is only investigated for the current stage. Calculations that were done before are not repeated. By this way, computation is completed faster. Figure 19 shows a sample decision tree for DP.

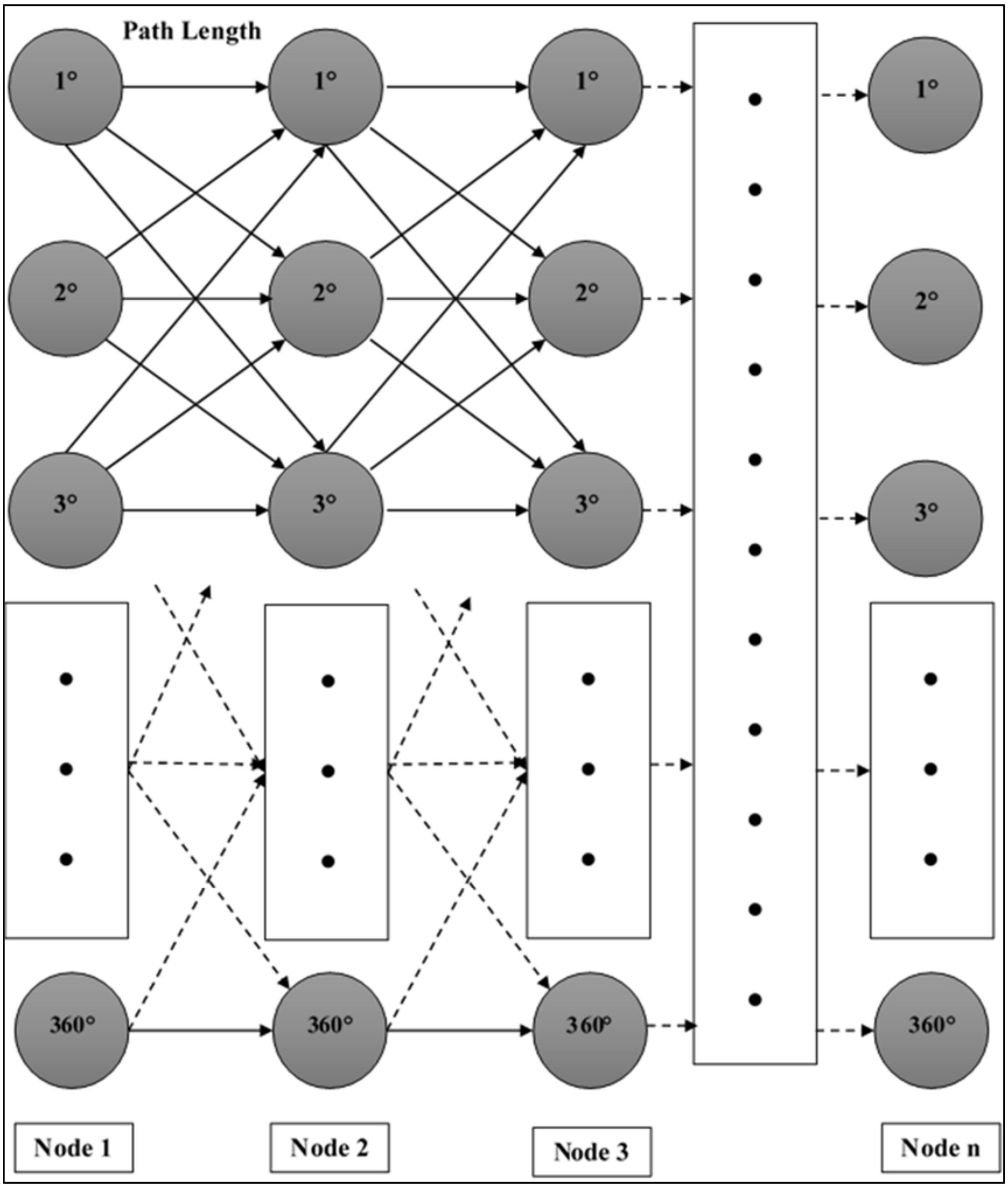


Figure 19 Sample decision tree for the shortest path algorithm using DP optimization

This sample decision tree represents a path planning problem for n nodes. Each column represents a node and each state stands for a heading angle. All of the states are connected to each other. Arrows connecting the pairs of heading angles in the two consecutive nodes represent the length of the shortest Dubins Path. Figure 20 shows the flowsheet of the shortest path algorithm by DP optimization.

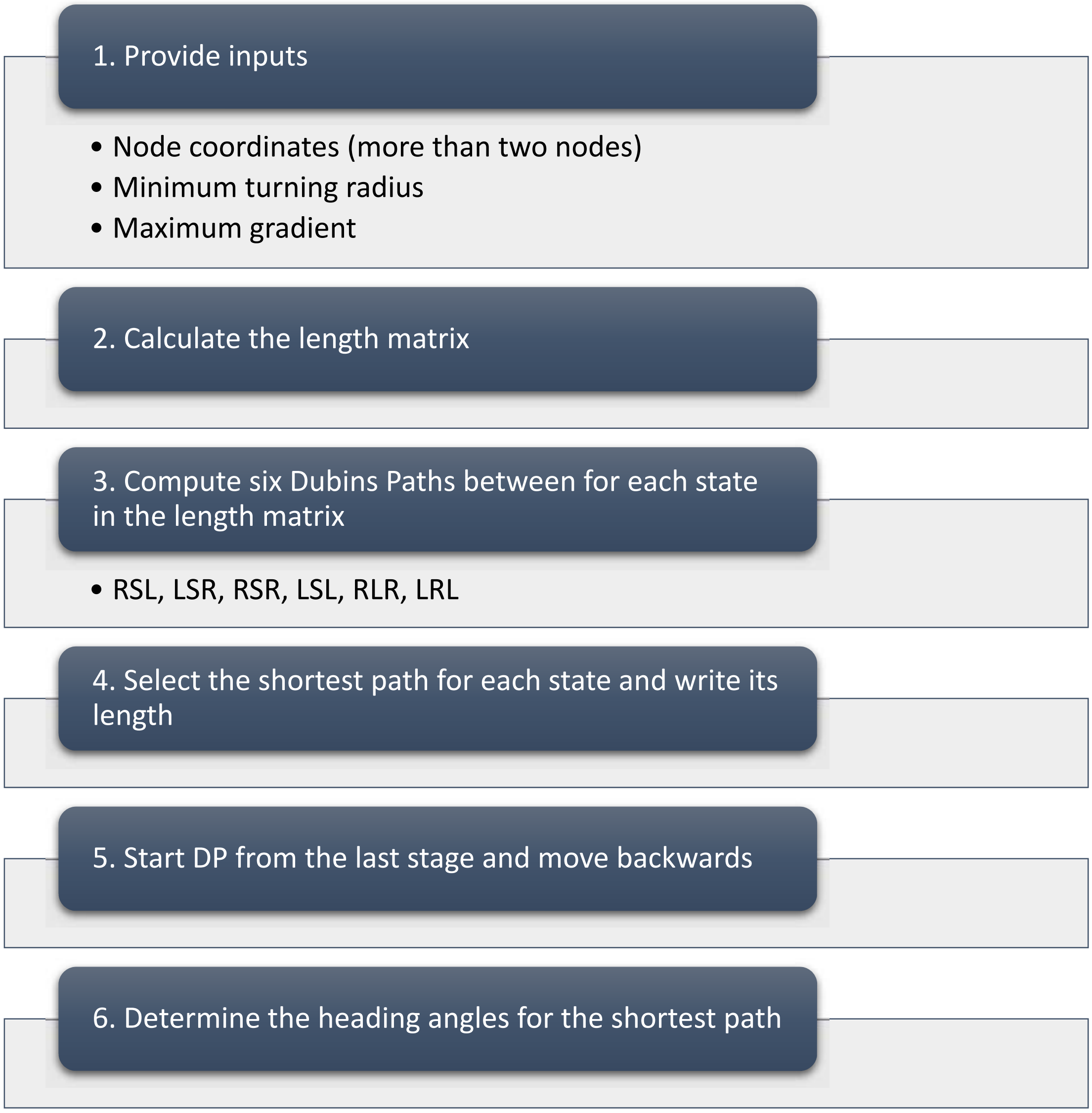


Figure 20 Flowsheet of the DP optimization for the shortest path in underground mine haul roads

The advantage of DP lies in the solution mechanism. The most primitive approach is to generate many sub problems and solve each of them, individually. However, DP seeks to solve each sub problem only once. If the solution to a sub problem has already been computed, it is stored: the next time the same solution is needed, it is simply called from memory. By this way, the number of computations is reduced. This approach is especially useful when the repeating sub problems grow exponentially as a function of the input size.

4.6 Genetic Algorithm

Constrained optimization of a 3D path is a complex computational problem. Depending on the number of variables, the problem converges to an exponential time problem. Complex underground mines with tens of sublevels represent a typical example for such difficult problems to solve. Exhaustive search is an inefficient but exact solver to obtain the global optimum. Heuristic algorithm improves the computational efficiency by adding some extra constraints to reduce the search space. However, degree of optimality is most likely to be poor. Intelligent algorithms are advantageous in path planning by learning through the generations instead of trying all the possible solutions. Although they provide near optimal solutions, if the difference is not meaningful compared to the global optimum then they can be used for increasing computational efficiency.

This study investigates the performance of evolutionary algorithms on path optimization that learns from the past experience. Genetic Algorithm provides flexibility to apply heuristic corrections on the path, where it is necessary. These corrections avoid some undesired regions and stay inside the desired region. Such heuristics are implemented by the proposed mutation operators. Prior to the optimization, travel sequence of nodes is certain. Otherwise, it would be necessary to determine the optimal sequence such as a Travelling Salesman Problem (TSP).

4.6.1 Objective Function

The fitness score of the haul road is defined in terms of five factors. In genetic algorithm terminology, objective function optimizes a fitness score that is similar to the cost in conventional optimization. Each of the cost factors is weighted in the objective function. Weighting defines the cumulative effect of cost factors on the overall cost. Sum of the weightings is one. Each cost factor may take different weightings depending on the characteristics of the problem. In some cases, catching nodes may be more vital while avoiding is more critical in others. In this study, weightings are determined by trial and error method and their values are (0.3, 0.3, 0.2, 0.1, 0.1). The objective function of the Genetic Algorithm is as follows:

$$\boldsymbol{Minimize}\ \left\{w_1 \times \left({}^{1}\!/_{PL_{cost}}\right) + w_2 \times FN_{cost} + w_3 \times \left({}^{1}\!/_{GRD_{cost}}\right) + w_4 \times UR_{cost} - w_5 \times DR_{award}\right\}$$

Where;

$PL_{cost} = Cost\ of\ the\ path\ length\ (m)$

$FN_{cost} = Cost\ of\ missing\ the\ final\ node(m)$

$GRD_{cost} = Cost\ of\ the\ gradient$

$UR_{cost} = Cost\ of\ violating\ the\ Undesired\ Regions$

$DR_{award} = Award\ of\ keeping\ inside\ the\ Desired\ Regions$

$w_n = Weighting$

$\theta_i = Heading\ angle\ of\ the\ nodes$

$\psi_i = Gradient$

$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$

$i = Node\ number$

$n = 1, \ldots, 5$

Subject to:

$$0 \le \theta_i \le 2\pi$$
$$0 \le \psi_i \le grad_{max}$$
$$0 \le v_i$$
$$0 \le w_n \le 1$$

Given;

$(east_i, north_i, elevation_{i^{th}\ node}, heading\ angle_i)$

$tr_{min} = minimum\ turning\ radius$

$grad_{max} = maximum\ graident$

4.6.1.1 Cost of Path Length

Length of a haul path is the major cost factor in the objective function. As an underground mine design rule of thumb, an efficient design must travel the shortest path. By this way, short term (cost of ramp construction) and long term (operating cost) costs can be reduced.

4.6.1.2 Final Node Missing Penalty

The algorithm requires to catch the predefined nodes, which are the sublevel entry points. In each calculation, the algorithm calculates the distance between the target node and the calculated path. The distance is added to the objective function as one of the cost factors.

4.6.1.3 Gradient Penalty

In order to travel the shortest path in 3D space, the algorithm must use the maximum available gradient. Gradient assignment to the path sections is a probabilistic task. Sometimes, the algorithm may assign a lower gradient than the maximum value it could pick. In order to reduce this probability, it is included in the objective function as a cost item. Through the generations, the algorithm minimizes the cost of using small gradient values.

4.6.1.4 Undesired Region Penalty

Structural anomalies like faults and joints, or pressurized underground spaces (like aquifers) are regions to be avoided in an underground haul road path. These regions may cause instability problems or increase the cost of construction. Therefore, the objective function includes a penalty factor these items.

4.6.1.5 Desired Region Award

Extents of the rock mass inside which the main haul road will be constructed are limited by the Desired Region. This region is defined in terms of x, y and z boundary coordinates. In order to keep the path inside this Desired Region, any node of the path inside this region is awarded by decreasing the fitness value.

4.6.2 Discretization

In order to simulate the travel path of the underground mine vehicle, the travel path is discretized. The total travel time $[t_1; t_n]$ is divided into $n > 0$ subintervals.

$$[t_1; t_2]; [t_2; t_3];\ldots; [t_{n-1}; t_n]$$

Each subdivision has an equal duration. In each discrete time interval, all of the control variables are assumed to be fixed. In other words, the underground mining vehicle is assumed to travel with the same heading angle in each subinterval. Discretization can be increased for a smoother path. However, in this study we observed that the number of control variables and the GA takes more time to converge. Also, we tried to decrease the discretization. This time, problems such as increased cost of missing final nodes are observed. Also, smoothness of the path decreases.

4.6.3 Finding the Seed Path

Genetic Algorithm (GA) requires a good starting point for path planning that satisfies the physical constraints. An initial path is generated by randomly assigned control variables. This path is called the seed path. Later, GA creates a population by randomly changing the seed path. Quality of the seed path controls the degree of optimality and convergence of the optimization solver.

In this study, alternative methods were investigated for seed path generation. Besides, the randomly assigned values for control variables, the heuristic algorithm was also used. It provides a quite fast and useful initial guess for the starting point of the optimization. The optimum heading angle intervals in each node are predicted and the heuristic solution is assigned to the GA population generation mechanism. In spite of its benefits, this method is observed to force the GA into local optima in some computational experiments. To overcome this effect, mutation rate is increased up to 90% when the change in fitness score is less than 1%.

4.6.3.1 Population Generation

This section presents the population generation procedure. Population is a set of candidate solutions (named as individuals) of the optimization problem. Each individual is composed of some chromosomes that can be altered by mutation and cross-over operators. This process is similar to the biological phenomena.

This path optimization problem has a population size of 50. Each chromosome has five parts. The first part is the number of steps that the underground mining vehicle travels with the heading angle in the second part. The third part is the final heading angle after the turn is completed. The fourth part is the number of turn in the helical ramp section and the final part is the gradient. Chromosome structure can be seen in Figure 21.

# of steps with fixed heading angle			Heading angle before			Heading angle after			# of turns in the ramp			Gradient		
100	50	…	π/2	π/4	…	π/4	π/6	…	2	1	…	0.10	0.08	…

Figure 21 Chromosome structure

4.6.3.2 Genetic Operators

Crossover

Crossover is a genetic operator that produces child chromosomes by replacing the genes from the parent chromosomes. Selection (reproduction) process enriches the population. Reproduction makes clones of good strings but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring. High fitness score increases the chance of a chromosome to be selected as a parent. Figure 22 illustrates a typical crossover operation.

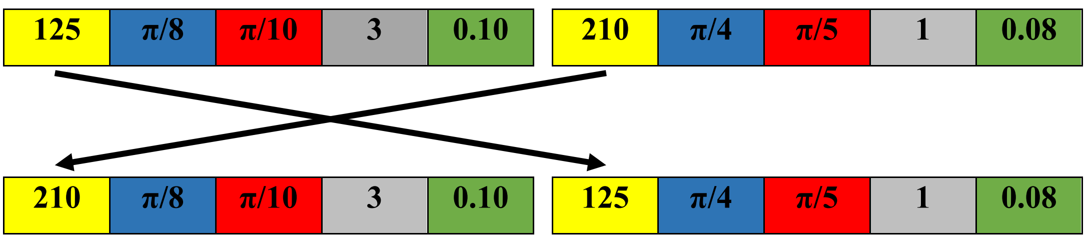


Figure 22 Crossover operator

Mutation

After crossover, the strings are subjected to mutation. Mutation prevents the path from trapping inside a local minimum. Mutation plays the role of recovering the lost genetic materials as well as for randomly disturbing genetic information. It is an insurance policy against the irreversible loss of genetic material. Mutation has traditionally been considered as a simple search operator. If crossover is supposed to exploit the current solution to find better ones, mutation is supposed to help for the exploration of the whole search space. Mutation is a background operator that maintains the genetic diversity. It introduces new genetic structures in the population by randomly modifying some of its building blocks. In this study, the mutation rate is fixed to 5%. Randomly selected control variables are changed by adding some values.

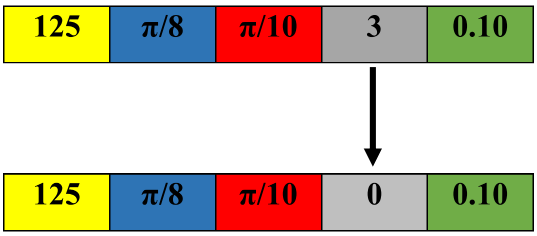


Figure 23 Classical mutation operator

4.6.4 Final Path with the Proposed GA Operator

In this section, the final step of the path planning algorithm is presented. Proposed mutation operators and the classical GA operators are used to plan the underground mine haul road path. The proposed operators are the most important outcomes of this research. They are described briefly and presented by illustrations. The chromosome structure is reviewed according to the requirements of this step. The chromosome is only composed of the 'number of straight motion steps' and 'heading angles'.

4.6.4.1 Population Generation

Population in this stage is based on the resultant path determined in the first step. It is also called the seed path. The population in this final step is created by randomly changing the randomly selected positions of the chromosome.

4.6.4.2 Proposed GA Operator: Avoid Undesired Regions (URAV)

The first proposed operator makes local corrections on the path in order to fix the undesired region violations. This section describes the basic workflow of the operator. Randomly generated chromosomes are calculated and the path is subdivided into at least four equally spaced sections. Later, the undesired region violations and their locations are examined. Violation entry and exit locations are described by the subdivisions. First, the operator searches for the chromosome section controlling the violation entry. This section is the first node of the entry subdivision. Number of straight motion steps is set to '0' and the target heading angle is increased by 45°. By this way, motion of the vehicle going through the undesired region is redirected. Later, the first node of the next subdivision is located on the chromosome. Number of straight motion steps is set to the number of steps in the violated region and the target heading angle is decreased by 90°. Finally, the first node of the third subdivision is set to a number of straight motion that is equal to the second part and the target heading angle is increased by 45°. The corrected path catches the original path from the exit of the violation and the rest follows the original path.

Undesired regions are defined by the polygon node coordinates. Regions are restricted from the lower and upper elevations and these elevations are fixed. Figure 24 illustrates the mechanism of the proposed operator.

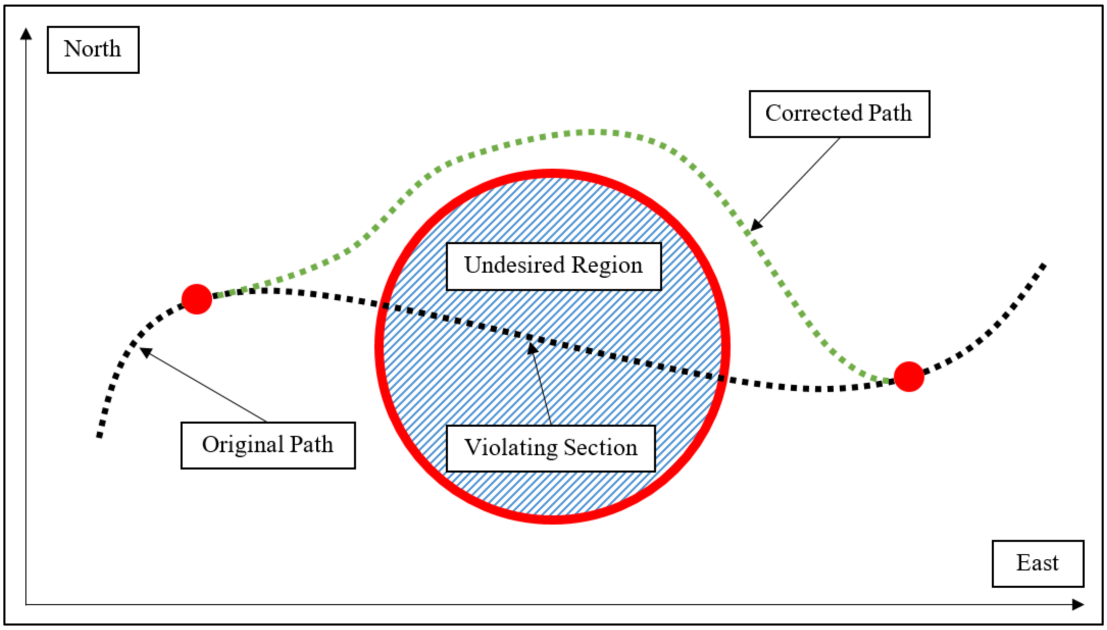


Figure 24 The proposed mutation operator to avoid undesired region violations (URAV)

Figure 25 shows the plan view of URAV operator applied on the Dubins paths that connect the (0,0,100) node to the (100,145,0) node. Blue lines show the original paths and red lines show the corrected path sections. Green polygon is the undesired region. The proposed operator calculates the shortest correction and avoids the violation.

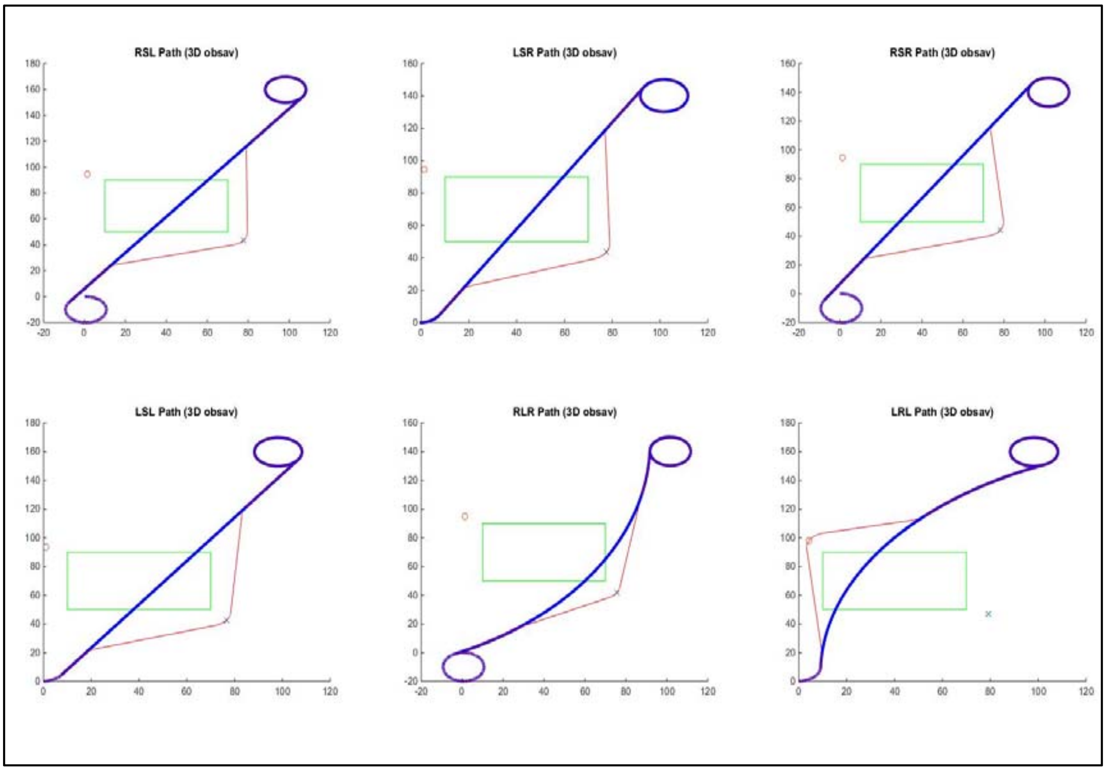


Figure 25 Plan view of the sample application of URAV operator

4.6.4.3 Proposed GA Operator: Keep inside Desired Region (DEREK)

In this path planning problem, extents of the rock mass covering the underground mine haul road can be defined. Exceeding borders is not recommended because it may result in tunneling inside poor quality rock mass or getting dangerously close to the orebody. This section presents the second proposed operator, which keeps the path inside the 'Desired Region'.

DEREK is a custom mutation operator that starts by calculating randomly generated chromosomes and subdivides the path into at least four equally spaced sections. Desired region violations and their locations are examined. The previous node before the violation and next node right after the path returns back to the desired region are determined. First, the operator searches for the chromosome section controlling right before the violation. Number of straight motion steps is set to '0' and the target heading angle is increased by 90°. Later, chromosome section of the second node is mutated by setting the number of straight motion to the step number of the violating section and increasing the target heading angle by 90°. This way, the corrected path catches the original path and the modification is limited to the problematic location. Figure 26 illustrates the DEREK operator.

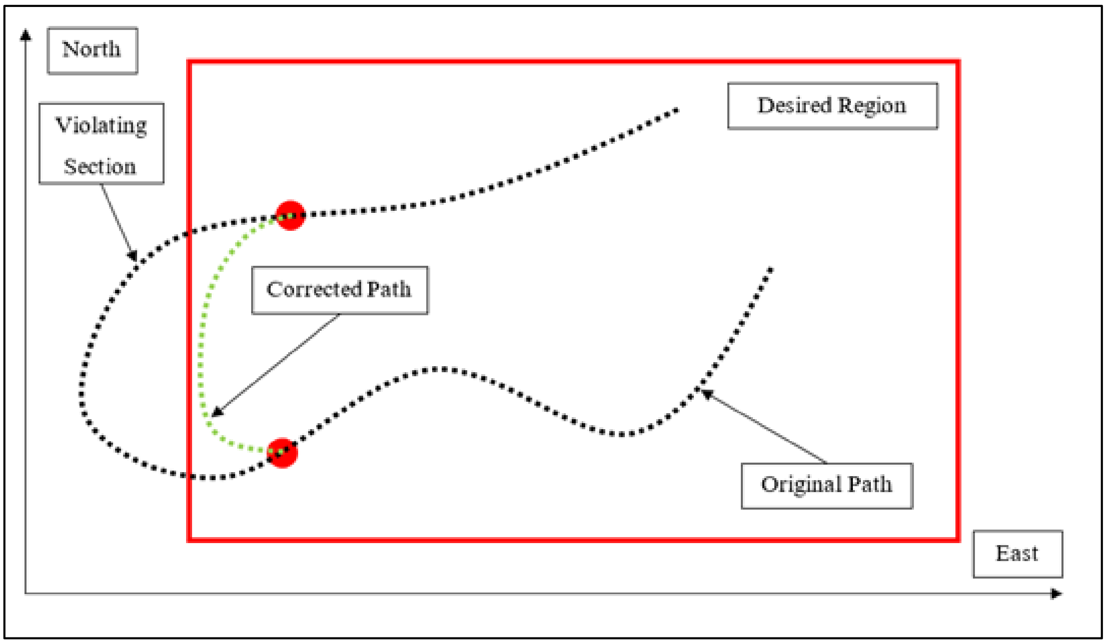


Figure 26 The proposed mutation operator to keep the path inside the desired regions (DEREK)

4.6.5 Workflow of the Algorithm

The flowchart of the algorithm is presented in Figure 27. Pseudocode is presented in Appendix B. Matlab Global Optimization toolbox functions for Genetic Algorithm were used. In addition to the classical GA operators, two new mutation operators are created. A special Graphical User Interface (GUI) is prepared for the ease of access to the created functions by Matlab programming. Output of this research is a standalone shortest path optimization software.

Inputs can be supplied to the software directly by entering data via the developed Graphical User Interface (GUI). Alternatively, common mining software file formats are recognized by the software. The algorithm takes the node coordinates and subdivides between each node pairs. Next, GA solver generates a seed path for the second optimization stage. This initial attempt only makes use of standard mutation and crossover operators. In the second stage, the seed path is used to generate a population of 50 individuals. Next, the algorithm calculates fitness scores for each path. The best 3 individuals are kept as parents of the next generation. In this stage, undesired region violations are detected and the proposed URAV operator makes local corrections on the path. Right after, the DEREK operator checks for the path sections that exceed the desired region boundaries. If there are any violations, then DEREK operator makes local corrections. Finally, classical crossover mutation operators are applied to obtain better off spring fitness values.

Stopping criteria of the algorithm drops 90% of the total population if there is no longer decrease in the fitness scores. A new population is generated that includes previously selected individuals. If the decrease in fitness values stops at the same levels the algorithm terminates, if not, the same procedure is applied until steady state is reached. By this way, trapping on the local optimum solutions is avoided.

The algorithm has a final node constraint. Therefore, each of the main nodes are needed to be traversed by the path. The algorithm detects distance of the path to each of the nodes and makes local corrections, if it is necessary.

Output of the algorithm is the list of coordinates for the optimum path. The path has dummy nodes as much as the ratio of the path length to the pace length. For each of the dummy nodes, coordinates are provided in the following format; (East, North, Elevation).

Inputs

- Node coordinates
- Minimum turning radius
- Maximum gradient
- Dicretization number
- Max steps of straight motion
- Max turns in a ramp section
- Desired region coordinates
- Undesired region coordinates

Genetic Algorithm (1st stage)

- Create a population randomly
- Generate a seed path
- Use classical GA operators
- **Output = Seed Path**

Genetic Algorithm (2nd stage)

- Generate a population from the seed path
- Calculate fitness scores
- For each of the individuals
  - Detect if there is any Undesired region violation
    - If Yes, apply URAV operator
    - If No, continue
  - Detect if the path violates desired regions boundaries
    - If Yes, apply DEREK operator
    - If No, continue
  - Apply classical GA operators
- End
- **Output = The shortest path**

Figure 27 Flowchart of the Genetic Algorithm for single objective optimization

4.7 Verification of the Algorithms

Path planning problems suffer from lack of verification problems. The analytical solution of the shortest path in a complex environment without violating kinematical constraints is a challenging task. However, the algorithms studied in this research requires to be verified before investigating its performance in real case studies.

In this study, an idealized mine layout is used to test the validity of the generated algorithms. A simple mine layout with a flat topography and orebody in the shape of a rectangular prism was generated. Crosscut entry coordinates in the East-North plane are the same and elevation difference between the successive crosscut entries are equal. There are no undesired regions and the desired region is a large volume. Sample view of the verification problem was shown before in Figure 7.

For this verification problem, the shortest path is apparent, which is a helical ramp. If the algorithms can predict the same path as the apparent solution, then we can conclude that the algorithms are prone to make meaningful predictions for more complex problems.

In this study, the shortest path is determined by the exhaustive search, the heuristic algorithm, dynamic programming, and the genetic algorithm. All of these methods are tested and the same helical ramp is obtained. Sample Matlab view from the verification can be seen in Figure 28.

Undesired region avoidance capability of the GA requires to be verified. Figure 29 shows the result of GA optimization on the verification problem shown in Figure 28 with an undesired region, coordinates of which are presented in Table 11. Apparently, the optimum keeps away from the undesired region.

Table 11 Coordinates of the undesired region

Node No:	East (m)	North (m)	Elevation (m)
1	70	60	30 - 70
2	90	60	30 - 70
3	90	90	30 - 70
4	70	90	30 - 70

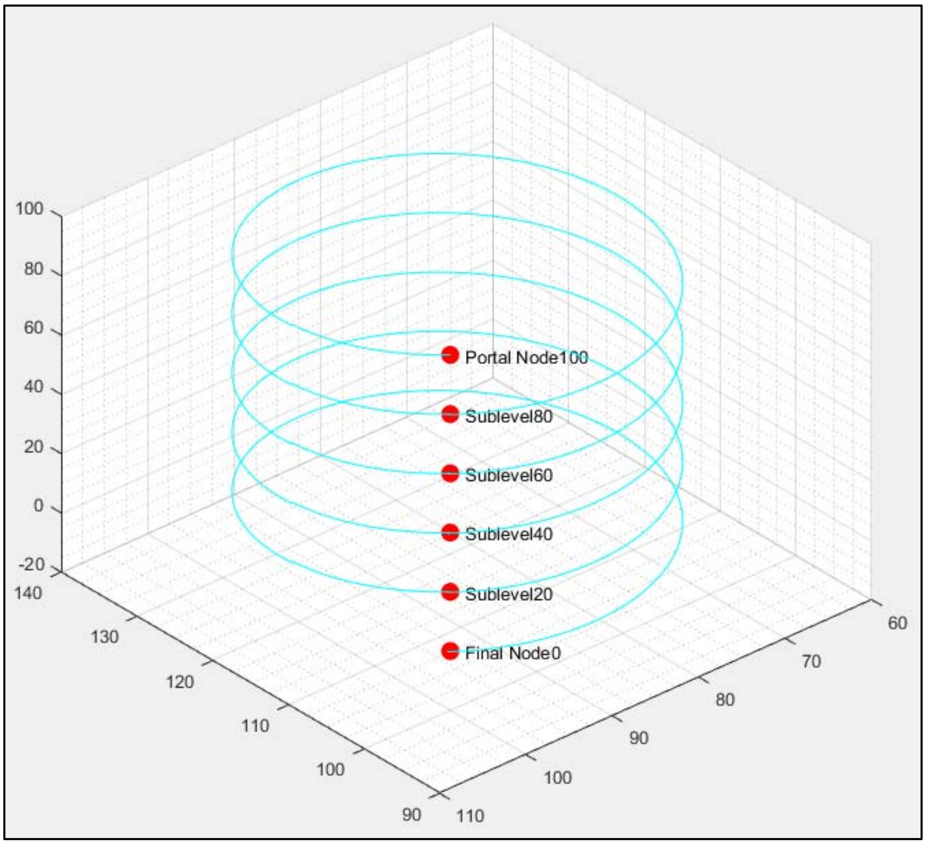


Figure 28 Result of the verification problem using exhaustive search, heuristic search, DP and GA

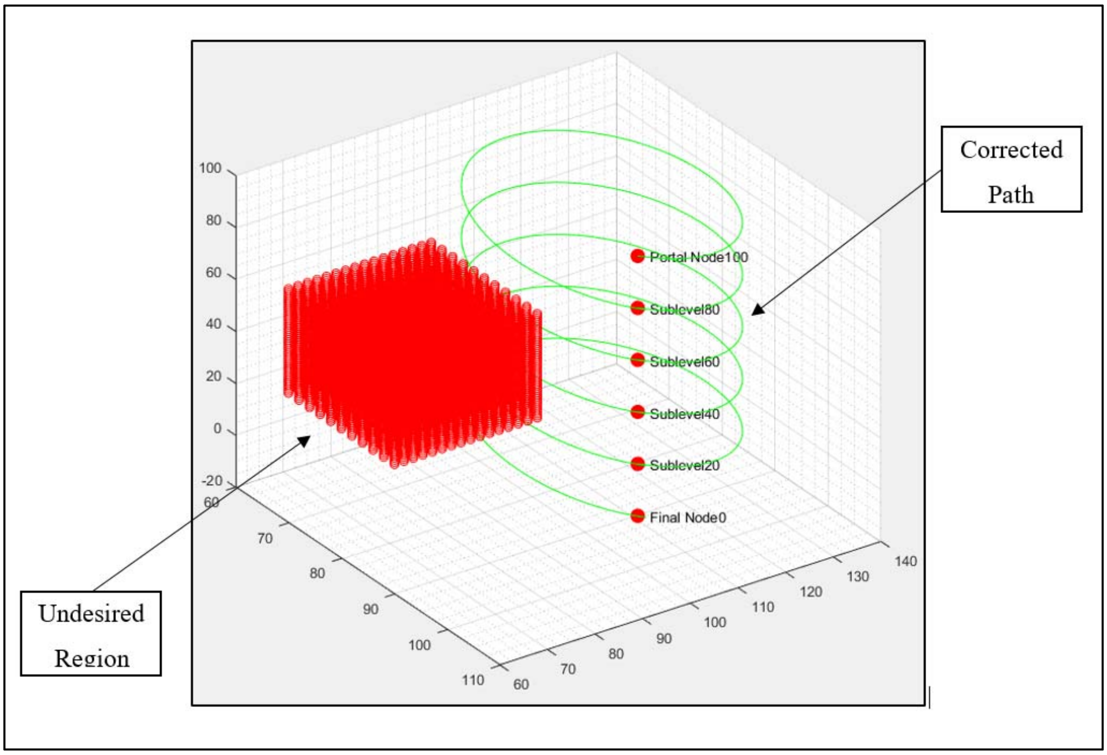


Figure 29 Result of the GA optimization on the verification problem with an undesired region

4.8 Research Output: An Optimization Software with a Unique Graphical User Interface

In the previous section, different shortest path optimization methods are described. GA is presented as an improved path optimization technique. Some unique features related to mining are included by the proposed genetic operators. Performance of intelligent algorithms is observed on underground mine haul road optimization.

This research investigates a complex path optimization problem. Solution is only possible by the computational methods. Therefore, the algorithms are created in Matlab [48] programming environment. Matlab is a high level developer tool that provides many of the basic mathematical libraries. By this way, the user can focus on the main task, rather than developing even for the basic operations. However, our problem requires unique features related to mining. Therefore, most of the algorithm is developed from scratch and implemented on Matlab. For GA optimization, Global Optimization Toolbox libraries were used.

Although Matlab provides a user-friendly environment for programming, regenerating such a complicated optimization problem cannot be efficiently performed by the command screen. Code screen is difficult for data entry and adjustment. Figure 30 shows a sample view from the Matlab command screen.

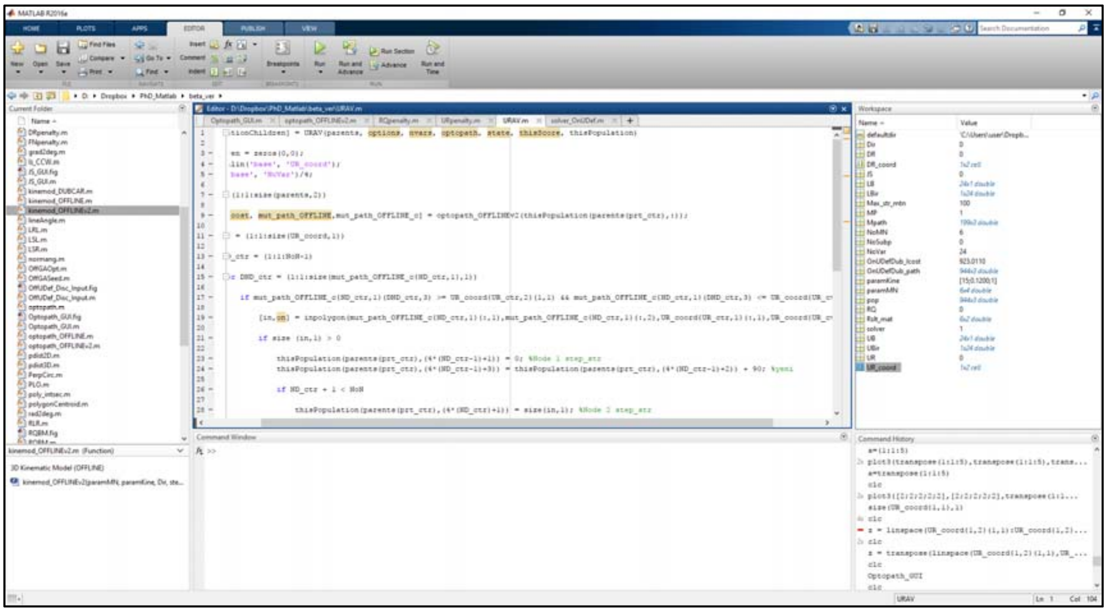


Figure 30 Sample view from the MATLAB command screen

As a research outcome, a unique ‘Graphical User Interface’ (GUI) was created. The GUI was bonded to the codes of the algorithms and different panels were arranged for node coordinate and kinematical constraints entry, optimization solver type selection, optimized paths plotting, and results summary reporting. The GUI and the codes were executed to a standalone software. This software is named as ‘Optopath’. Overview of the Optopath main screen can be seen in Figure 31.

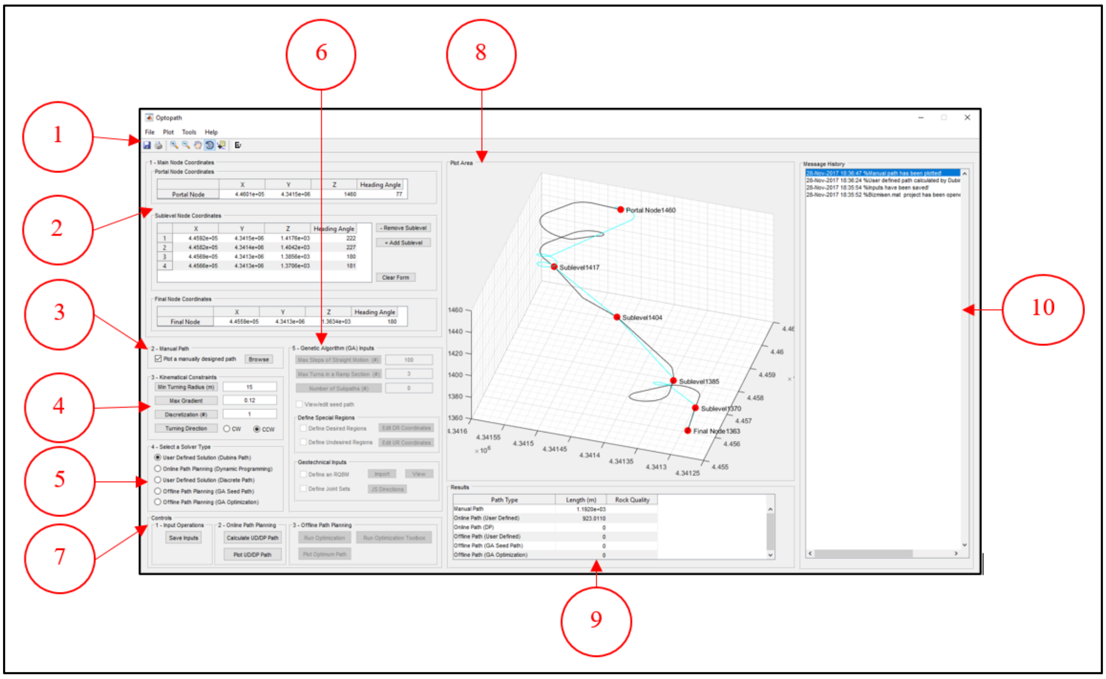


Figure 31 Overview of the GUI

Now, the GUI will be presented in detail. Each panel is assigned a number and the magnified view will be described in detail.

Figure 32 shows the menu bar and toolbar. A new project can be opened or an existing project can be called. Node coordinates can be imported or exported from or to an Excel file. In addition, optimized paths can be plotted using the related menu. Toolbar contains pan tool, rotation tool, and magnifier for managing the plot screen.

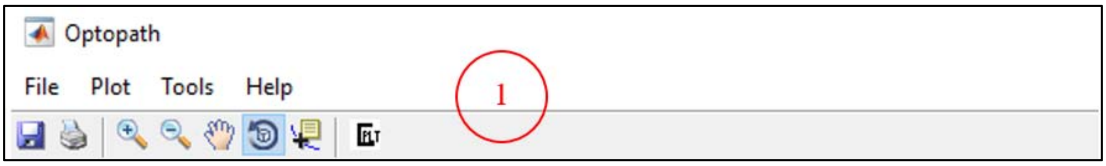


Figure 32 Menu bar and toolbar

Figure 33 show the node coordinate panel. The coordinates are either imported from an Excel file or manually entered. Sublevels can be added or deleted

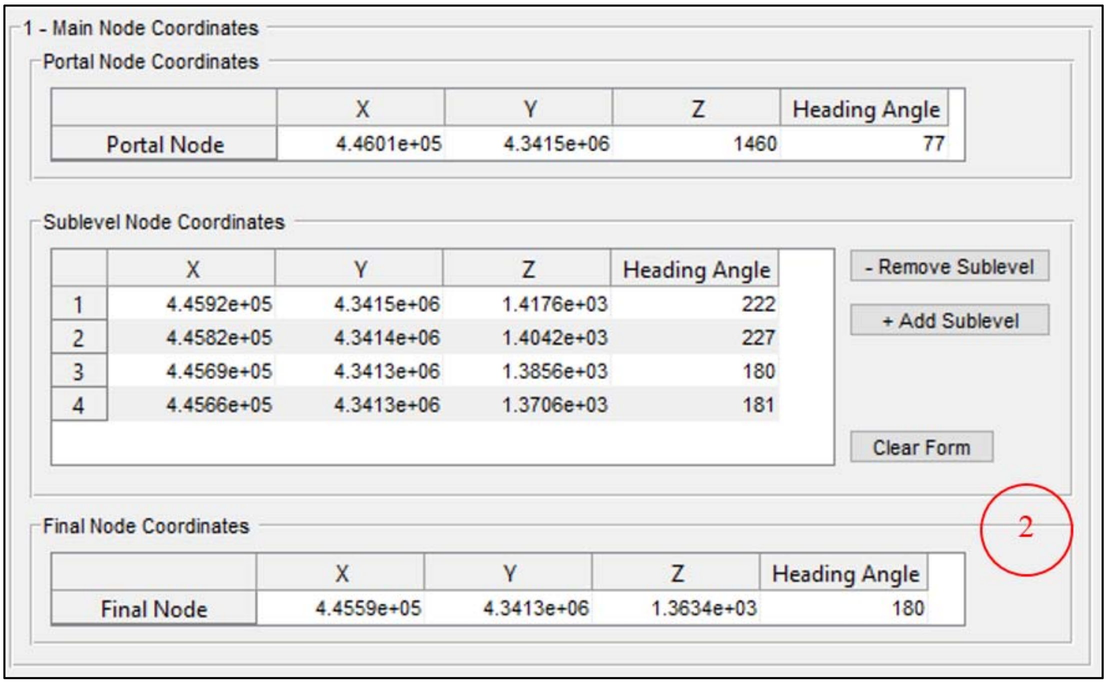


Figure 33 Node coordinate entry panel

Figure 34 illustrates the panel that is used for plotting the manually designed path

Figure 34 Manual path plot panel

Figure 35 shows the kinematical constraints panel. Here, the user can define the minimum turning radius, maximum gradient, and pace length. In addition, desired turning directions can be defined. Underground mine haul roads are different from other paths by their turning directions. Global optimality may be provided by turns on both sides, however; in underground mines, most of the times, a single turning direction is preferred. Although the path length increases, it might be desired for an ergonomic haul road path design.

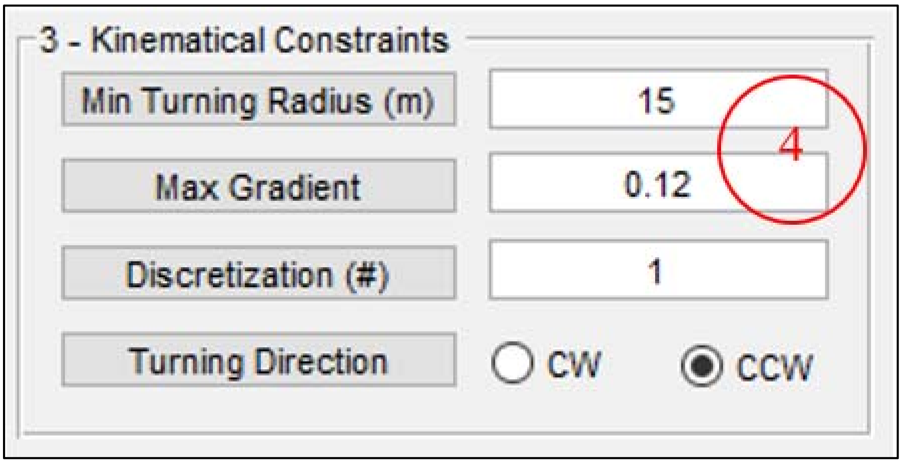


Figure 35 Kinematical constraints and selection of the turning direction panel

Figure 36 shows the optimization solver selection panel. The first selection provides the shortest path with Dubins Paths. The second option makes use of Dynamic Programming to calculate the optimum path. The third option is based on the kinematical model that is used in GA; however, the path is calculated for a single chromosome. The fourth solver calculates the seed path for the second stage GA. The final option optimizes the seed path including the proposed GA operators.

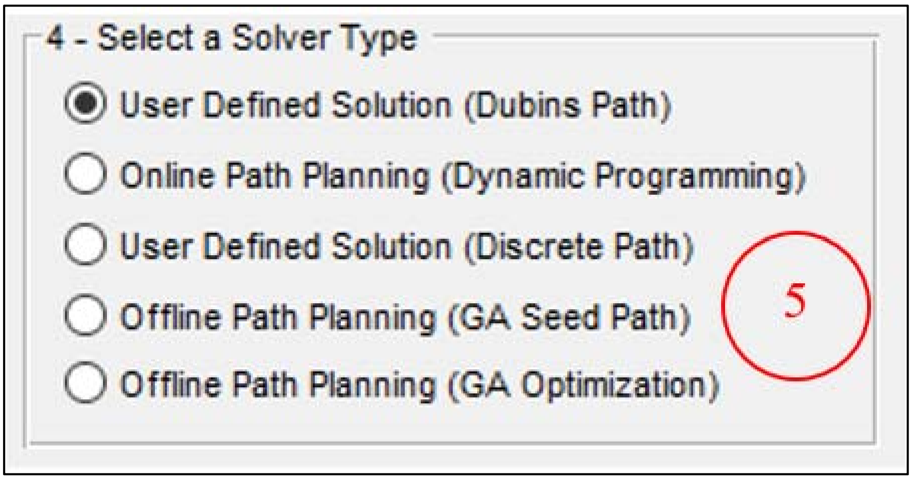


Figure 36 Optimization solver type selection panel

Figure 37 illustrates the GA input parameters. Here, the maximum number of straight motion steps can be adjusted. Also, the maximum turns in a ramp section can be set. Subdivision number is determined in this panel. Undesired region and desired region coordinates entry GUI can be called from this panel. For the least cost optimization, it is possible to provide the rock mass quality block model using the related section.

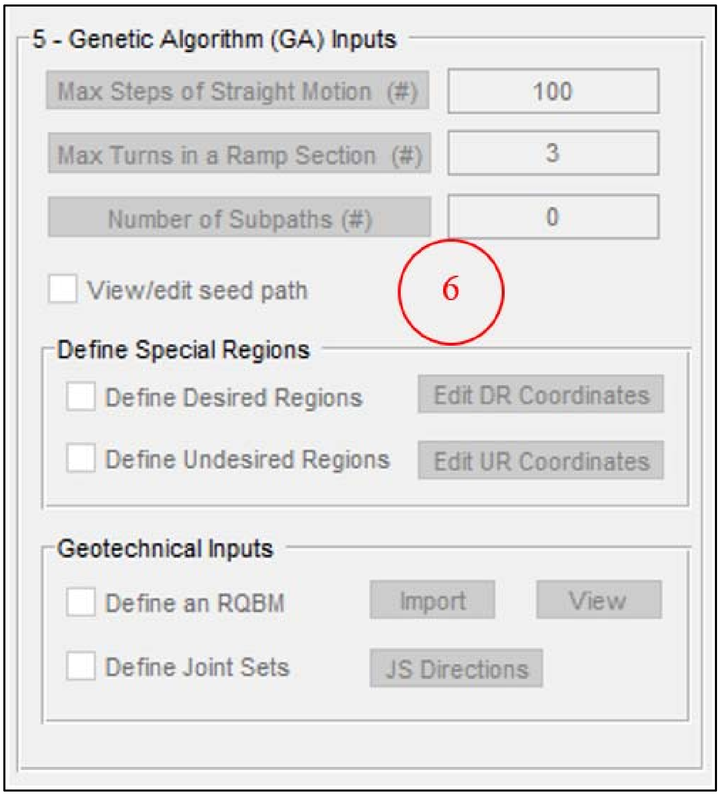


Figure 37 Genetic algorithm inputs panel

Figure 38 contains buttons for saving the input data, optimization using different solver types and plotting the results. In addition, Global Optimization Toolbox can be called for detailed GA setting adjustment.

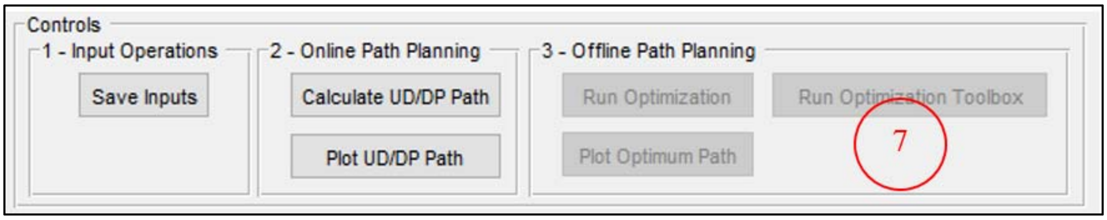


Figure 38 Controls panel

Figure 39 shows the plot screen. Optimized paths can be displayed in 3D environment. It is also possible to rotate the plot, pan, and magnify the screen. Node coordinates can be selected and read from the screen.

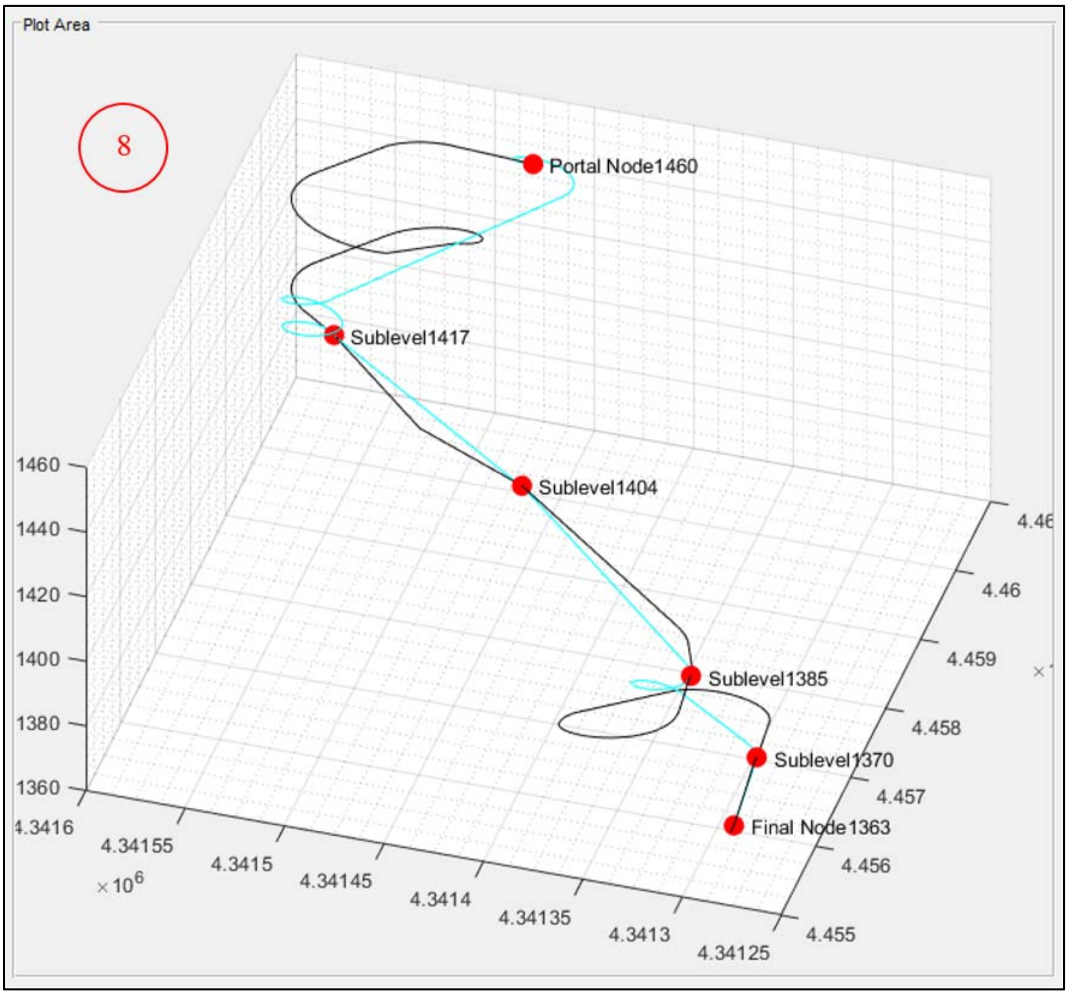


Figure 39 Plot screen showing the result of optimized paths

Figure 40 shows the result of optimization. Each row represents a different optimization solver. Path length and rock mass quality can be seen.

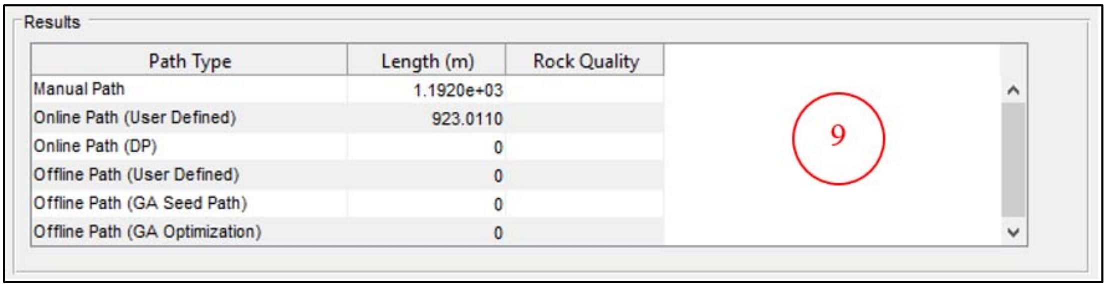


Figure 40 Optimization results table

Finally, Figure 41 presents the message history panel in which the feedbacks from the software can be seen. Log of each operation is recorded and displayed in this panel.

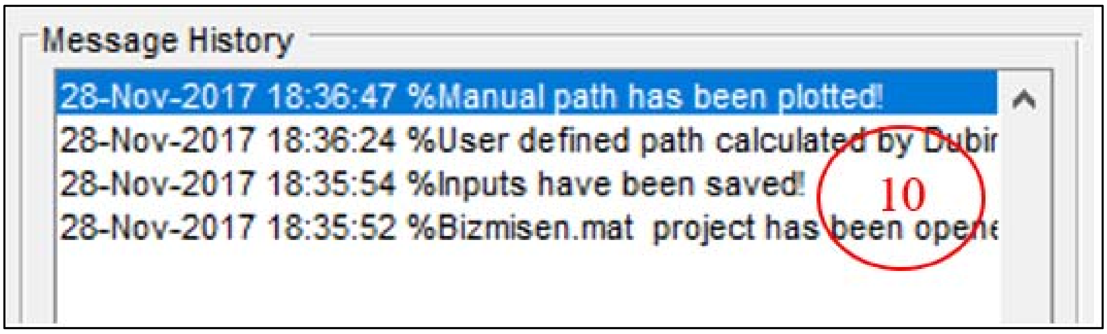


Figure 41 Message history panel showing the notifications from the software

4.9 Case Studies

This study presents a novel methodology for a mine design task that has been previously carried out by manual ways. The developed algorithm was applied on real underground mines. By this way, it was possible to check the superiority of the algorithmic design over the manual design. Some of these mines are already operating and the others are in development phase. The mines are presented below.

The first case study is an underground iron mine in Erzincan/ Bizmisen region of Turkey. Two sectors in Bizmisen region have been operated by shallow depth open pit mines. Outcropping orebody part of Donentas dips with 23° in the opposite direction to the overlying hillside. By referencing to the outcrop, orebody depth is estimated as 345 m.

As a consequence of the opposite dip direction to the topographical surface, depth of any open pit exploiting the complete orebody would extent more than this depth. Due to economic and legal problems, upper part of the orebody was planned to be exploited by an open pit mine. A crown pillar was planned to be left below the open pit to sustain safety in the underground operation, which was planned to produce remaining ore in the lower parts.

Figure 42 illustrates the mine location, orebody geometry and Donentas open pit layout (Google Earth, 2016). Donentas sector is located on the North East of Bizmisen district of Erzincan / Turkey. Satellite view of the mine, plan and cross-section view of the 3D orebody model and orebody dimensions can be seen in Figure 42.

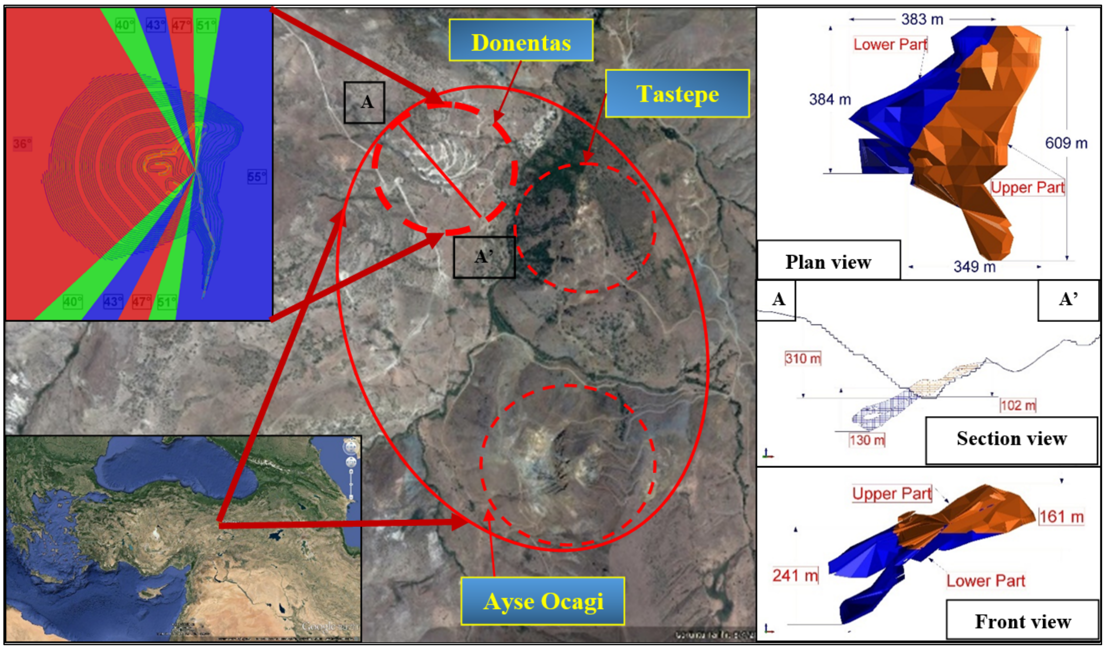


Figure 42 Overview of the Erzincan/Bizmisen underground mine

Studies of Durand et al. [49] tectonic units of Turkey report that all the mine sites settle in the south of Ankara-Erzincan suture zone and north of the Toros Mountain Chain.

The oldest formation around the region is carboniferous-campanian aged Munzur limestone embedded as blocks in serpentines. Granite rock formations are covered incompatibly by sedimentary rocks with nummulites. In the region, this formation is abducted by Oligocene-Upper Miocene including various local inconsistencies. Plio-anthropogene, aged terrestrial sediments are the youngest rock formation [50].

The tectonic subgrade of the region is composed of lower carboniferous-campanian aged Munzur limestone and aged ophiolite rocks consisting of intense serpentinized periodititic rocks. In the upper layer, aged Maastrichtian is incompatibly involved. Paleocene aged granitic rocks possibly interrupt these formations. Mineralization and granitic rocks are non-conformably covered by Neogene aged formation consisting of partly limestone. The youngest formations around the region are Anthropogenic aged slope debris and alluviums.

Three of the other case studies are from the Kayseri city of Turkey. Karacat underground mine is located right below the open pit (see Figure 43). Apparently, open pit slope stability will be risky if proper filling design is not applied in underground mining operation. Three critical items of underground mine design are investigated: stope dimensioning, pillar design, and backfill design. As part of the design project, production stope dimensioning is first conducted. Later, pillar stability work is carried out for the multiple stope production operations at different levels of mine. Finally, economically optimum backfill alternatives are assessed from the point of local and global structural stability by numerical modeling.

Karacat mine is located in Yahyali district of Kayseri / Turkey. A satellite view of the mine, plan view from the 3D model showing the orebody, orebody dimensions and production levels from the cross section view can be seen in Figure 43. Besides from the Karacat mine, there are four active mines: two open pit and two underground mines in the area.

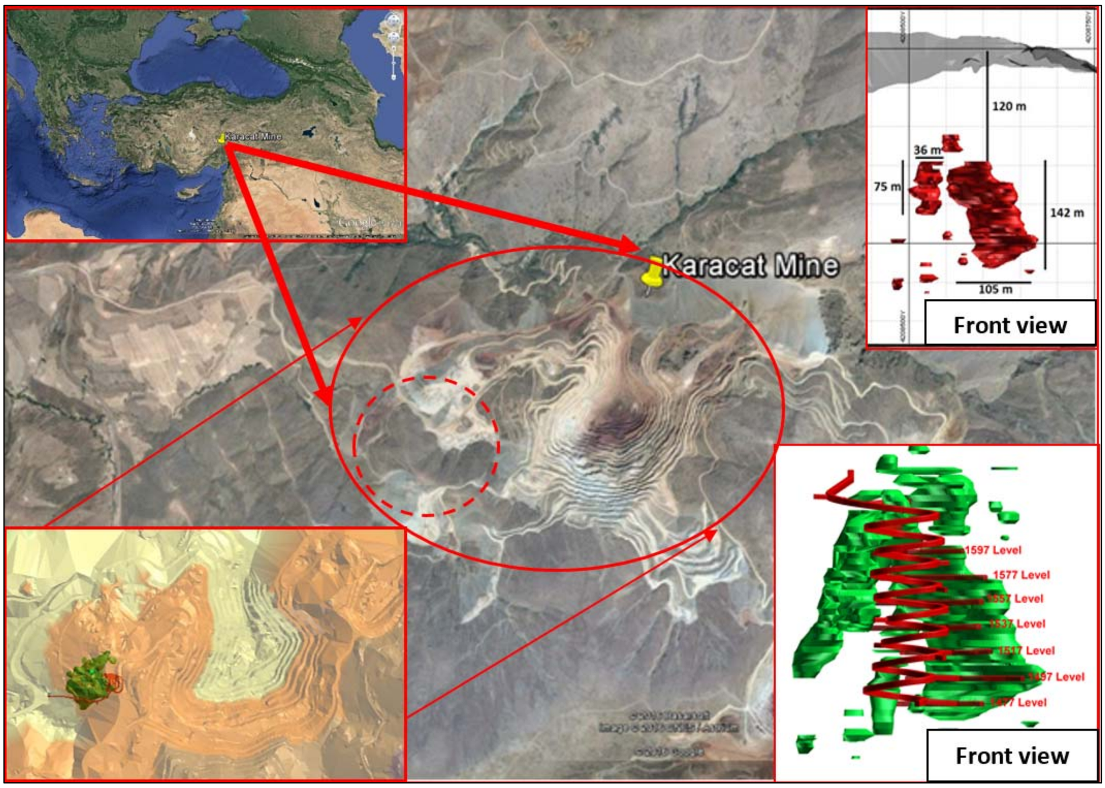


Figure 43 Overview of the underground mines in Kayseri

Geology of Karacat iron orebody was studied by Tiringa [51] in the scope of a Master of Science work. The Geyikdag unit was described to be located in the Taurid Tectonic Belt hosting the Karacat iron orebody. The orebody was reported to be surrounded by Emirgazi (Precambrian), Zabuk (Lower Cambrian), Değirmentaş (Middle Cambrian), and Armutludere (Ordovisian) formations.

Hematite and goethite are the major ore minerals which are believed to have originated as a product of siderite alteration. The ore body and country rocks interrelation (Zabuk formation, Değirmentaş formation, and Armutludere formation) can be stated to be controlled by tectonism.

Surface reaction mechanism and karstification processes are the result of post-mineralization faults. Altered siderite and iron minerals transform into limonite and goethite predominated by atmospheric conditions where surface reaction mechanisms are active. Products of the mineralization process mentioned above are exploited and served to industry as raw material.

Karacat Iron ore deposit can be described as a deformed deposit occurred by flow of hydrothermal fluids from Precambrian aged primer iron deposits.

Besides Karacat, Mentes, and Madazi, underground mines are located on the same region and investigated within the scope of this study. Geological features and mining methods are quite similar.

An underground metallic mine in Albania and an underground metallic mine in Sweden are also studied. Input parameters for GA optimization of the case studies can be seen in Table 12.

Table 12 Input parameters of the case studies

Case Studies		**Kinematic Constraints**		
No	Location	Minimum Turning Radius (m)	Maximum Slope (%)	Number of Nodes
1	Erzincan/TURKEY	15	12	6
2	Kayseri, Karacat/TURKEY	17.5	12.5	12
3	Kayseri, Madazi/TURKEY	25	12	6
4	Kayseri, Mentes/TURKEY	25	10	9
5	An U/G mine in Albania	10	17.5	15
6	An U/G mine in Sweden	20	15	7

4.10 Results and Discussion

Real underground mine haul roads are compared with the routes of the developed algorithms. Optimization is carried out by the Dynamic Programming and Genetic Algorithm. Resultant paths and path lengths are presented in this section.

The first case study is the Erzincan/Bizmisen underground iron mine. Appendix A Figure 55 shows the manually designed path and optimized paths by the developed algorithms. The first path designed by a human mine design expert and has a length of 1192 m. Dynamic Programming optimization provides a path of 925 m. Apparently, improvement is considerable. Solution takes a computation time of 3.5 hours. Genetic algorithm optimizes the path that has a length of 962 m. As it is predicted, GA provides a suboptimal solution. Compared to the manually designed path improvement is still satisfactory. In addition, the solution takes around two minutes, which is a significant improvement in terms of computational efficiency. On the other hand, considering the monetary cost of tunneling per meter is around 2,000$ the saving is around 460,000$ when Ga is used.

Appendix A Figure 56 presents a sample plot for GA generations. As it is a minimization type optimization, fitness value decreases. Generations stop when there is no considerable improvement in the fitness value. Also, optimum values of the control variables can be seen in the plot for the best individual.

The second case study is the Kayseri/Karacat underground iron mine. In Appendix A Figure 57 the manually designed and optimized paths can be seen. The first path designed by a human mine design expert and has a length of 1930 m. Dynamic Programming optimization provides a path of 1887 m. Apparently, improvement is considerable. Solution takes a computation time of around 6 hours. Genetic algorithm optimizes the path that has a length of 1897 m. Again, GA provides a suboptimal solution. Compared to the manually designed path improvement is satisfactory. In addition, the solution takes around five minutes. Computational efficiency has been improved significantly.

The third case study is the Kayseri/Madazi underground iron mine. Appendix A Figure 58 shows the manually designed path and optimized paths by the developed algorithms. The first path designed by a human mine design expert and has a length of 877 m. Dynamic Programming optimization provides a path of 805 m. Apparently, improvement is considerable. Solution takes a computation time of around 3.5 hours. Genetic algorithm optimizes the path that has a length of 825 m. Again, GA provides a suboptimal solution. Improvement in length is satisfactory if compared with the manually designed paths. In addition, the solution takes around three minutes. Compared to the manual design, monetary value of the saving is around 104,000$.

The fourth case study is the Kayseri/Mentes underground iron mine. Appendix A Figure 59 shows the manually designed path and optimized paths by the developed algorithms. The first path designed by a human mine design expert and has a length of 1949 m. Dynamic Programming optimization provides a path of 1482 m. Apparently, improvement is considerable. Solution takes a computation time of around 5 hours. Genetic algorithm optimizes the path that has a length of 1581 m. Again, GA provides a suboptimal solution. Compared to the manually designed path improvement is satisfactory. In addition, the solution takes around four minutes. Compared to the manual design, monetary value of the saving is around 736,000$.

The fifth case study is from an underground mine in Albania. Appendix A Figure 60 shows the manually designed path and optimized paths by the developed algorithms. The first path designed by a human mine design expert and has a length of 1165 m. Dynamic Programming optimization provides a path of 1137 m. Apparently, improvement is considerable. Solution takes a computation time of around 3.5 hours. Genetic algorithm optimizes the path that has a length of 1144 m. Again, GA provides a suboptimal solution. Compared to the manually designed path improvement is satisfactory. In addition, the solution takes around ten minutes.

The final case study is an underground mine in Sweden. Appendix A Figure 61 shows the manually designed path and optimized paths by the developed algorithms. The first path designed by a human mine design expert and has a length of 1463 m. Dynamic Programming optimization provides a path of 1197 m. Apparently, improvement is considerable. Solution takes a computation time of around 4.5 hours. Genetic algorithm optimizes the path that has a length of 1299 m. Again, GA provides a suboptimal solution. Compared to the manually designed path improvement is satisfactory. In addition, the solution takes around three minutes. Compared to the manual design, monetary value of the saving is around 328,000$.

Summary of the optimization results and the manually designed path lengths can be seen in Table 13. Apparently, the developed GA algorithm makes remarkably good predictions for the sub optimum path. Dynamic Programming provides better results in longer computation times. GA seems to improve the computational efficiency. In addition, heuristic corrections are added into the GA algorithm. GUI makes it simple to carry out a shortest path optimization. Data entry is far easier compared to the, command window entry. In addition, optimized paths can be exported to the widely used mine planning software.

Table 13 Summary results of the manually designed and optimized path lengths

Location	**Path Length (m)**		
	Manual Design	**Dynamic Programming**	**Genetic Algorithm**
Erzincan / Bizmisen	1192	925	962
Kayseri/Karacat	1930	1887	1897
Kayseri/Mentes	1949	1482	1581
Kayseri/Madazi	877	805	825
Albania	1165	1137	1144
Sweden	1463	1197	1299

CHAPTER 5

THE LEAST COST UNDERGROUND MINE ACCESS ROAD BY MULTI OBJECTIVE OPTIMIZATION

5.1 Overview

In the previous chapter, minimization of the path length is presented as the main concern in underground main haul road design. Considering haul road development cost and operating cost of mining cars depend on the path length, this approach can be accepted to be correct. However, monetary cost of tunneling is also governed by the quality of rock mass that the tunnel is driven inside.

In this chapter, the underground mine haul road optimization considering the shortest path length and the rock properties is investigated as a multi objective optimization problem. Genetic Algorithm solver is used. Multiple objectives may have some tradeoffs. In other words, improvement in the fitness value of an objective may have an opposite effect on the other objective. To observe this effect more clearly, 'Pareto Front' is determined for the objective values. The optimum path is determined after a second optimization stage in which the objective values are weighted and summed up to provide a final objective value. Weighting is useful to determine the effect of each objective function on the cumulative cost. By this way, user can set either a length or rock mass quality driven optimization that will match the specific needs of the case study.

A sample application for a multi objective optimization is presented. The algorithm is an improved version of the shortest path algorithm that was presented in the last chapter. Implementation is carried out in Matlab. 'Genetic Algorithm Multi objective optimization' solver in Global Optimization Toolbox is used.

5.1.1 Objective Function

The objective function is composed of two objectives. The first one is similar to the previous chapter and aims to minimize the path length. The second one is about the rock mass quality that the haul road will be driven inside. Both of the functions contain final node missing cost, gradient cost, undesired region violation cost, and desired region award for the sake of generating feasible paths. Rock mass quality score is provided in terms of the widely used Geomechanical classification system, Rock Mass Rating (RMR). RMR is a quality score between 0 – 100 and presents the rock mass quality. As it is known, increasing score indicates higher quality rock mass. Since our optimization is a minimization, it would not be appropriate to directly add this score to the objective function. Therefore, difference of this score from the highest value (100 - RMR) is used to represent the deficiency in the rock mass.

Weighting the factors in an objective function is a widely used approach, where it is critical to determine the effect of each factor on the cumulative objective value. For instance, Oleiwi et al. [52] carried out multi-objective optimization for route planning of a robot. They had three objectives; which are path length, path smoothness, and path safety. Each of the three functions were weighed with factors which have a value between 0 and 1. Weightings are told to be tuned through simulations by trial and error.

Another study investigating optimization with weighted objective function factors is presented by Ergezer and Leblebicioglu [53]. Their goal was to determine the path that maximizes the information collected by multiple UAVs. Although the optimization has a single objective function, items of the objective function were weighted by some factors. Path length, forbidden region cost, desired region cost, and final point distance are the items of the objective function. Using the weighting factors, impact of each of these items can be adjusted on the final optimum route.

Weighting factors are determined by trial and error method for the cost factor. However, objective function weightings can be adjusted to suit the requirements of the problem, as given below;

$$\boldsymbol{Minimize}\ (w_1 \times \boldsymbol{f(1)}) + (w_2 \times \boldsymbol{f(2)})$$

$$\boldsymbol{f(1)} = \left\{w_1 \times \left({}^{1}\!/_{PL_{cost}}\right) + w_2 \times FN_{cost} + w_3 \times \left({}^{1}\!/_{GRD_{cost}}\right) + w_4 \times UR_{cost} - w_5 \times DR_{award}\right\}$$

$$\boldsymbol{f(2)} = \left\{w_1 \times RMD_{cost} + w_2 \times FN_{cost} + w_3 \times \left({}^{1}\!/_{GRD_{cost}}\right) + w_4 \times UR_{cost} - w_5 \times DR_{award}\right\}$$

Where;

$PL_{cost} = Cost\ of\ the\ path\ length\ (m)$

$RMD_{cost} = Rock\ mass\ quality\ cost$

$FN_{cost} = Cost\ of\ missing\ the\ final\ node (m)$

$GRD_{cost} = Cost\ of\ the\ gradient$

$UR_{cost} = Cost\ of\ violating\ the\ Undesired\ Regions$

$DR_{award} = Award\ of\ keeping\ inside\ the\ Desired\ Regions$

$w_n = Weighting$

$\theta_i = Heading\ angle\ of\ the\ nodes$

$\psi_i = Gradient$

$v_i = Pace\ length\ of\ the\ underground\ mining\ vehicle$

$i = Node\ number$

$n = 1, \dots, 5$

Subject to:

$$0 \leq \theta_i \leq 2\pi$$

$$0 \leq \psi_i \leq grad_{max}$$
$$0 \leq v_i$$
$$0 \leq w_n \leq 1$$

Given;

$(east_i, north_i, elevation_{i^{th}\ node}, heading\ angle_i)$

$tr_{min} = minimum\ turning\ radius$

$grad_{max} = maximum\ graident$

5.1.2 Workflow of the Multi-Objective Optimization Algorithm

Multi objective optimization workflow is quite similar to the GA optimization for the shortest path. The main difference is the objective function. The overall cost includes the path length and rock mass quality costs. Therefore, the result is a least cost path. RMR scoring system in the geotechnical block model is shown in Figure 44. Geotechnical block models are studied by Jenkins et.al. [54]. They commented on the advantages of these models while transferring a representative rock mass and structural geology data into numerical and limit equilibrium models. This study makes use of a geotechnical block model to define the rock mass quality.

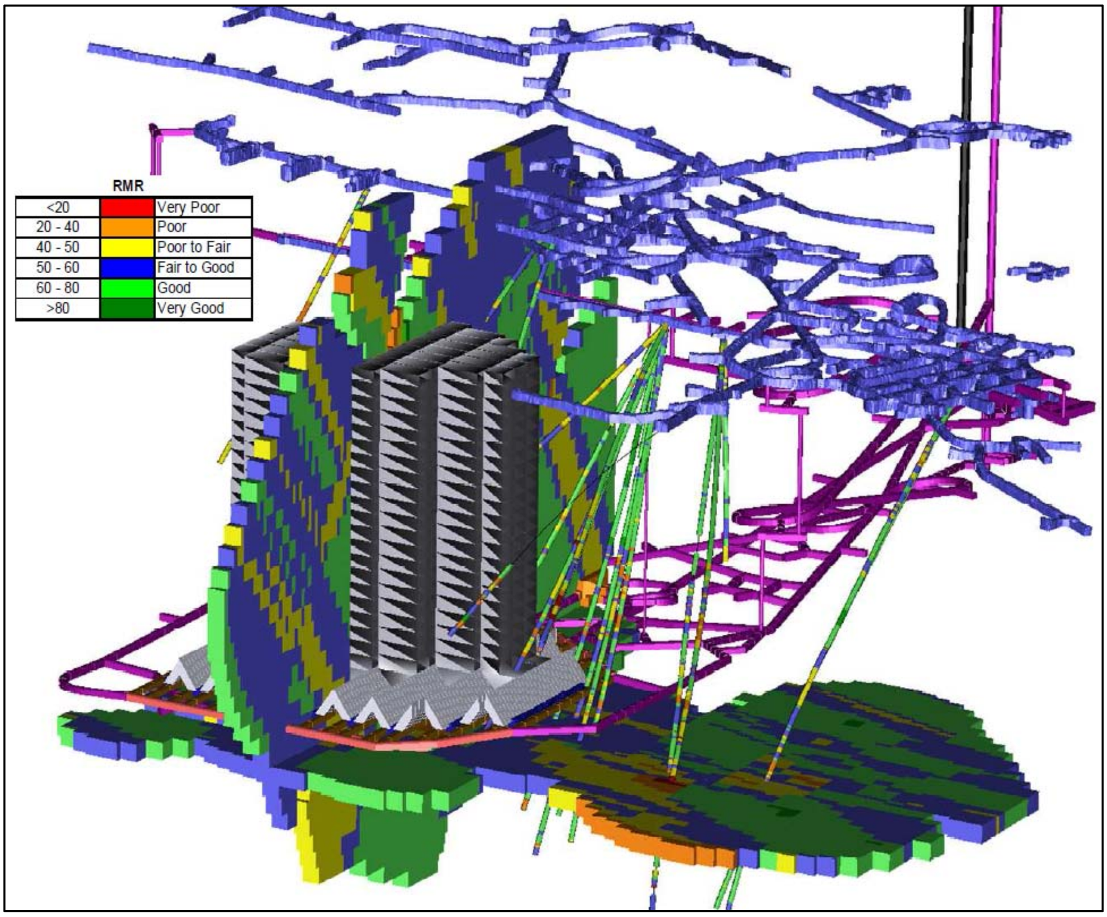


Figure 44 Sample view from a Geotechnical block model of Jenkins et.al. [54]

After the seed path generation is completed multi-objective optimization is carried out by the GA solver. As a result, the pareto front is plotted. The pareto front expresses the relationship between the objective values. Finally, the least cost path is determined from the weighted objective function. Flowchart of the algorithm can be seen in Figure 45.

Inputs

- Node coordinates
- Minimum turning radius
- Maximum gradient
- Dicretization number
- Max steps of straight motion
- Max turns in a ramp section
- Desired region coordinates
- Undesired region coordinates
- Rock mass quality block model

Genetic Algorithm (1st stage)

- Create a population randomly
- Generate a seed path
- Use classical GA operators
- **Output = Seed Path**

Genetic Algorithm (2nd stage)

- Generate a population from the seed path
- Calculate fitness scores
- For each of the individuals
  - Detect if there is any Undesired region violation
    - If Yes, apply URAV operator
    - If No, continue
  - Detect if the path violates desired regions boundaries
    - If Yes, apply DEREK operator
    - If No, continue
  - Apply classical GA operators
- End
- **Output = Pareto Front**

Minimization of the objective values

- Weighted objective function
- **Output = Least Cost Path**

Figure 45 Flowchart of the Genetic Algorithm for multi objective optimization

5.1.3 Verification

This least cost path problem also suffers from the lack of verification problems, with real mine data. Therefore, the same approach presented in the shortest path problem is followed. A simple and a complicated mine geometry was investigated. In the simple geometry, there are only two nodes, an initial node and a final node. The rock mass quality blocks model contains only two large blocks to keep the problem simple.

Node coordinates are presented in Table 14. The rock mass block model coordinates are given in Table 15. Kinematic constraints can be seen in Table 16

Table 14 Node coordinates of the verification problem

Node No:	East (m)	North (m)	Elevation (m)
1	100	100	150
2	100	100	50

Table 15 Extents of the rock quality block model

Block No:	East Extents (m)		North Extents (m)		Elevation Extents (m)		RMR
	Min	Max	Min	Max	Min	Max	
1	50	100	50	150	0	200	50
2	100	150	50	150	0	200	100

Table 16 Kinematic constraints for the verification problem

Kinematic Constraints	
Minimum Turning Radius (m)	Maximum Gradient (%)
15	10

GA multi objective optimization solver runs for three minutes to find the results. Pareto front can be seen in Figure 46. Assuming an equal weighting for the path length cost and rock mass quality cost, the least cost path can be observed in Figure 47. As expected, most of the path traverse inside the block with the higher RMR score. Considering the algorithm works properly in this simple problem, it can be expected to work in more complicated problems.

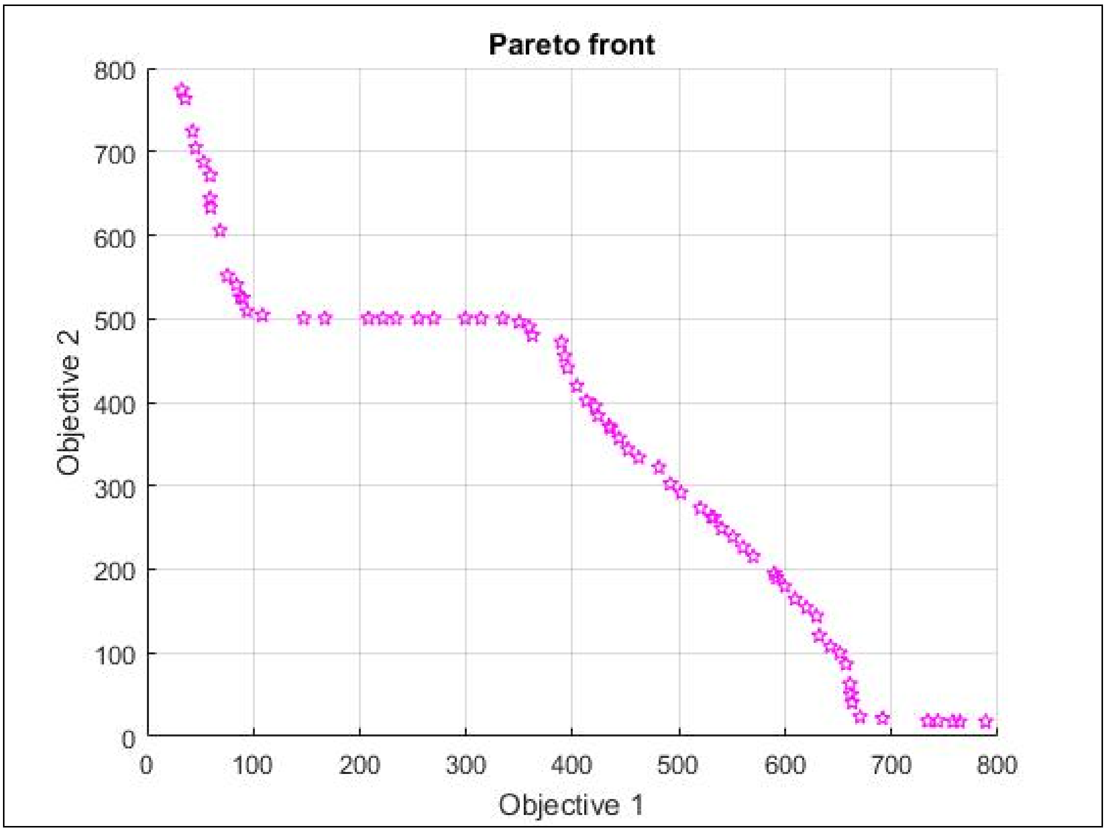


Figure 46 Pareto front of the verification problem

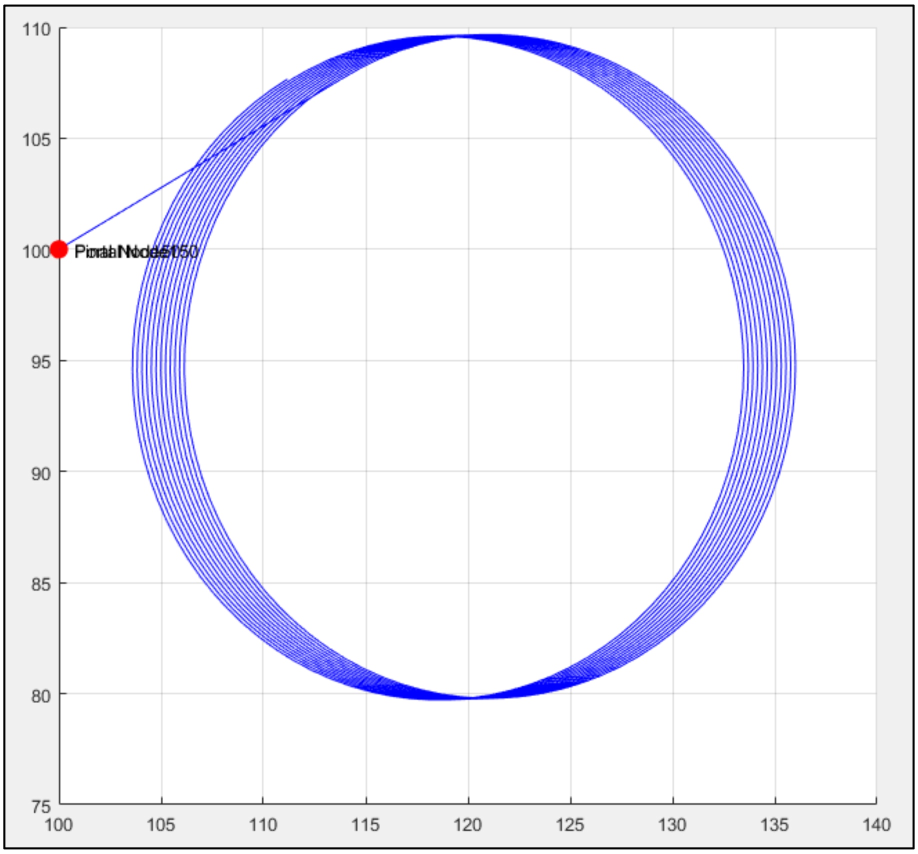


Figure 47 Optimum path from the multi objective optimization

Later on, the problem is repeated by increasing the number of blocks. It has been observed that increasing the block model complexity also increases the time required for the algorithm to converge.

5.1.4 Case Study

In this section, the least cost path optimization algorithm, which is developed in the scope of this research, is applied on a more complex case. This case was investigated in the previous section for determining the shortest path. The Bizmisen underground production levels were connected to the surface portal by an optimized path using the shortest path algorithm, which is the first outcome of this study. The location remains the same but the current goal is to find the path that passes inside the highest quality rock mass with a reasonable path length. Importance weighting for both of the objectives are the same.

Geological units are identified on core samples. Twelve representative drillholes are selected and rock mass quality characterization is carried out on dominant geological units in terms of RMR_{89}. Figure 48 shows the average RMR scores in Donentas sector of Bizmisen region.

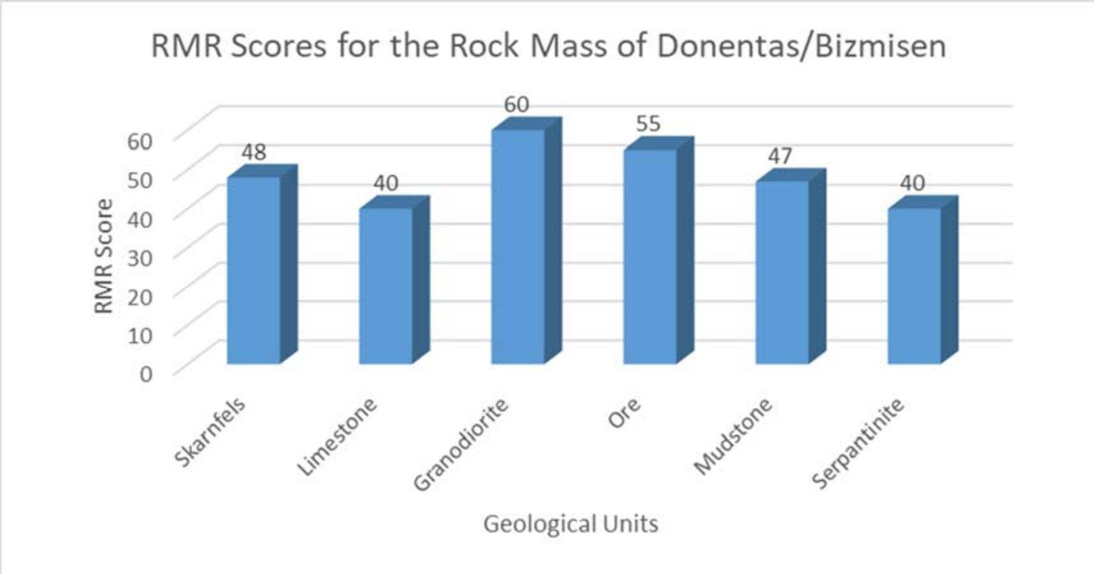


Figure 48 Average RMR_{89} scores in Donentas sector of Bizmisen region

Rest of the drillholes covering the region of interest are assigned with these RMR scores. In Figure 49, perspective view of the drillhole plan with RMR score color legend can be seen.

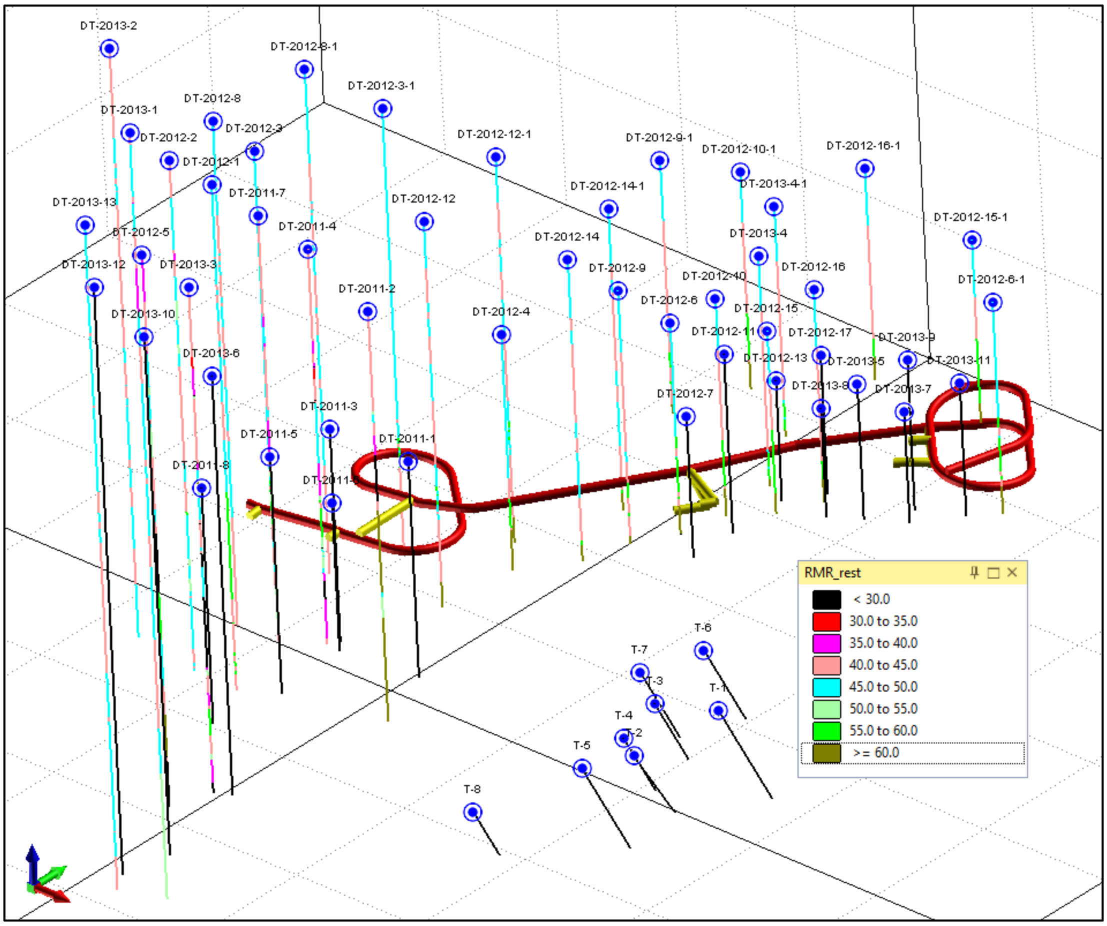


Figure 49 Perspective view of Donentas drillhole plan

Rock mass of the potential region for a suitable main haul road is called as the region of interest (ROI). ROI is divided into blocks of 25m x 25m x 25m in all dimensions. In this problem, ROI contains 1609 blocks. Interpolating the RMR scores by 'Inverse Distance Weighting (IDW)' method, a rock quality block model is created. Formulation in Eqn. 14 expresses the IDW method for a power of '2'.

$$z_2 = \frac{\sum_{i=1}^{n}\left(\frac{z_i}{d_i^2}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i^2}\right)} \tag{14}$$

Although RMR scores are used in this study, the block model can be attributed by any numerical value representing the rock mass quality. For instance, alternative rock mass quality systems (like Q-tunneling index, Geological Strength Index (GSI)) or even Geophysical assessment methods are potential replacements. RMR block model can be seen in Figure 50.

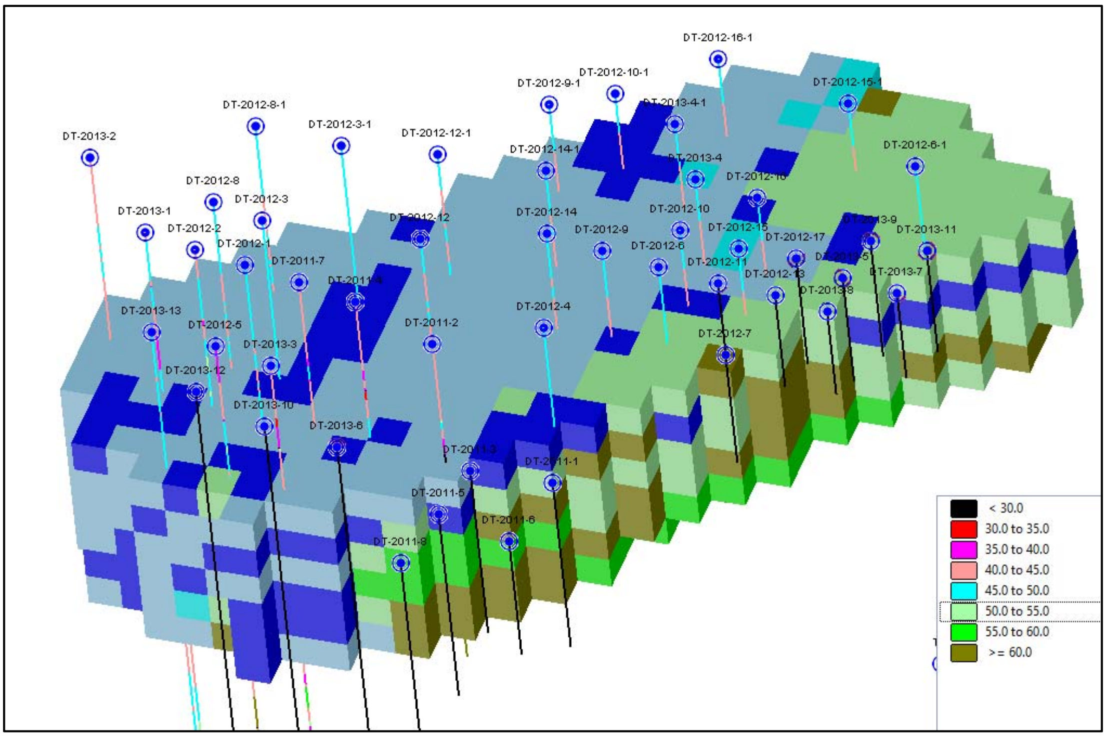


Figure 50 RMR block model

Optimum path is shown in Appendix A Figure 62 by a green line. The black line shows the manual design with a length of 1192m. The optimum path is 140m shorter with a total length of 1052m. In the previous section, a shorter path length (962m) was calculated for the same case; however, rock mass quality was not taken into consideration.

Comparing the average rock mass quality, the manual design is driven inside a rock mass with 50 RMR. However, the optimum path has an average RMR of 56. RMR score interval is so narrow that the minimum score is 40 and the maximum score is 60. This clarifies the restricted improvement. Apparently, there is improvement in both of the path length and the rock mass quality. However, both of the objectives might be better improved, if they were the single objective.

Figure 51 presents the plan view of the manual design (red line) and the path optimized by the developed algorithm (black line). Block model is a three dimensional object. In order to better observe the improvement by optimization three section views are presented.

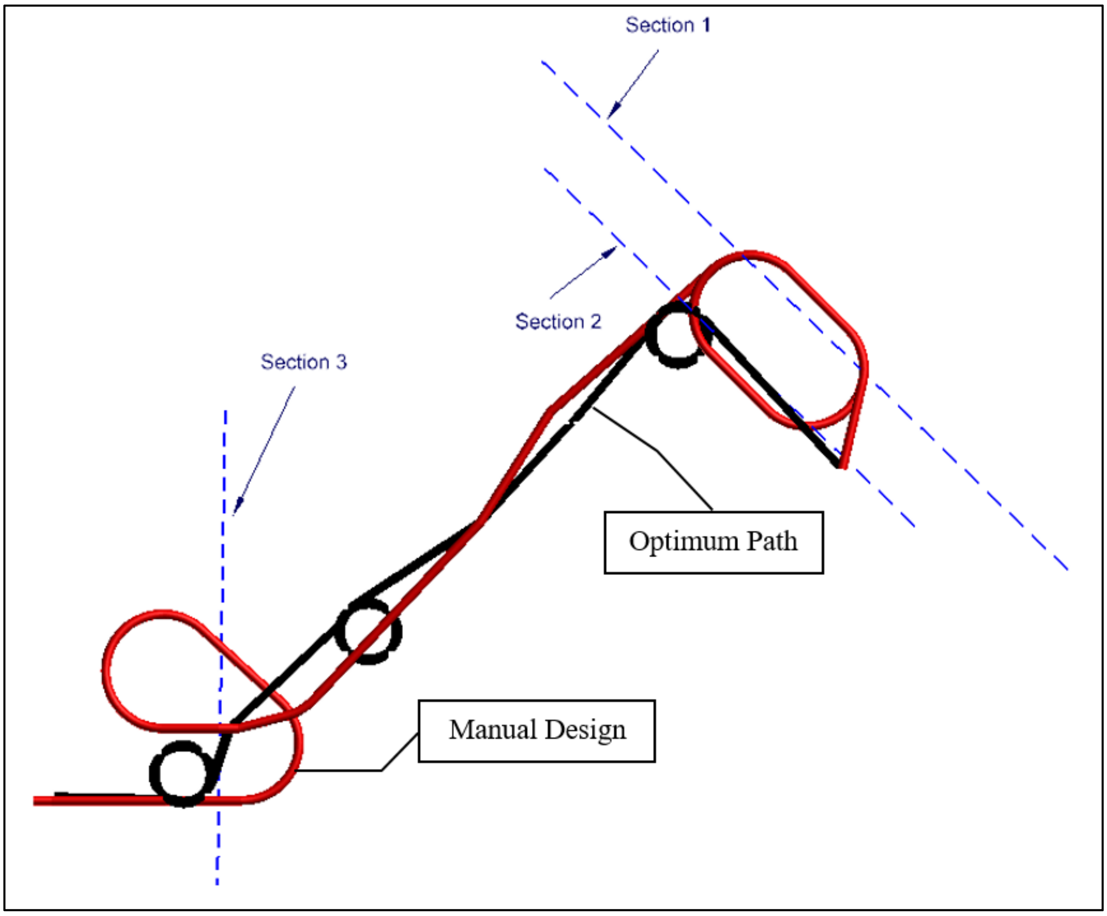


Figure 51 Plan view of the manual design (red line) and the path optimized by the developed algorithm (black line)

Section 1 is presented in Figure 52. Most of the path is inside the blocks with an RMR interval of 55 – 60. However, the horizontal decline passes inside a lower RMR block region.

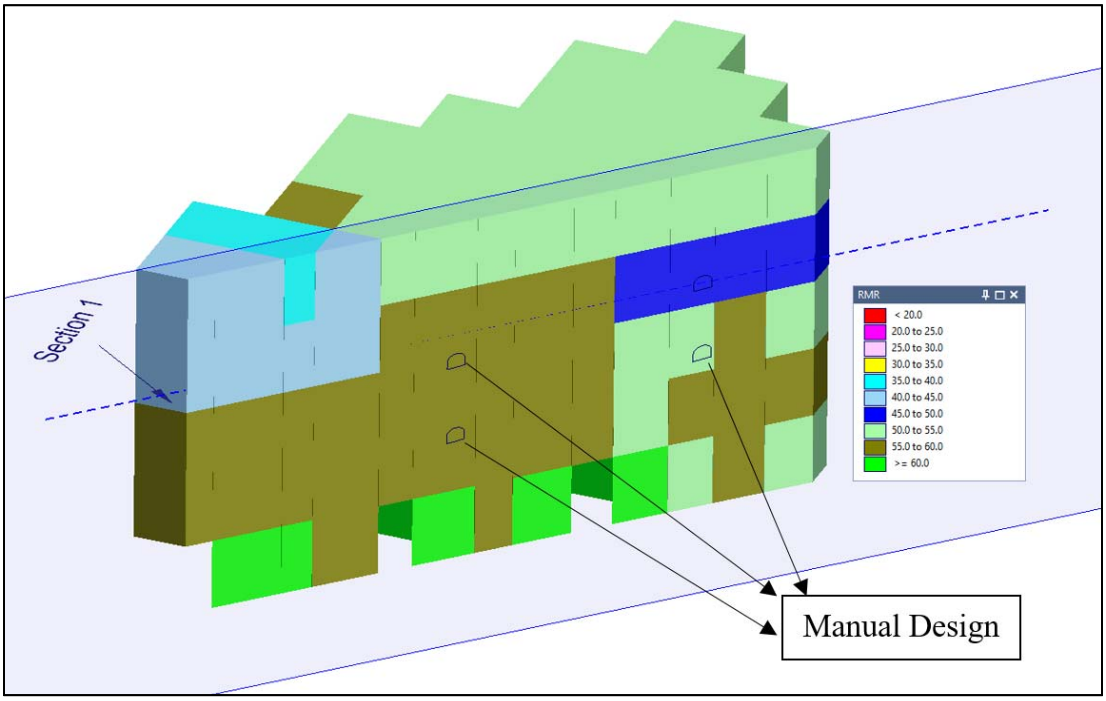


Figure 52 Perspective view of section 1

Figure 53 focuses on the section 2. The manual design is shown by a horse-shoe shape while the optimum path is represented by a black line. Apparently, the algorithm moves the path to the core of the high RMR region.

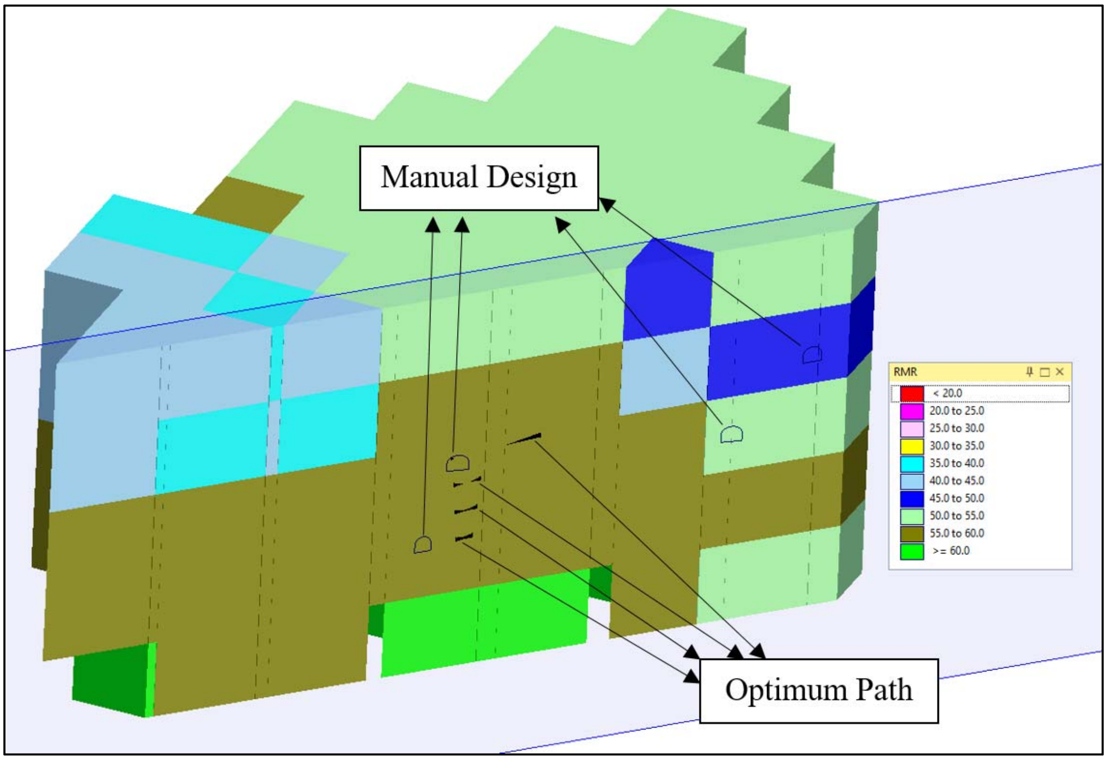


Figure 53 Perspective view of section 2

Figure 54 proves that the bottom of the manual design is located inside rock mass with 35 to 50 RMR blocks. However, optimum path passes only inside the high RMR blocks (45 - 50).

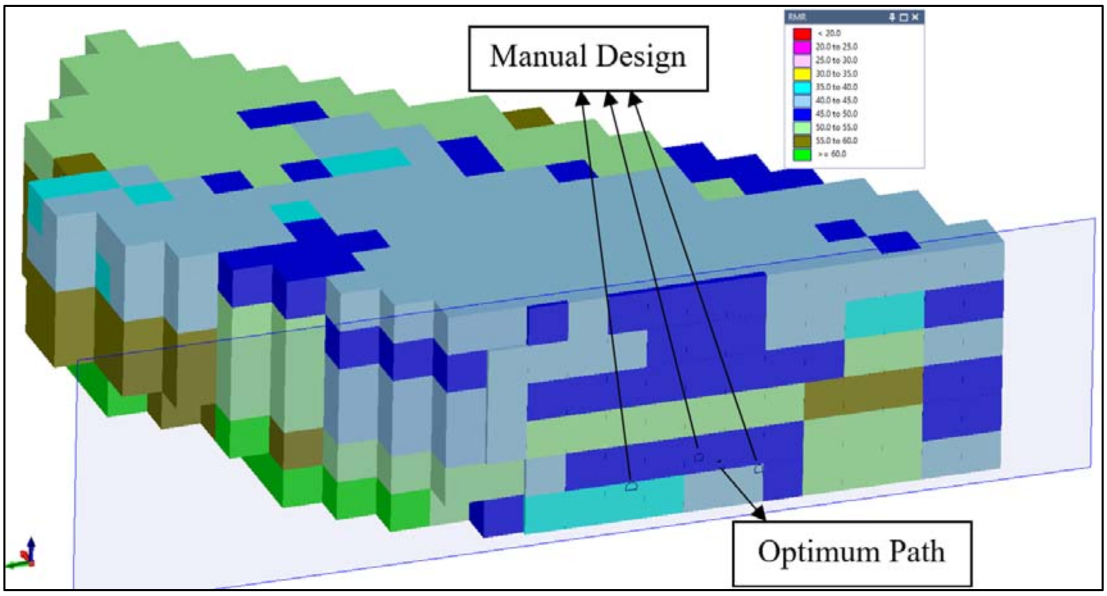


Figure 54 Perspective view of section 3

CHAPTER 6

CONCLUSIONS AND FUTURE STUDIES

Deep orebodies are preferably accessed by underground mine ramps due to the availability of high-level mechanization and higher production rates. Development and operation of underground mine ramps have short and long term influences on the mine economy. Most commonly, expert view dominates the manual ramp design. Apparently, optimization of the ramp design may improve the mine economy.

In this study, the underground mine haul road optimization problem is outlined. Kinematics of the mobilized underground mining equipment is modelled as a Dubins Car.

Optimization methods for determining the shortest path are compared. The curvature constrained path with directed nodes is optimized using the Dubins path. Exhaustive search is an exact method; however, computational efficiency is very low. Complicated problems require an exponential time solution. If the optimal path can be predicted, heuristic solution is more effective. However, the result is most likely to be suboptimal. Dynamic Programming improves the solution mechanism by polynomial time solutions; however, still it takes long to determine the optimal path. Alternatively, an evolutionary algorithm is proposed for the path length minimization. Genetic Algorithm applies heuristic corrections such as avoiding undesired and desired region violations. In this way, any different properties such as fault zones, aquifers, or restricted regions (for any reason) can be avoided. Two custom mutation operators are proposed as the main contributions of this research. The algorithmic path designs are compared by the manual paths. It is concluded that the intelligent algorithms clearly provide shorter paths than the human design. In complex geometries, the difference becomes even more apparent. The algorithm is implemented in Matlab and a custom 'Graphical User Interface (GUI)' is prepared for the ease of repeatability.

Additionally, Genetic Algorithm is used to carry out a multi-objective optimization. The result is a least cost path for underground mine ramps. The cost function includes path length and rock mass quality. Rock mass quality is defined into a block model in terms of a widely used Geomechanical Classification System. Pareto front is used to calculate the optimum solution from an objective function with some adjustable weighting factors. Those weighting factors can be tuned for the specific needs of each case study. For instance, it may be more critical to have the shortest path mine access in some cases, while the rock mass quality around the access is more critical in another.

Path planning problems do not have verification problems. Therefore, a generalized approach is used. A simple mine layout is designed and performance of the algorithms are tested. Optimum path for the simple layout is easily predictable even by observation. If the algorithm makes close predictions, then it can be used for more complex geometries.

Although Genetic Algorithm does not guarantee the global optimum, the sub-optimal solution offers a significant improvement compared to the manual design. In addition, computational performance is plausible.

To summarize the research outcomes; an automated methodology is presented to replace the conventional design method for underground mine access.

Minimizing path length is the major concern in this haul road optimization since length governs the road development and mine operating costs. The shortest path optimization algorithm offered an efficient solution. The properties of the developed methodology is as follows:

- Intelligent algorithms are used more effectively to optimize underground mine haul roads.
- Underground mine access avoids and considers some special regions such as, discontinuities and aquifers.
- Genetic Algorithm is used for making heuristic changes on the optimum path.
- Two custom mutation operators are proposed.

Optimizing the rock mass quality around the haul road is the second concern since it is important for decreasing the tunnel development cost. The least cost path optimization is used as a tool.

Some of the minor outcomes are presented below:

- Turning direction of an underground mine access road should be rather fixed for the sake of ergonomics. Mine car drivers should not be confused by different turning directions. However, fixing this direction may decrease the level of optimality. The algorithms proposed in this study are capable of selecting a single turning direction or even both of them. Effects of restricting the turning directions are investigated and presented.
- The algorithm is implemented in Matlab and a custom Graphical User Interface is developed.

Future studies may develop the algorithm for multiple orebody problems. Current solution assumes that the mine production plan is already prepared. However, novel research may include the production plan optimization and the whole underground mine design process can be automated. In addition, other mine access options can be integrated into the algorithm. Weightings of the objective function may also be optimized for each case.

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APPENDIX A

FIGURES

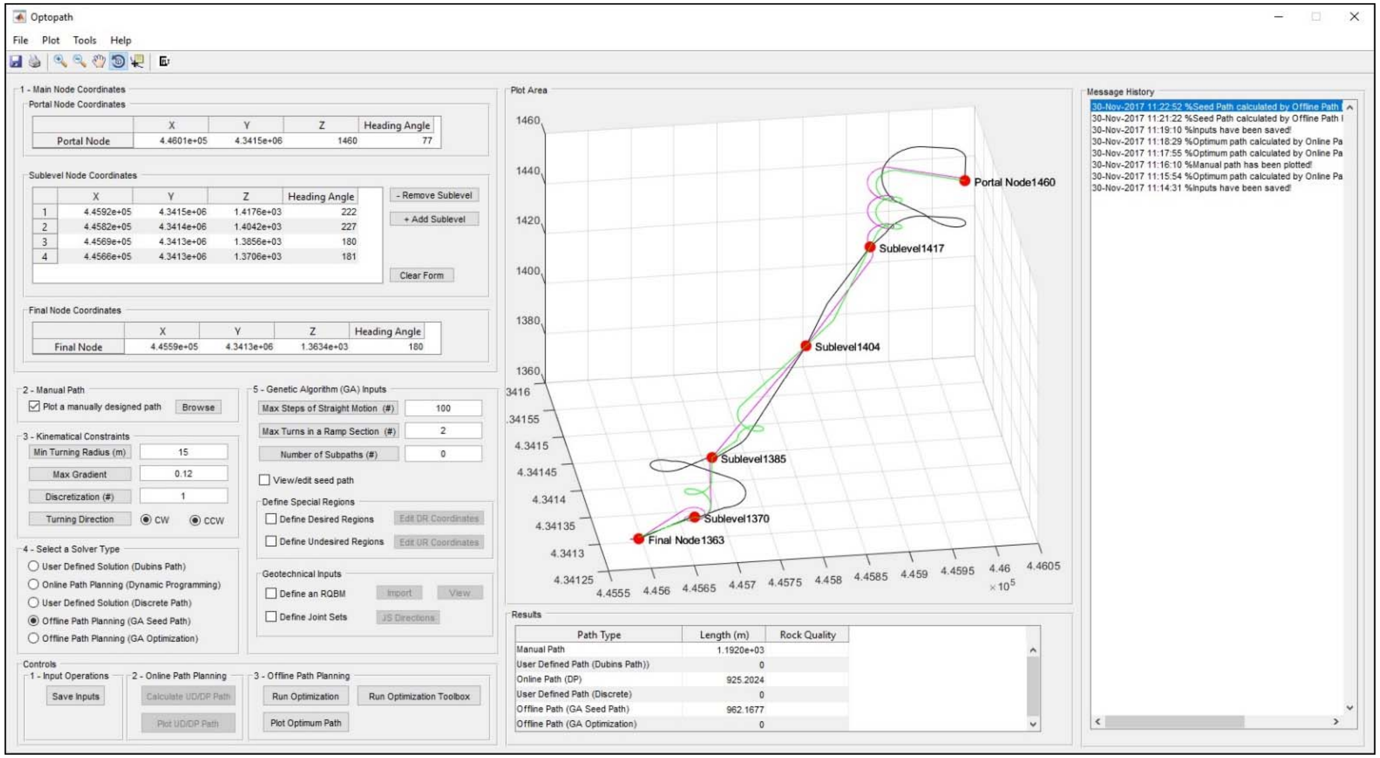

Figure 55 Underground mine access optimization in Erzincan/Bizmisen

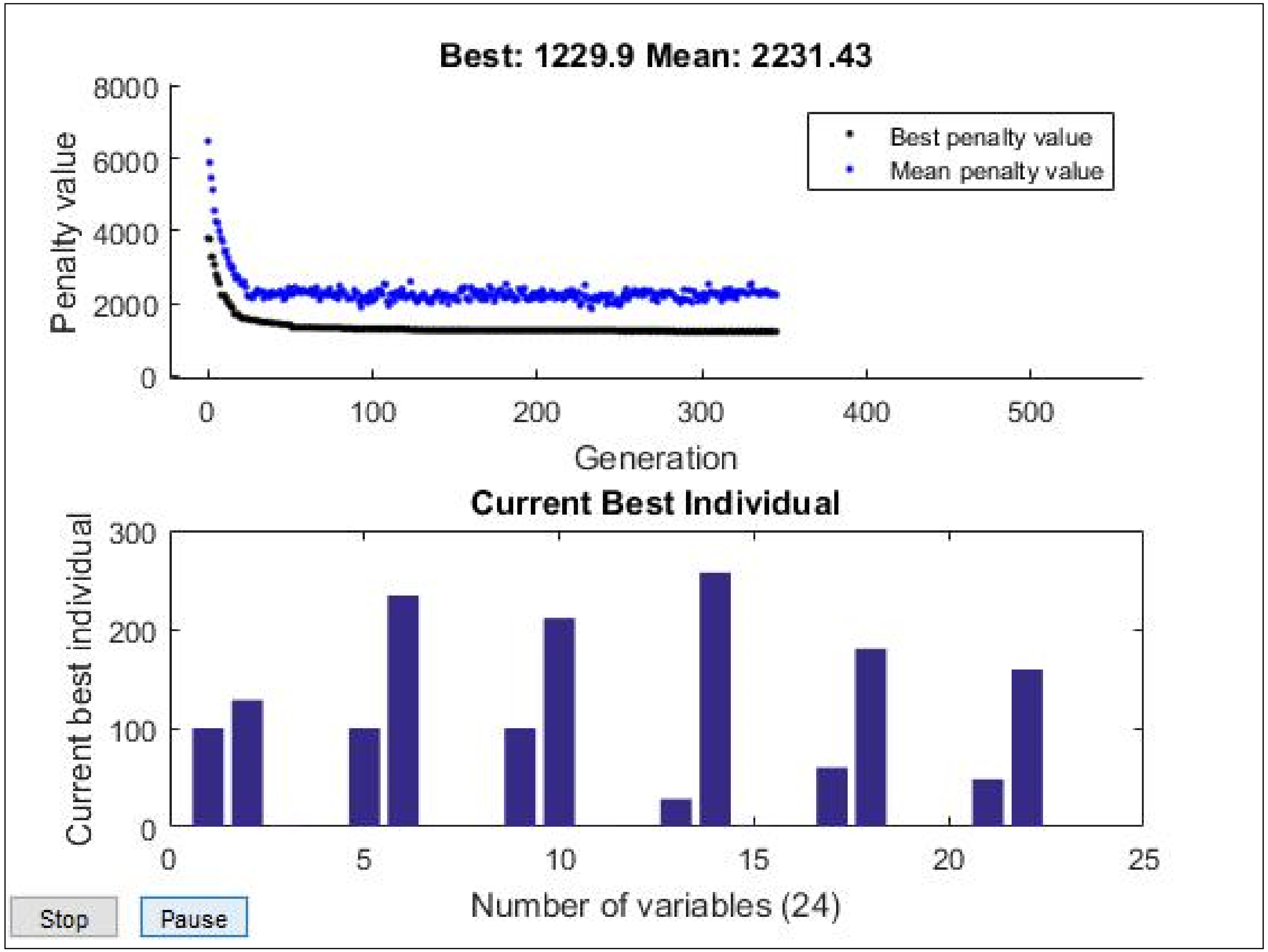

Figure 56 Plot of improved fitness scores through generations and best individual in GA optimization

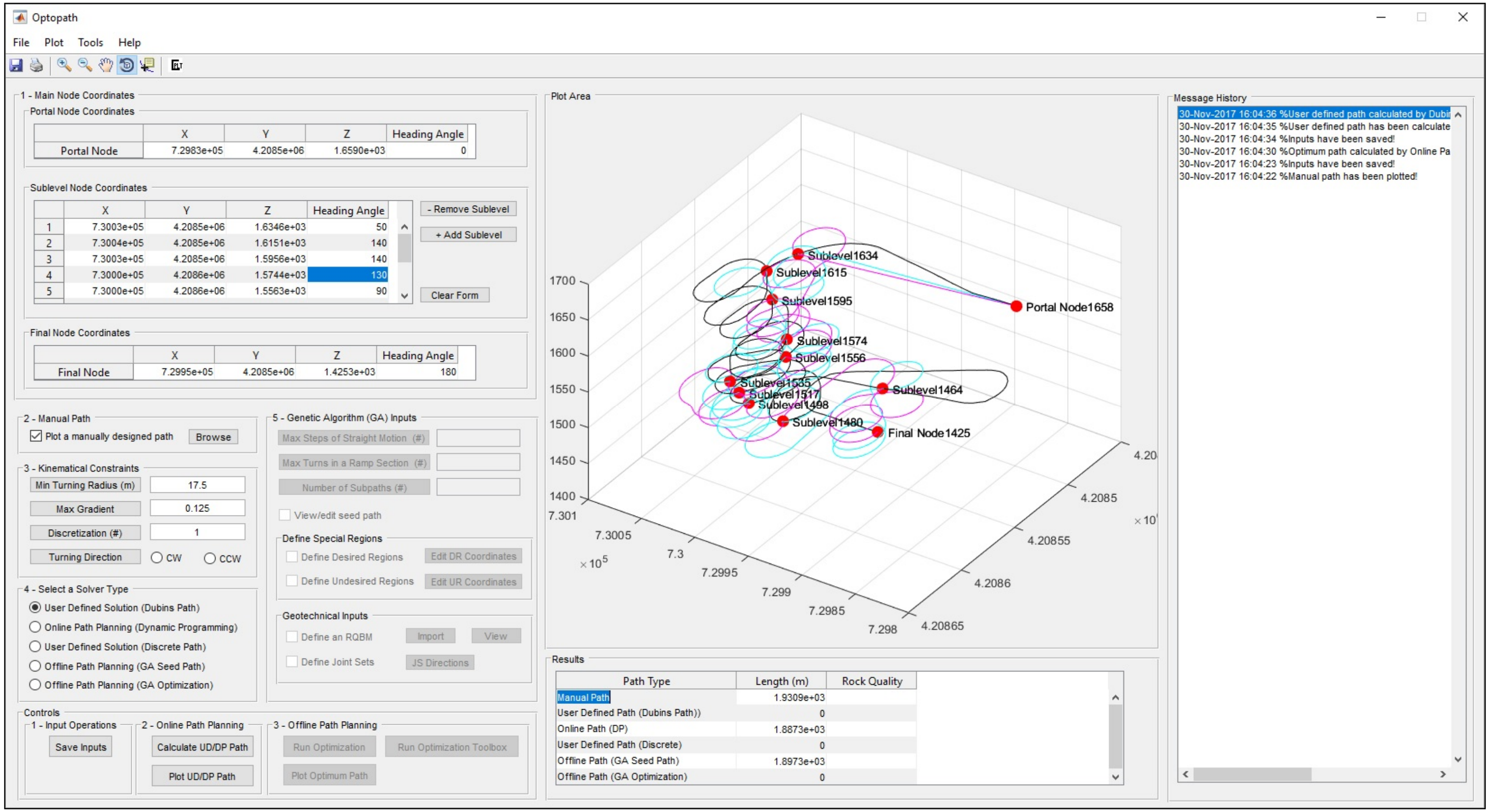

Figure 57 Underground mine access optimization in Kayseri/Karacat

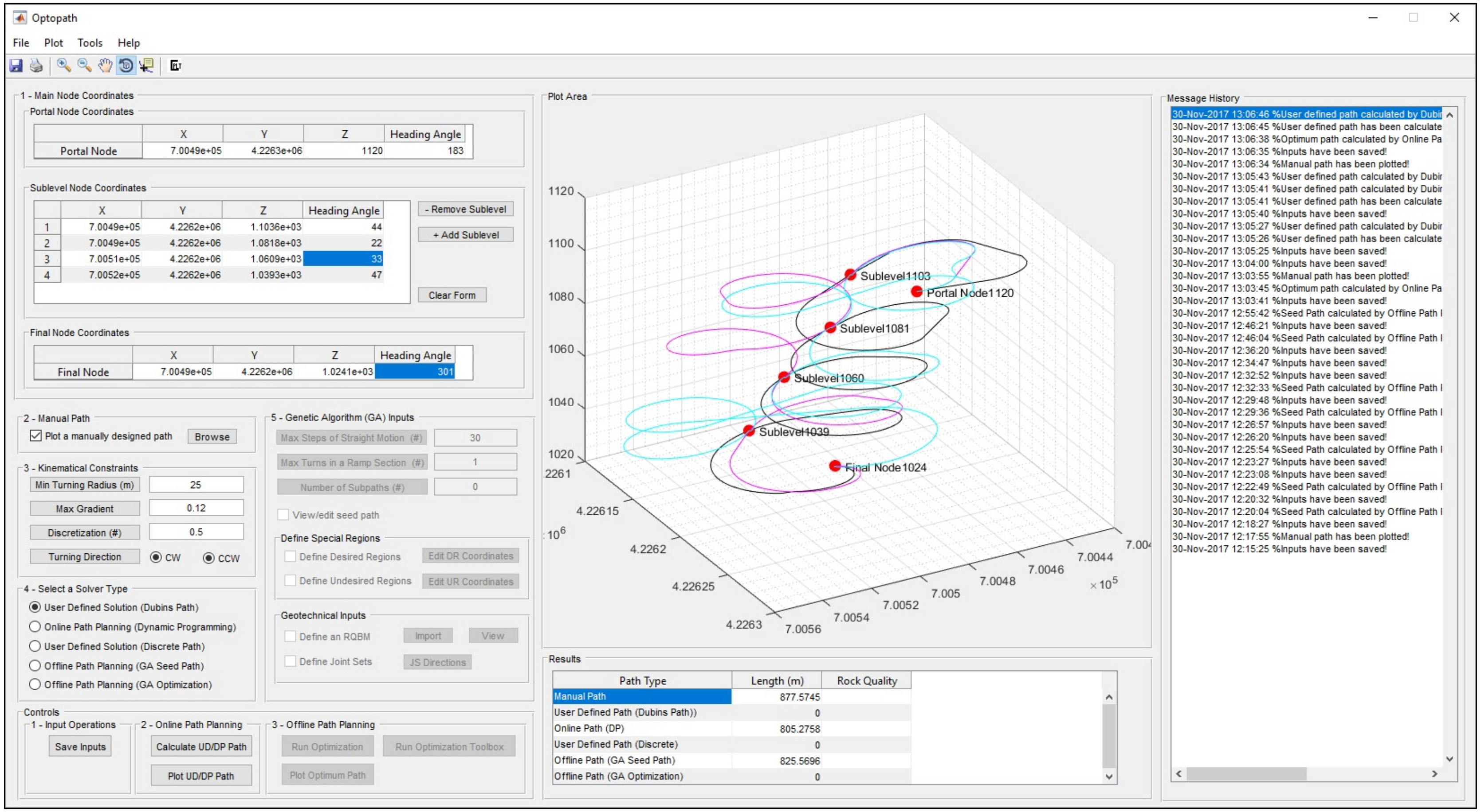

Figure 58 Underground mine access optimization in Kayseri/Madazi

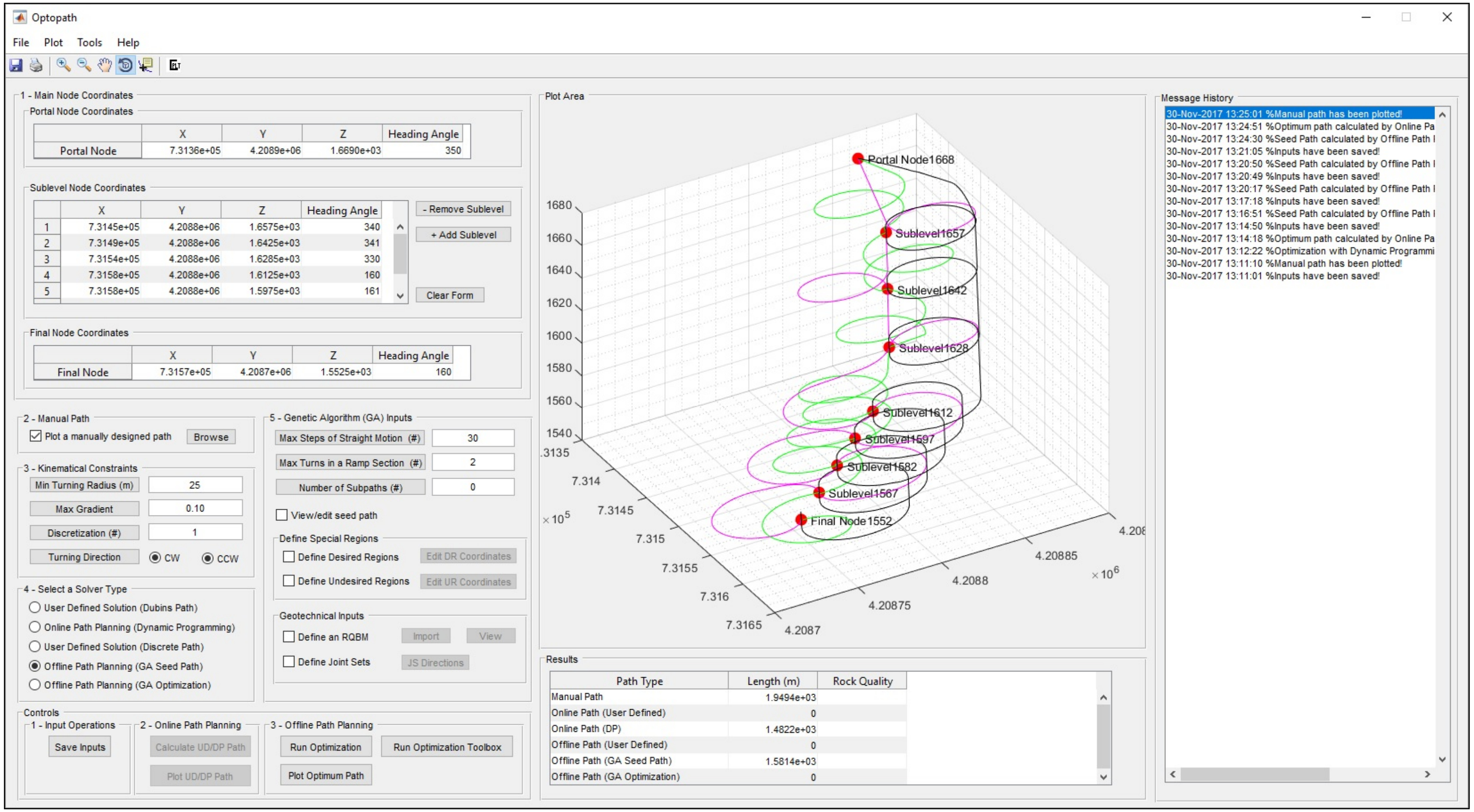

Figure 59 Underground mine access optimization in Kayseri/Mentes

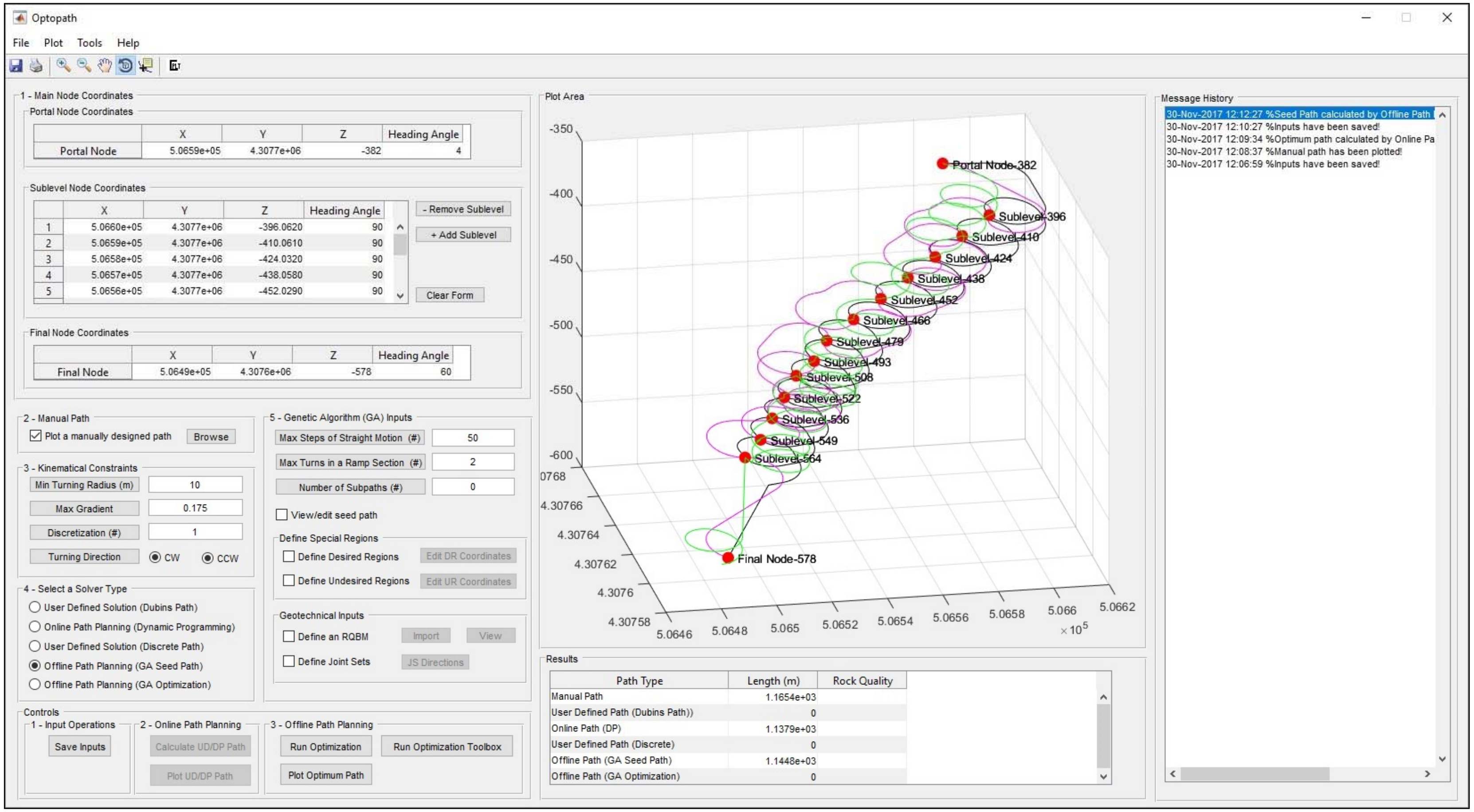

Figure 60 Underground mine access optimization for a mine in Albania

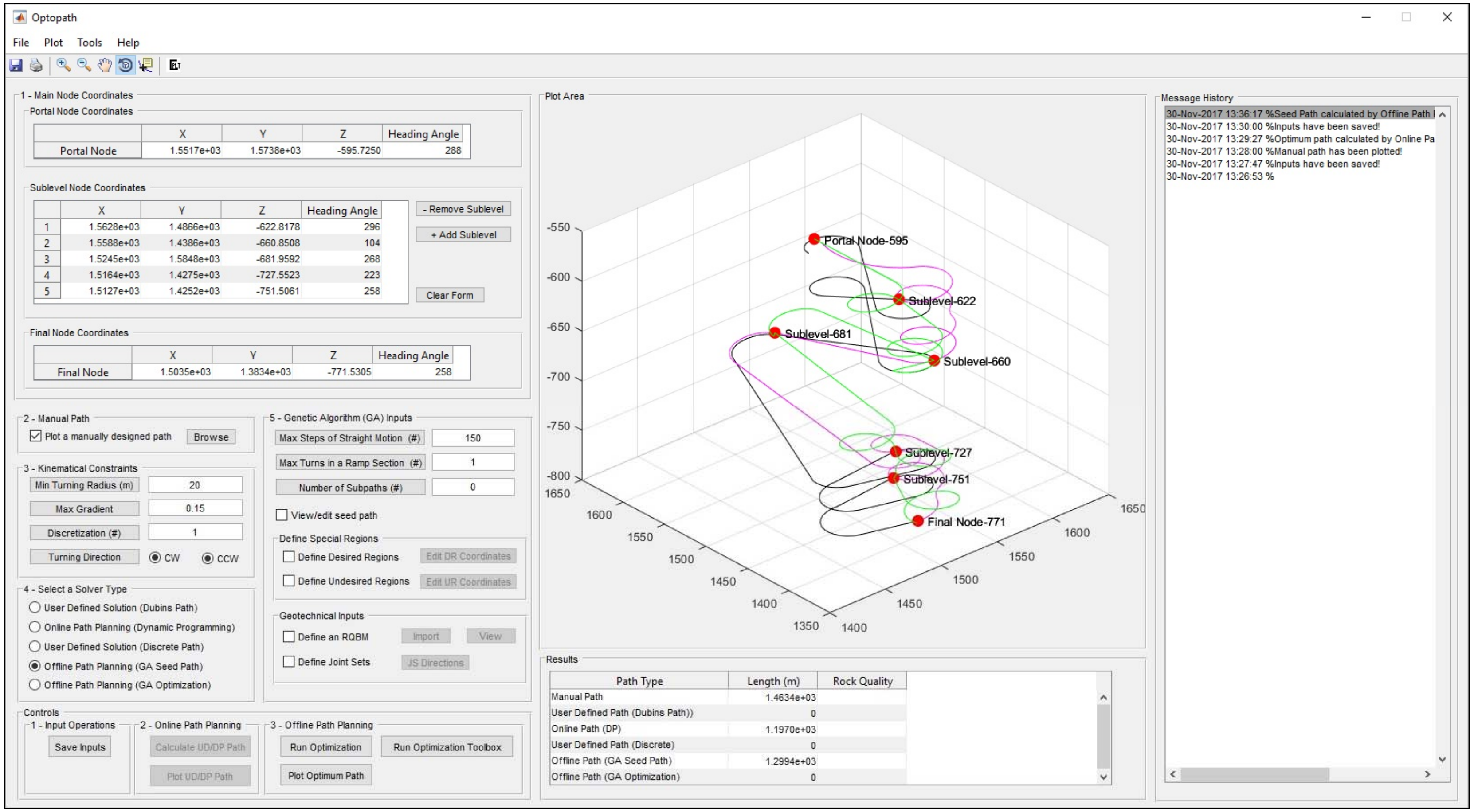

Figure 61 Underground mine access optimization for a mine in Sweden

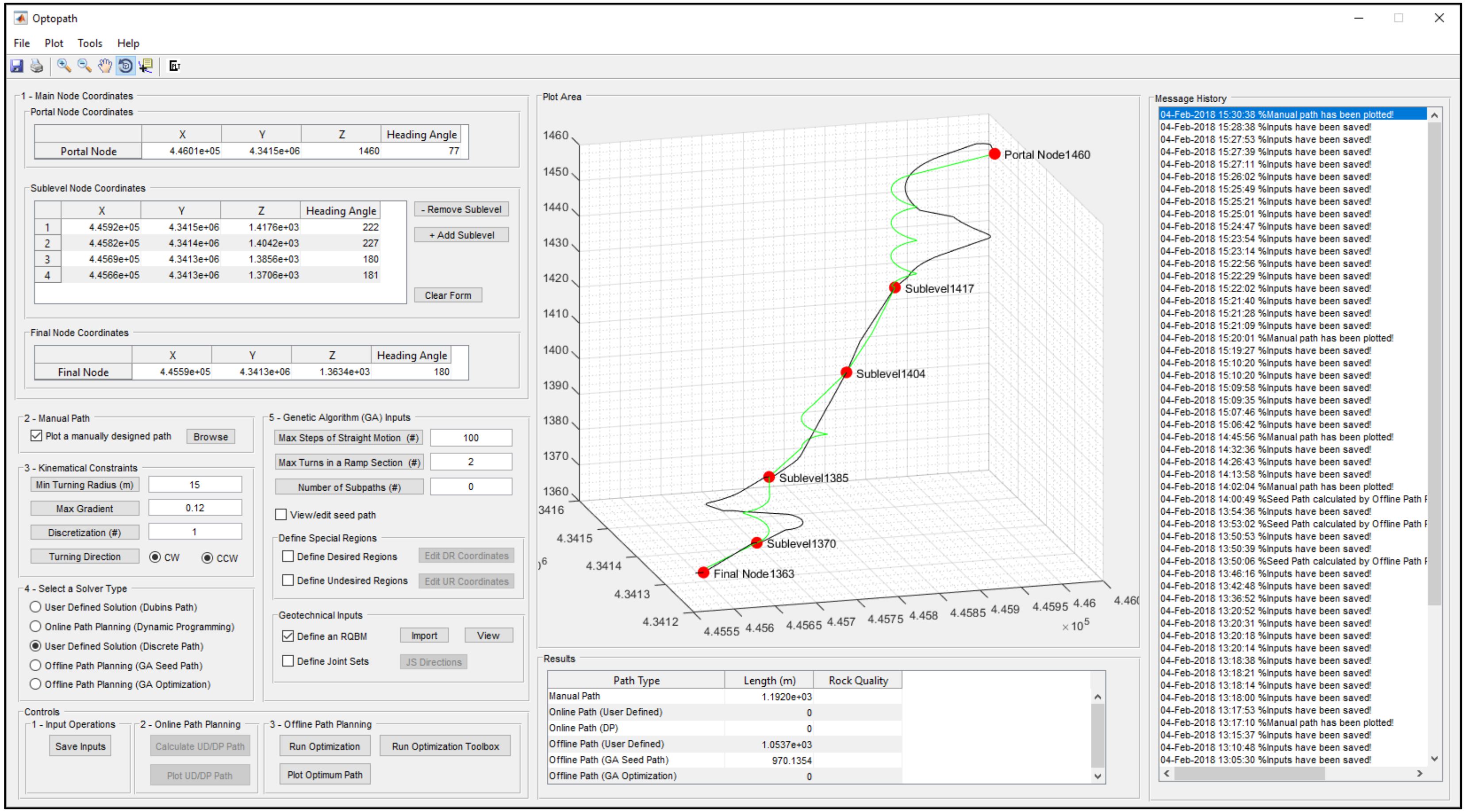

Figure 62 Manual design and the result of multi objective optimization by genetic algorithm

APPENDIX B

PSEUDO CODE

```
Set Inputs
Init Population
Set Best Objective Value to Infiniti.
Set SameResult to 0
Read SameResult Limit
Set POP SIZE to 50
Call Seed Path Finder
Set Operation List as Classical Crossover and Mutation
Repeat
    For each path in the population
        Call Simulation
        Compute Objective Values
    End For
    Repeat
        Select a path from present population randomly.
        Select Operation from Operation List
        Case Selected Operation is Crossover
            Select another path from present population randomly to
                generate new   chromosomes.
            Call Crossover Routine
        Case Selected Operation is Mutation
            Call Classical Mutation Routine
    Until new generation is created.
Until SameResult equals to SameResult Limit

Call Path Optimizer
Set Population as the seed path
Set Best Objective Value to Infiniti.
Set SameResult to 0
Read SameResult Limit
Set Operation List as Proposed Operators, Crossover and Mutation
Repeat
    For each path in the population
        Call Simulation
```

```
        Compute Objective Values
        Determine whether it enters to UR or not.
    End For
    Sort Objective Values and keep best three for next
    If Objective Values (1) less than Best Objective Value Then
        Set Best Objective Value to Objective Values (1)
        Set SameResult to 0
    Else
        Increment SameResult
    End If
    Repeat
        Select a path from present population randomly.
        Select Operation from Operation List randomly
        Case Selected operation is ”Proposed Operators”
        For three times apply proposed operators
            If it flies over to any UR Then
                Call URAV
            End If
            If it avoids to the DR Then
                Call DEREK
            End If
        End For
        Case Selected Operation is Crossover
            Select another path from present population randomly to
                generate new chromosomes.
            Call Crossover Routine
        Case Selected Operation is Mutation
        Call Classical Mutation Routine
    Until new generation is created.
Until SameResult equals to SameResult Limit
```

CURRICULUM VITAE

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EDUCATION

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B.S.	METU, Mining Engineering	2011
High School	Deneme Super High School, Ankara	2005

WORK EXPERIENCE

Year	*Place*	*Enrollment*
2011 Oct. – 2018 Jan.	METU Dept. of Mining Engineering	Research Assistant
2011 June – 2011 Oct.	Fe-Ni Mining Co.	Mining Engineer

FOREIGN LANGUAGES

Advanced English, Intermediate French, Beginner Swedish

PUBLICATIONS

Journal Publications

1 A. G. Yardimci and C. Karpuz, "Fuzzy approach for preliminary design of weak rock slopes in lignite mines," Bulletin of Engineering Geology and the Environment, vol. 77, no. 1, pp. 253-264, 2018.

Book Chapters

1 A. G. Yardimci and C. Karpuz, “Fuzzy Rock Mass Rating: Soft-Computing-Aided Preliminary Stability Analysis of Weak Rock Slopes, in N. Ceryan (Ed.), Handbook of Research on Trends and Digital Advances in Engineering Geology (pp. 97-131). Hershey, PA: IGI Global, 2018

International Conference Publications

1 A.G. Yardimci and C. Karpuz, “Optimized Path Planning in Underground Mine Ramp Design Using Genetic Algorithm,” in *26th International Symposium on Mine Planning & Equipment Selection, MPES2017*, Luleå/Sweden, 08/2017

2 A.G. Yardimci and C. Karpuz, “Optimization of Underground Haul Roads Using an Evolutionary Algorithm,” in *25th International Mining Congress and Exhibition of Turkey, IMCET 2017*, Antalya/Turkey, 04/2017

3 A.G. Yardimci and C. Karpuz, “Shortest Path Estimation Considering Kinematical Constraints of Main Haulage Roads in Underground Mines: A Heuristic Algorithm,” in *6th International Conference on Computer Applications in the Minerals Industries, CAMI2016*, Istanbul/ Turkey, 10/2016

4 A.G. Yardimci, L. Tutluoglu, C. Karpuz, H. Ozturk and D. Guner, “Quality Assessment of Backfill Performance for an Underground Iron Mine in Turkey,” in *Ground Support 2016*, Luleå /Sweden, 09/2016

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50th US Rock Mechanics / Geomechanics Symposium, ARMA 2016, Houston/Texas, 06/2016

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