Shaft Location Selection Based on Case-based Reasoning Cost Estimation Model

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Abstract

In the mining industry, the selection of the location of a given piece of infrastructure is one of the most critical decision-making problems; some examples of infrastructure in the mine are the concentrator plant, the workshops, the waste dump, the tailing pond, the warehouse, the shaft, and others. Among all these, the shaft is one of the most expensive infrastructures in the lifetime of the underground mine. The principal function of a shaft is to transport ore, materials utilities, and the staff from the mine to the surface and vice versa, in addition is often the sole access to the underground operations. Given that the shaft location significantly affects the profitability and underground operations at a mine, its location is a key consideration in the mine design process.

Selecting the shaft location is a complex process influenced by various factors, the primary ones being the positions and shapes of the orebodies, ore tonnage, rock characteristics, sinking method, mining equipment, and presence of water. The cost of excavating and transporting the ore, which depends on a complex combination of these factors, serves as the principal metric to evaluate the shaft location selection. Additionally, due to the high level of uncertainty around some of the problem's parameters, the selection of the shaft location can also be seen as a high-risky decision-making process.

In this research study, a technically feasible polygon is initially defined for shaft localization, then it is discretized on the surface. For each discrete pattern a shaft sinking cost is calculated using a robust cost estimation model, and with the operational cost, the total cost associated to this discrete pattern is obtained. The best location for the shaft will be the grid cell with the minimum total cost. Given that there are many parameters are uncertain in this localization problem, a Monte-Carlo scheme is applied to evaluate the associated risks. The proposed methodology is tested through a case study. It provides a framework to facilitate the selection of the shaft location while considering the inherent uncertainties associated with some of the project parameters.

Résumé

Dans l'industrie minière, le problème de décision de l'emplacement d'installation se révèle d’importance critique; quelques exemples d'installation liés à l’industrie minière peuvent être par exemple l’usine de traitement du minerai, les ateliers de maintenance, la verse à stérile, le parc à résidus, l'entrepôt, le puits, et encore d’autres. Parmi toutes ces installations, le puits est l'une des installations les plus coûteuses construite au cours du cycle de vie de la mine souterraine. La fonction principale d'un puits est de transporter le minerai, les matériaux, et le personnel de la mine vers la surface et vice versa, étant dans de nombreux cas le seul accès vers les opérations souterraines. Étant donné que l'emplacement du puits affecte considérablement la rentabilité et les opérations souterraines d'une mine, son emplacement est un facteur clé dans le processus de conception de la mine.

La sélection de l'emplacement du puits est un processus complexe influencé par divers facteurs. La position et la forme des corps minéralisés, la quantité de minerai, les caractéristiques de la roche, la méthode d’excavation du puits, l'équipement minier et la présence d'eau sont les principaux facteurs à considérer. Les coûts d'excavation et de transport du minerai, qui dépendent d'une combinaison complexe de ces facteurs, servent de métriques principales pour évaluer un choix de placement de puits minier. De plus, en raison du niveau élevé d'incertitude entourant certains des paramètres du problème, la sélection de l'emplacement du puits peut également être considérée comme un processus de prise de décision risqué.

Dans cette étude de recherche, un polygone techniquement faisable est initialement défini pour la sélection de l'emplacement du puits. Ensuite, ce polygone est discrétisé en surface. Pour chaque patron discret, un coût d'excavation de puits est calculé à l'aide d'un modèle d'estimation de coût robuste, et avec le coût opérationnel, le coût total associé à ce patron discret est obtenu. Le meilleur emplacement pour le puits sera la cellule de la grille avec le coût total minimum. Étant donné qu'il existe de nombreux paramètres incertains dans ce problème de sélection d'emplacement, un schéma de Monte-Carlo est appliqué pour évaluer les risques associés à ces incertitudes. La méthodologie proposée est ensuite appliquée à une étude de cas. Cette

montrent que la nouvelle approche fournit un cadre pour faciliter la sélection de l'emplacement d’un puits de mine, tout en prenant en compte les incertitudes inhérentes associées à certains des paramètres du projet.

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Contributions of Authors

The author of this thesis has written all the chapters and is the sole contributor to this thesis.

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List of Abbreviations

CBR case-based reasoning

k-NN k-nearest neighbor

PDF probability density function

1 Introduction

1.1 Problem Statement

A shaft is a vertical infrastructure that connects the surface with the production zones of an underground mine. The shaft is among the most critical pieces of infrastructure in an underground mine because it is an expensive investment that will be used during the entire life of the mine. The shaft location selection directly affects the production rate and materials handling costs. In other words, time and cost directly depend on this selection decision.

Selecting the shaft location is a complex process influenced by various factors, including orebody position and shape, ore tonnage, mining equipment, geomechanics condition and presence of water. The cost of excavating the shaft and transporting the ore depends on a complex combination of these factors and serves as the principal metric to evaluate shaft position. The cost of excavating the shaft depends on the sinking method chosen and the conditions present during sinking, which can vary among location. The shaft sinking is the process to excavate the rock-mass between the surface and the operating zone of the underground mine. This variability makes estimating the sinking cost difficult and has led to the lack of a universally accepted cost estimation technique. Also, the uncertainties in the parameters and the knowledge of the orebody to be exploited affect the underground mine design and location of facilities.

Given the uncertainty in the parameters involved in the underground mine design process, selection of the shaft location can also be seen as a high-risk decision-making process. An appropriate approach is necessary to minimize the associated global costs, that is, all costs that can vary with a given location of the shaft. These include the cost of sinking, of transporting ore from the orebody sectors to the shaft, and of drift excavation from the shaft to the orebody sectors. This new approach of shaft location selection needs to be accompanied by a robust cost estimation of shaft sinking, as this process is influenced by diverse factors.

1.2 Research Objectives

- Identify the factors affecting shaft selection in underground mines
- Propose a new approach to select shaft location, considering the cost of sinking the shaft and other technical factors
- Develop and apply a new cost model for shaft sinking, considering the principal influential factors, such as rock mass quality and water conditions
- Assess risks associated with the uncertainty of the mineral contained in the orebody in relation to the location of the shaft

1.3 Economic Benefits

The principal economic benefit is minimizing the global cost related to the shaft through a 1) location selection approach and 2) cost estimation technique. According to InfoMine (2021), shaft sinking represents 40–50% of the global cost related to the shaft; conditions surrounding shaft sinking can make the global cost vary by up to an additional 15%. Furthermore, evaluating uncertainty associated with ore tonnage will help decision-makers mitigate the effect of unexpected realizations. Thus, optimizing shaft localization will also reduce ore and worker transportation costs.

1.4 Originality and Success

The originality of this research lies in proposing a new shaft localization method based on a new cost estimation approach tailored to underground mines that considers the uncertainty of the ore tonnage.

1.5 Thesis Organization

This research is organized in the following chapters:

Chapter 1 introduces the research with the statement of the problem, the aims, the economic benefits, and the originality of the research.

Chapter 2 reviews existing literature about facility localization.

Chapter 3 introduces a methodology for selecting shaft location, considering the investment cost in shaft sinking and a new approach for this cost estimation.

Chapter 4 presents a case study to demonstrate the performance of the proposed approach.

Chapter 5 assesses risks associated with ore tonnage linked to the selection of the shaft location.

Chapter 6 provides the conclusions and future work for new researchers.

2 Problem Description and Literature Review

2.1 Mining Shaft Infrastructure

2.1.1 Shaft versus inclined drift (ramp)

A critical decision in underground mine design is the material handling and worker transportation system. In other words, the decision-making problem is whether mine access will be through a shaft or inclined drift (Figure 2.1). A shaft is vertical infrastructure, and an inclined drift is a secondary or tertiary inclined (horizontal or subhorizontal) development opening. Both shafts and inclined drifts are used to transport ore and waste from the mine to the surface, and equipment, materials, and workers to and from the surface.

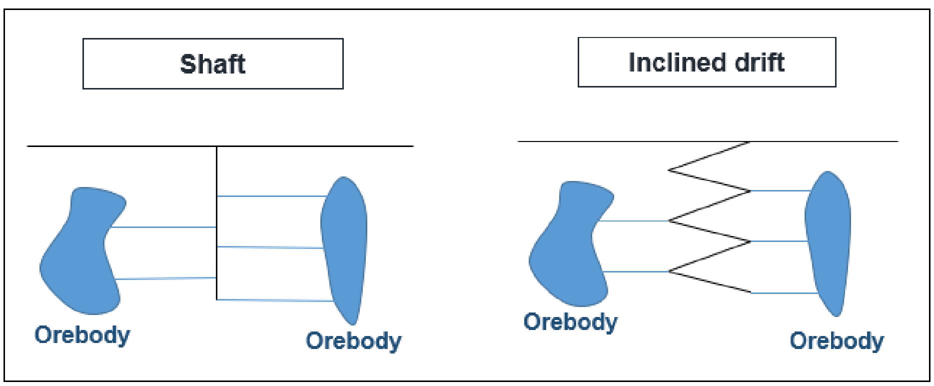

Figure 2.1. Two possible access routes in an underground mine

Hartman and Mutmansky (2002 indicated that shaft requires more cost per meter than the inclined drift, but after certain deep, the shaft will be the only acceptable opening for a profitable mining project. Bloss, Harvey, Grant and Routley (2011) compared the different ore-handling-system for different access models, considering different factors such as the safety and health, capital cost, capacity, economic, flexibility, reliability and operability. From this reference, a shaft has the following benefits.

- Lower costs of transporting ore and waste from the mine to the concentrator plant and waste dump, respectively
- Higher production capacity due to more rapid transportation of the ore from the mine to the concentrator plant
- Lower ventilation costs and greenhouse gas emissions because inclined drift access requires the use of trucks
- Faster transportation of the workers from the surface to the work zone and back up to the surface
- Lowe costs as mine goes deeper
- Safer in poor rock quality
- Less time required to construct in deep orebodies
- Less accident probability because there are no trucks and vehicle
- Less maintenance costs due to shorter distance of access

2.1.2 Shaft types

Shafts can be classified according to shape or slope. Tuck (2011) concluded that the circular shafts were the most common access to underground due to the higher stability of a circular excavation in contrast to a rectangular, and other shapes, such as elliptical. Other factors impacting the shape of the shaft are the purpose of the shaft, the size of the equipment that will be moved by shaft and the expected lifetime of shaft. Regarding to the slope, vertical (90° from horizontal) shafts are the most common due to their capacity to transport not only the material but also, equipment and workers using a skip and hoisting system and the possibility to reach deeper areas. USACE (2014). Inclined shafts are most commonly between 60 to 80°, they are used to move principally ore and waste due to the inclination, while the transportation of personnel and material is limited, the inclined shafts were more preferred in coal mining due to the shape and geometry of the orebodies (Figure 2.2).

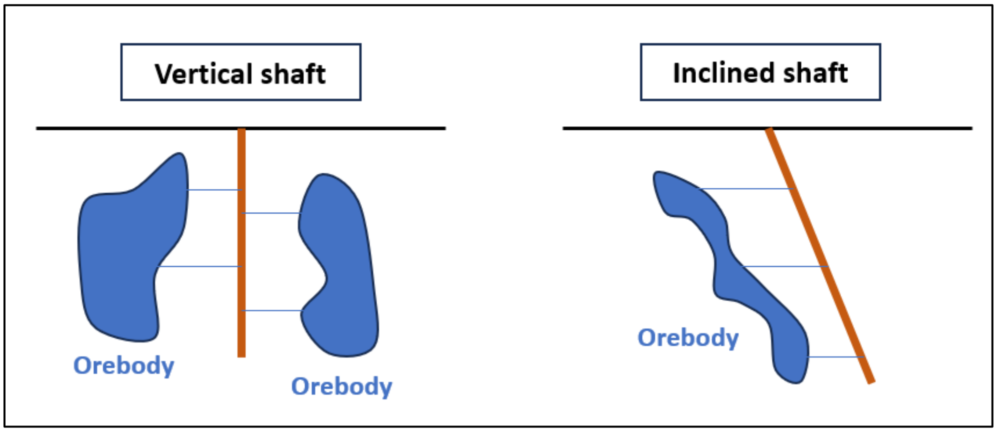

Figure 2.2.- Comparison between Vertical shaft and Inclined shaft

2.1.3 Methods to sink shafts

Conventional sinking uses drilling and blasting (Figure 2.3). It was the most used method before mechanical excavation was possible. Although it is relatively inexpensive, it is labor-intensive, requires a longer sinking time, and is prone to safety problems.

Figure 2.3.Conventional sinking (White, 2011)

Mechanical sinking is relatively new and has been adopted around the world since it is less labor-intensive, safer, and allows a more rapid advance in blind shafts. Neye et al. (2015) provide some examples of the machines developed for mechanical sinking (Figure 2.4).

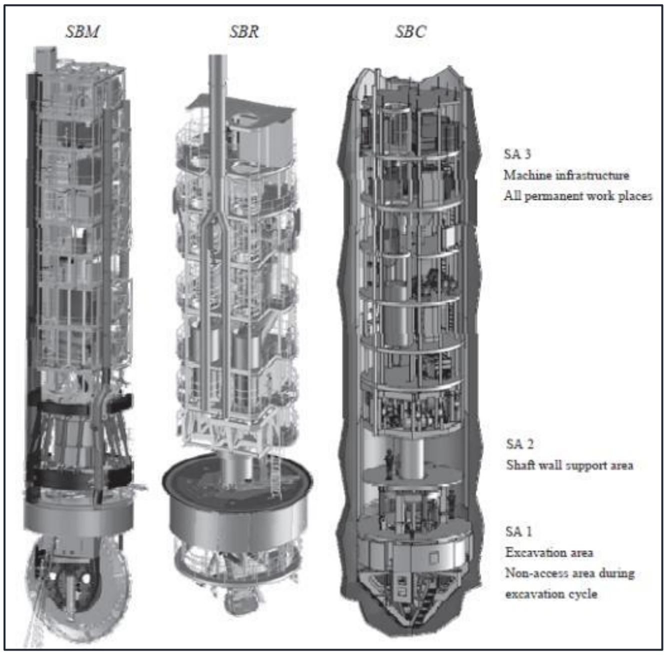

Figure 2.4. Shaft boring machine (SBM), shaft boring roadhead (SBR), and shaft boring cutterhead (SBC) (Neye et al., 2015)

2.2 Cost Estimation Methods

The cost estimation methods are techniques used to estimate costs. Two commonly used methods for cost estimation are the Quantity-Based Method and the Cost-Based Method.

2.2.1 Quantity-Based Method

This method estimates the cost through the quantities and resources required to complete the project. The quantities and resources estimated (e.g., labor, materials, energy) will be multiplied by their respective unit costs to calculate the total cost of the project.

The principal advantage of this method is to provide detailed cost estimation, breaking down the total project cost in the resources required. However, this method can not be used in the early stages of the project since the quantities required are still not defined completely. Additionally, other factors that can affect the project's total cost (e.g., efficiency or productivity) are not considered.

2.2.2 Experience-Based Method

This method estimates the overall cost of the project using the information of historical data of similar projects. It requires an analysis of the historical data and comparison with the conditions of the new project; it involves the use of cost models, the judgment of the estimator, and other characteristics.

The advantages of this method are the consideration of a project's unique characteristics, relying on the information of the historical data with similar conditions. Nevertheless, this method needs accurate historical data that sometimes may not be available.

2.3 Cost Estimation Models

The cost estimation models are mathematical process that has been applied in different domains, nevertheless, this process has been increased in accuracy and complexity after the development of computer processors, after which several cost estimation approaches have been proposed. Layer, Brinke, Houten, Kals and Haasis (2002) classified trends in cost estimation. Hashemi, Ebadati and Kaur (2020) extended this classification (Figure 2.5) by compiling information from projects spanning over 30 years. They collated and compared cost estimation methods from a variety of fields (e.g., building projects, public projects, roadway projects). They reported that 68% of the operations under their research used analogous approaches, 28% parametric, 3% intuitive and 1% analytical. Among all the analogous and parametric approaches, regression analysis, artificial neural networks, and case-based reasoning (CBR) have been the most widely adopted. Kim, An and Kang (2004) elaborated a comparison between these three approaches used in building industry cost estimation. Table 2.1 shows a comparison through the advantages and disadvantages of these three approaches in the context of cost estimation in general.

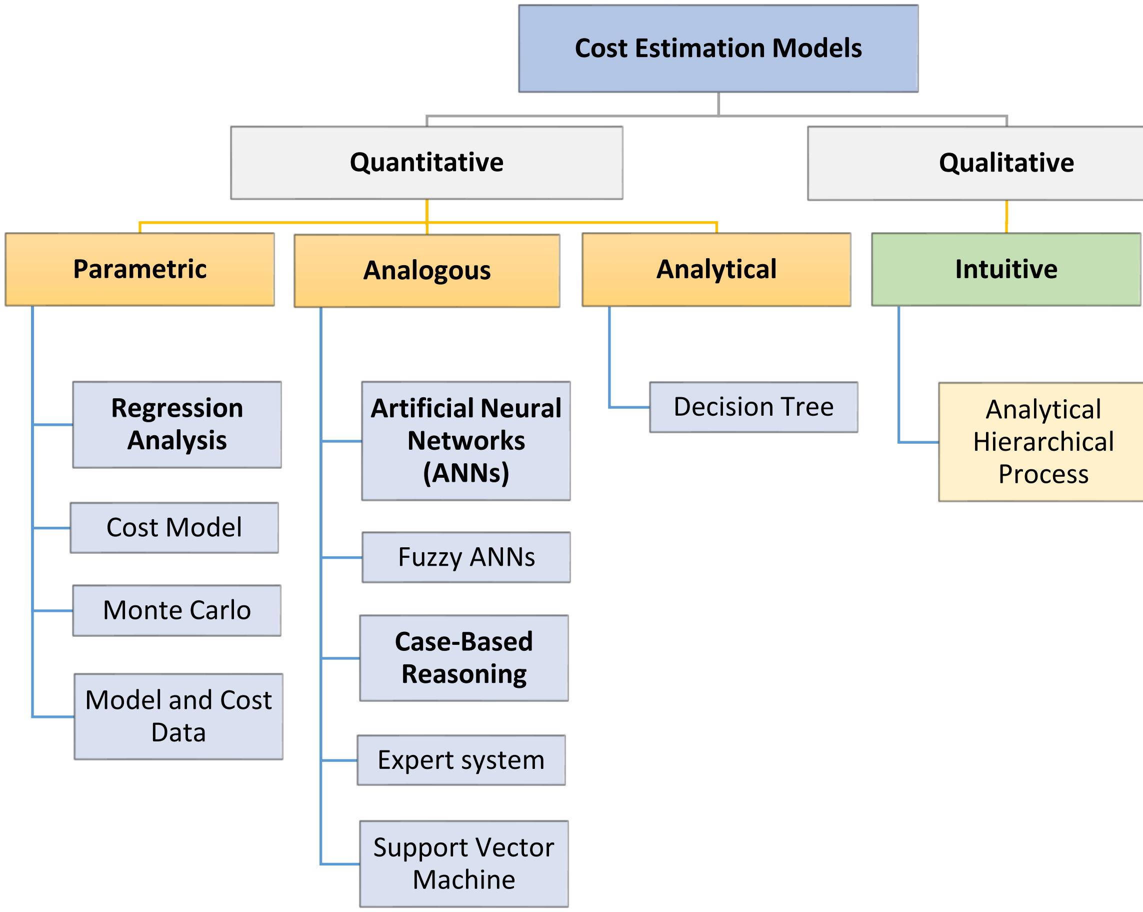

Figure 2.5. Cost estimation methods (modified for the mining industry from Hashemi et al., 2020)

Table 2.1. Advantages and disadvantages of three cost estimation methods (adapted from Kim et al., 2004)

	Multiple Regression Analysis	**Artificial Neural Networks**	**Case-Based Reasoning**
Advantages	A simple and easy to apply Allowing statistical inference	More accurate for cost estimation than regression model Unrestricted number of inputs and outputs	Handling projects with complex and dynamic inputs Can consider the new estimations as a new case learned for future process
Disadvantages	Based on historical data, therefore may not replicate a future cost estimation May not generate a good fit to measured data	Trial-and-error process to determine neurons is time-consuming Requires large dataset Arbitrary selection of some parameters	Depends on the quantity of the data available for the estimation The division of the range in some influencing factors can be subjective and bias the results

The CBR is an approach widely used in cost estimation, specially in construction industry. Kim et al. (2004) conducted a comparison on 40 projects, evaluating the three approaches mentioned before. The results demonstrated that CBR and artificial neural network had a better performance than the multiple regression analysis. CBR exhibited superior clarity in the explanation of the cost estimation process. Moreover, CBR had more advantages in long-term applications. Koo, Hong, Hyun and Koo (2010) presented a CBR-based hybrid model for the cost prediction in building industry. Different techniques were mixed with the CBR to improve the results in cost estimation, the techniques used were the artificial neural network, multiple regression analysis. These techniques focused in two principal factors of the CBR, “the type of attribute weight” and “the minimum criterion for scoring the attribute similarity”. The optimization was completed using genetic algorithms, improving the accuracy and flexibility of CBR. Ji, Park and Lee (2011) employed CBR for cost estimation. In their study, an optimization process was applied to define the scoring and weight of the attributes (two process that have not find consensus of best approach until today). The suggested methods for the optimization in the attributes were the Euclidian distance-based similarity and the genetic algorithms.

Zima (2015) applied CBR for cost estimation in the preliminary stage of a construction project. The author noted that CBR is simple and accurate. However, the method has drawbacks, such as a lack of the differences that should exist in the cost structures due to the different locations and time gap between the new projects and the projects in the database and the large amount of data required for the transformation process. Ji, Ahn, Lee and Han (2019) overcame some drawbacks through a modified CBR model that applied a quantity-based method for cost estimation and a parameter-making process. The modified CBR model proved to be better than the typical CBR through a case study in the cost estimation for construction projects.

2.4 Cost Estimation in the Mining Industry

Cost estimation in the mining industry has been a major topic because mining operations require high capital and operating costs. Therefore, the accuracy of cost estimation is critical. Nevertheless, there is no single method applied for the cost estimation of the underground mine.

The initial stages of cost estimation in the mining industry are related to the engineers' experience involved in the estimation and the available data at that moment (experience-based method). These estimations did not have a robust mathematical procedure and lacked accuracy.

O'Hara (1980) proposed a cost estimation model for underground and open-pit mines based on the actual costs of mining projects, principally in Canada, for fifteen years. The cost estimation was divided into different categories, such as capital cost, equipment, maintenance, development, shaft sinking, plant concentrator, and others. Figure 2.6 shows an example of this method for the cut & fill method, with different dimensions of stopes.

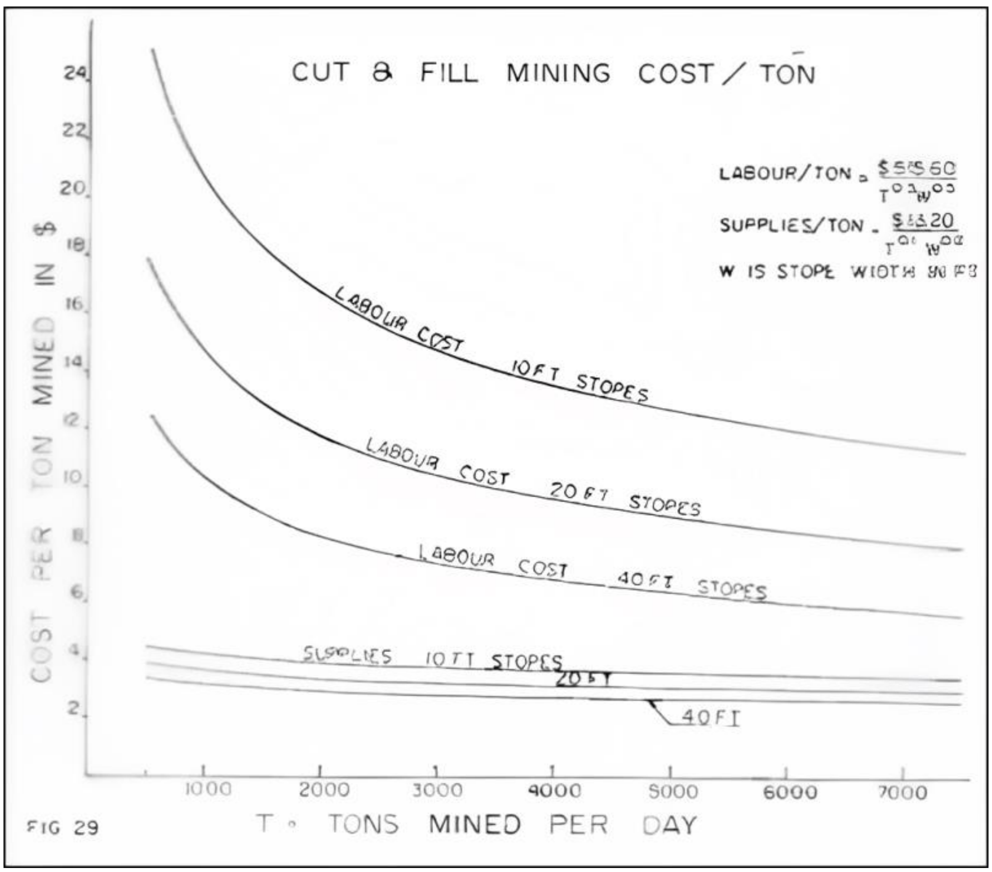

Figure 2.6. Curves for cost estimation for cut and fill mining (O'Hara, 1980)

With the graphic created the equation (2.1) is used to estimate new values for future projects.

$$x = a * (y)^b \qquad (2.1)$$

Where *a and b* are values based on a regression model that depend on mining and excavation methods, rock characteristics, and geology; *x* is the estimated cost; and *y* is the parameter in question (e.g., capacity, production tonnage, diameter, or length). The production tonnage is the most used parameter. This type of equation ignores the time effect associated with inflation. Therefore, it should be used with an appropriate cost index.

Stebbins (2011) described a cost estimation process for underground mines based on the two-step process. The first step determines the distance required for openings (e.g., shaft, ramps, and drift) from the surface to the production area. Three principal parameters, the equipment, labor, and supply requirements, are estimated according to these distances. It is a common practice to use different mathematical approaches to estimate the distance required to reach production zones. The other option is based on the use of stope models. A preliminary design of the stope according to the mining method is made. Figure 2.7 shows an example of the stope model for cut and fill, with the respective opening required. Camm and Stebbins (2020) published a handbook for pre-feasibility cost estimation with stope models for the principal methods for underground mining.

The second step of the estimation process is the determination of the cost parameters. After the application of the production rates in the first step, the cost of them if found regarding the selected mining method. Supply material, workforce and equipment costs fitting can be found in the mining handbooks (e.g., InfoMine USA, Inc.). This cost structure should be updated as macroeconomic parameters change.

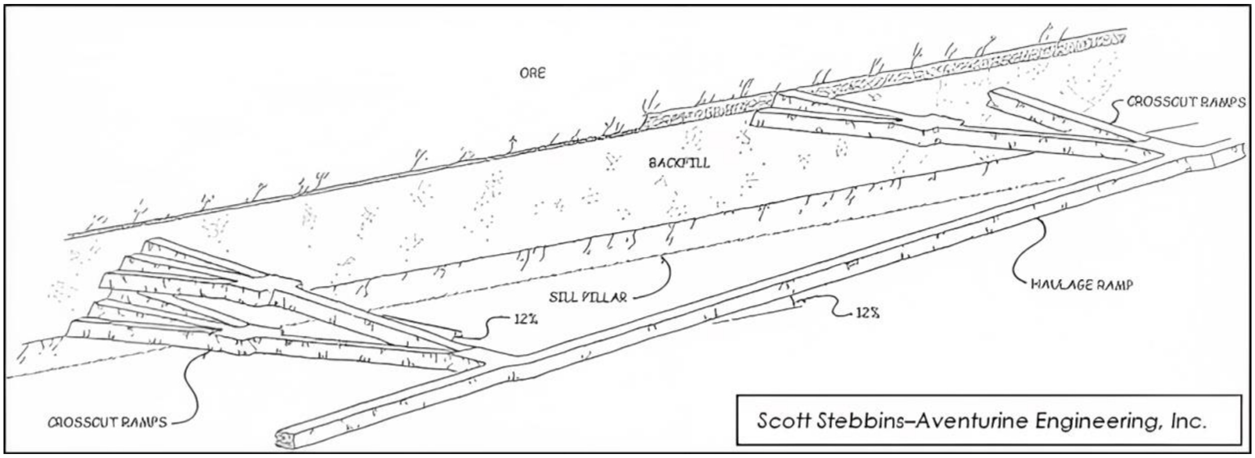

Figure 2.7. Example of costs associated with cut and fill model (Camm & Stebbins, 2020)

The two processes presented above could estimate the costs for the shaft sinking as part of the underground mine cost estimation analysis, nevertheless, due to the conditions for shaft sinking, mining companies commonly work with specialized contractor companies. During the tender process, contractors can estimate costs with a high degree of accuracy and help avoid unexpected costs. The contractor with the lowest bid wins the contract.

2.5 CBR background

CBR is a knowledge-based system that solves problems through experience accumulated of previous projects: the similarity in the previous projects is kept in memory and used in future projects. In other words, previous cases are adapted to a *new query project* through numeric and non-numeric parameters. CBR has its origins in the late 1970s and is strong potential to benefit from emerging artificial intelligence techniques.

CBR appeared In the 1980s. The application of this method was in medicine in the early development. Emerging data management and updating methods improved the process of problem solving and modifying the database cases to create a better fit for the new query problem, extending his applications to estimations in industrial process, agriculture, banking, cost estimation, supplies, and others. Prentzas and Hatzilygeroudis (2011) compiled CBR applications in various disciplines (e.g., medicine, banking, construction, agriculture), either alone or integrated with other artificial intelligence methods.

In this research, the new query project will be the estimation of the shaft sinking cost for underground mines. CBR is based on the four principles listed below (Lopez, 2013).

1. **Analogical reasoning** is a type of artificial intelligence. It compares two or more projects or objects and uses their similarities to make predictions about new projects or objects.
2. **Knowledge representation and reasoning** is another component of artificial intelligence. The objective is to represent the characteristics or conditions of a project in a way that can be read and processed by a computer.
3. **Machine Learning** is integrated in CBR through memory-based learning, in which the available training data are stored until a new prediction is required and the computing process starts.
4. **Mathematical foundation** methods provide similarity measures that allow the retrieval of similar cases for solving new query cases.

There are many ways to manage the CBR process. Table 2.2 shows different versions that can be configurated, according to the requirements of the problem that is being solving.

Table 2.2. Case-based reasoning systems (Lopez, 2013)

Knowledge Source	Function	Organization	Distributive Class
Structural	Classification	Sole	Single memory
Textual	Recommendation	Multi-level	Multiple memories
Conventional	Tutoring	Hybrid	Single agent
Temporal	Planning	Meta	Multiple agents
Images	Monitoring		
	Knowledge management		

The data organization can be plain or hierarchical (Figure 2.8). This different representation and order will be important when the CBR process generates code. The way the data are organized is significant because the new query project analysis will use the database (Bichindaritz, 2008). Table 2.3 shows the advantages and disadvantages of these data organizations.

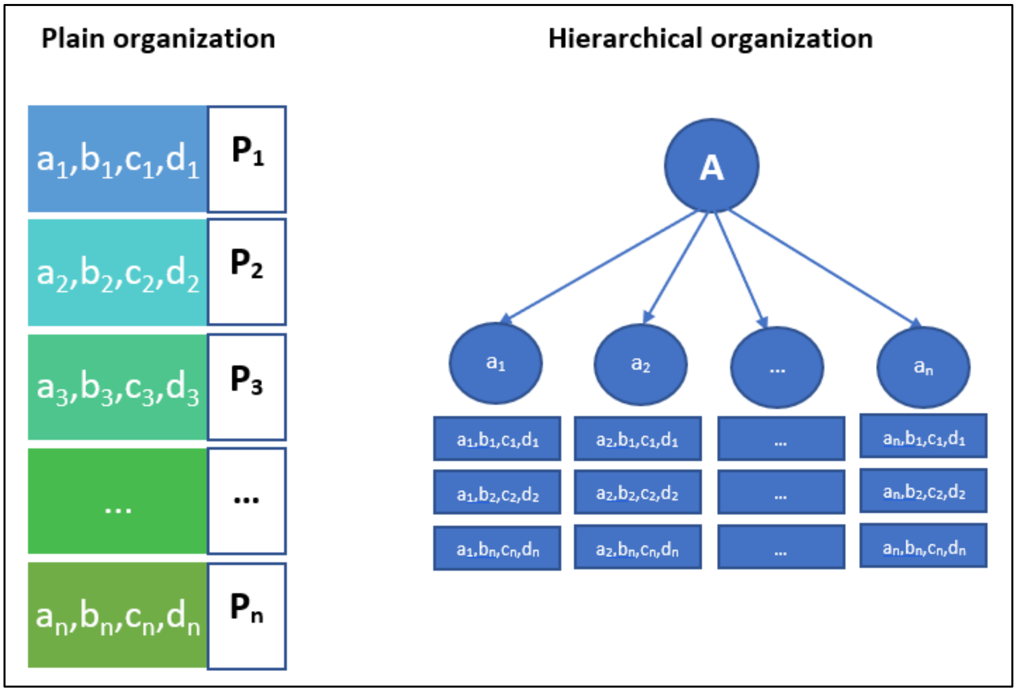

Figure 2.8. Information organization of case-based reasoning, where the influential factors are {A,B,C,D}

Table 2.3. Advantages and disadvantages of data organization

Data Organization	Plain	Hierarchical
Advantages	i. requires less effort to implement due to its simplicity ii. can be adapted to different conditions of database	improves the process of data selection since the data is presented in an order
Disadvantages	treats all the information in the database as the same categories	less adaptable for different conditions of the database

2.5.1 K-Nearest Neighbors (K-NN) Background

K-NN is a principal algorithm in the machine learning field (Cover & Hart, 1967). It is a non-parametric, instance-based learning technique used for classification and regression tasks. K-NN operates on the principle of similarity: it classifies or predicts a new input based on the average value of its K nearest neighbors in the dataset (Han, Kamber, & Pei, 2011). In conclusion, "K" represents the number of neighbors considered for making predictions. K-NN assumes that similar inputs often share similar outcomes.

The process of applying K-NN involves a straightforward sequence of steps. Given a dataset with labeled information, the algorithm calculates the distance between the input data point and every other information in the dataset (Han et al., 2011). Common distance between the inputs includes Euclidean distance, Manhattan distance, or other custom-defined distances. The next step is to select the K-nearest neighbors based on the calculated distances. Choosing an appropriate value for K is important, a small K could lead to noise sensitivity, while a large K might lead to over-smoothing.

K-NN has a close similarity to the principles of CBR. Both methods rely on the idea that similar cases in a dataset can provide insights into new cases. The link between K-NN and CBR highlights the utility of experience-based reasoning in making decisions, whether by the K-NN process or by retrieving and adapting solutions using the CBR (Kolodner, 1993).

2.6 Localization Problems in Mining

Selecting the location of an underground mine waste dump, tailings pond, processing plant, in-pit crusher, refuge chamber, and other infrastructure is complex. Mostly it is a cost minimization problem related to the capital costs, operating costs associated with haulage, and maintenance costs, it can also be a dynamic problem if that facility is moved over time. The principal factors impacting the final location of the facilities in mining are geomechanics considerations, orebody size, shape and orientation, the location of other facilities, environmental considerations, socio-economic conditions, legal requirements.

The geomechanics considerations plays an important role in the location of the facilities, even if there are multiple options to support the most difficult conditions of the rock mass, this condition is challenging due to the high cost involved in the support or the safety of the personal involved in the construction of the facility. Ground and rock conditions of facilities and connection roads are critical.

The orebody size, shape and orientation are some of the most important factors in facility locations selection. The facilities should be as close as possible to the orebodies to minimize haulage cost.

Since the mining production is a sequential operation, many facilities will be related to other facilities, for instance, the tailings should be as close as possible to the concentrator plant, or the workshops to the points with high density of equipment.

The environmental considerations are also helpful in the location selection; for instance, the presence of rivers can change the final location of a facility. The socio-economic conditions are also a factor that facilities can impact a community near to the mine operations, this condition is strongly related to the legal requirements, where the space that is available to the use of the mine facilities can impact the suitability of the selection of the best position.

Many research studies have been conducted for the location of mining facilities Over the years the research studies have been increasing in complexity and in parameters involved, most of them related to open-pit mining industry, the principal objective of these research studies has been to involve most of the parameters or impacting factors in the mine.

For instance, Zambó (1968) introduced a mathematical and graphical procedure to achieve two objectives: minimize the movement cost and minimize investment in the transport network. Robertson (1982) described a process to select the position of the tailing in a uranium mine, following two phases: the preliminary evaluation and the detailed investigation and evaluation, where the main options are evaluated through a “Fatal-flaw screening criteria”, considering ecological, topography, stability, and other factors. Osanloo and Ataei (2003) elaborated a procedure of five stages for the selection of pit rock-dumps, where the locations that are not suitable are discarded, and the remaining possible locations are evaluated trough four weighted impacting factors: the distance tock haulage, the capacity, the environmental disturbance, and rock stockpiling cost. Kumral (2005) proposed a genetic algorithm-based approach to select the location of a mineral processing plant for a multi-mine operation. Akbari, Osanloo and Hamidian (2007) proposed a methodology for tailing dam site selection using four significant factors:

environmental factors, hydrological factors, geological factors, and cost factors. These significant factors were organized by hierarchy and weightings, and the best site was obtained through an Analytical Hierarchy Processing. Kumral and Dimitrakopoulos (2008) applied a tabu search algorithm, which is based on a local neighborhood search procedure until a termination criterion is satisfied to select waste dump locations at an open pit mine, considering the associated operational and the capital cost and a given number of possible locations. Fazeli and Osanloo (2013) discusses the impact of environmental factors in the mine facility location selection, analysing seventeen impacting factors and their respecting environmental components, applying Folchi algorithm. The method applied was flexible and allows the ranking of different alternatives. Shao, Yang, and Kumral (2023) proposed two models to select the optimal position of refuge chambers in underground mines. The models considered the distance between working face and refuge chambers dynamically. Also, Shao, Meyrieux, and Kumral (2022) focuses on determining a junction location on a shaft to minimize the evacuation distance of worker. The problem was formulated as a minimax problem.

2.6.1 Shaft Location

Choosing the shaft location selection is a key decision-making problem. The shaft is among the costliest of the underground mining operation infrastructure, and in most of the cases it serves during the entire lifetime of the mine. Materials handling, worker transportation, maintenance, and other activities are directly related to shaft location. The shaft location It is a cost minimization problem related to the capital costs, operating costs associated with haulage (i.e., excavation of drifts from the shaft to the orebodies, transportation of ore from orebodies to the shaft, and total amount of material to be transported through the shaft), and maintenance costs. Therefore, it needs a detailed analysis. The techniques suitable to shaft localization can be classified into three groups (Farahani & Hekmatfar, 2020):

- **The centroid of masses** is used in physics when a point represents the average position of a group of points through the coordinates of the points and their weights. Shim and

Siegel (1999) and Chase, Jacobs and Aquilano (2006) used this method for facility location problems. This technique is calculated using equation below.

$$C_x = \frac{\sum_i^n m_i * x_i}{\sum_i^n m_i}; C_y = \frac{\sum_i^n m_i * y_i}{\sum_i^n m_i} \quad (2.2)$$

Where C_x and C_y represent the centroid of masses and the potential new location of the facility, x_i and y_i are the coordinates of the point i and m_i is the weight of the point i.

- **The Weiszfeld algorithm** is an interactive method to find a median point among a set of points, with the principal objective of reducing the sum of the distances from the median point to all points. It has been widely used for selecting facility locations for cities (e.g., police stations, schools, and others).
- **The Elzinga-Hearn algorithm** minimizes the maximum distance between the median point and any point in the group of points (minimax formulation). It is used principally for the location of emergency or first-aid facilities (Daneshzand & Shoeleh, 2009).

In addition to these techniques, the studies have been conducted to select a position of the shaft that can fit criteria listed above. Initial approach proposed was based on a geometric approach. With new computational resources, more parameters (e.g., geomechanics) were ingrained. The proposed methodologies expanded such that optimization models and simulation analysis are incorporated.

Lizotte and Elbrond (1985) presented the centroid of masses and the Multifacility Hyperboloid Approximation Procedure, a method that uses the Steiner minimal spanning tree, for underground mining levels. Bhattacharya (1998) applied the Weiszfeld algorithm for the location of the mining facilities, including the shaft. Bhattacharya, Kumar, and Sanjay (2001) assessed different algorithms, such as Weiszfeld, Elzinga-Hearn, and Quasi-Newton, considering the orebodies and the concentrator plants. Gligoric, Beljic, and Simeunovic (2010) used the network optimization to define a set of alternative solutions for shaft location. Subsequently, the parameters of transportation cost, total development and operational cost were utilized in the Steiner minimal tree, to create an order of the best alternatives for the location of the shaft.

Bakhtavar, Yousefi, and Jafarpour (2019) evaluated the selection of shaft location (ventilation and production) using a fuzzy multi-objective optimization, adding more parameters to the orebody conditions, such as the topography surface.

The methods above approach the problem as a two-dimensional problem. Since a shaft has a vertical direction, the shaft selection problem must be converted from a three-dimensional to a two-dimensional problem (Figure 2.9). This conversion can be achieved through different techniques, in the research studies reviewed, the principal technique is the orthogonal projection. This arrangement will simplify the process and analysis of shaft location.

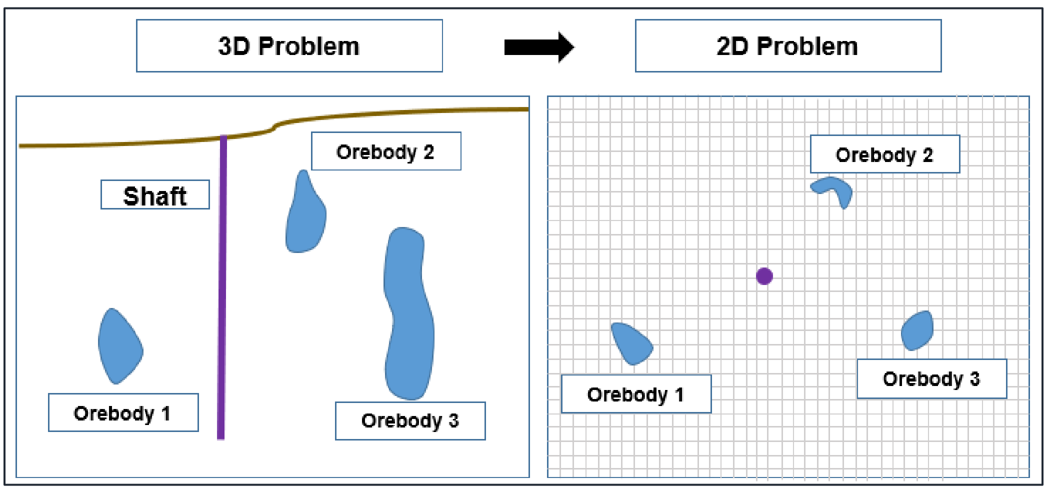

Figure 2.9. Longitudinal (left) and plan view (right) of a vertical shaft serving three orebody sectors

3 Methodology

3.1 New Approach to Shaft Location

Shaft localization is an optimization problem focused on minimizing costs. It considers three parameters: the new approach adds a fourth parameter, the sinking cost, which represents the capital costs associated with excavating the shaft by a mechanical or conventional method (Figure 3.1). The primary benefit of using this cost model estimation is that it considers the conditions encountered throughout the entire shaft axis.

New approach to Shaft Location

- Excavation of the drifts from the shaft to the orebodies
- Cost of transportation of the ore from every orebody to the shaft
- Total amount of material production of the structures to be transported through shaft
- Sinking cost

Figure 3.1. Parameters used for the selection of the shaft location

The methodology follows the following steps.

1. **Identify parameters related to the orebody sectors**

Orebody sectors differ qualitatively and quantitatively. The distance between orebody sectors and the shaft differs, as do the geologic conditions in drifts. Therefore, three types of transportation costs vary from drift to drift (Figure 3.2).

i. **Cost of drift excavation** ($/km) that connects the orebody sector and the shaft.

ii. **Cost of transportation** ($/km.t) from the orebody sector to the shaft.

iii. **Production** (t) is the ore quantities of the orebody sector that will be transported to the surface using the shaft.

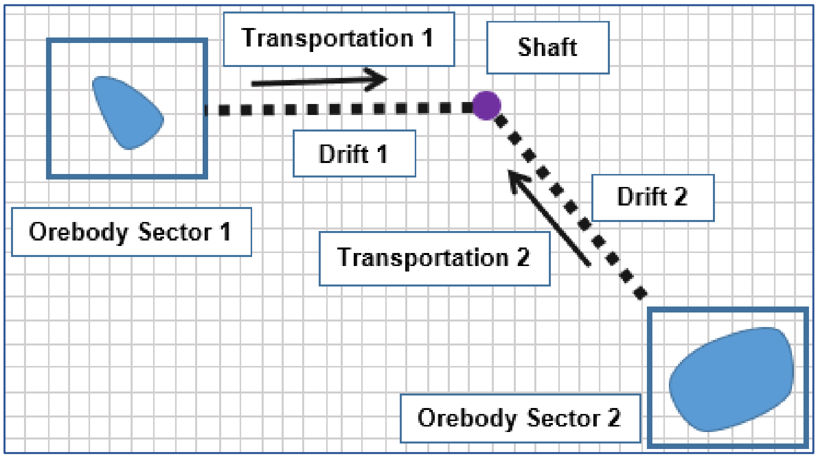

Figure 3.2. Parameters of the orebody sectors (plan view)

2. Calculate weights of the orebody sectors considering the parameters

To account for quantitative and qualitative differences among orebody sectors, a weight was assigned to each sector from the three costs in step 1.

$$W_i = CD_i + CT_i * P_i \tag{3.1}$$

Where W_i is the weight of orebody sector i, CD_i is the cost of drift excavation for orebody sector i, CT_i is the cost of transportation for orebody sector i, and P_i = production of orebody sector i.

3. Create a model considering the cost related to the weight of the orebody sectors

The total area of the surface was divided into 1 m x 1 m grid cells (Figure 3.3) to assign a total operating cost and investment value for any grid cell based on the assumption that the shaft will be located in that specific grid cell. The global cost will change at every grid cell.

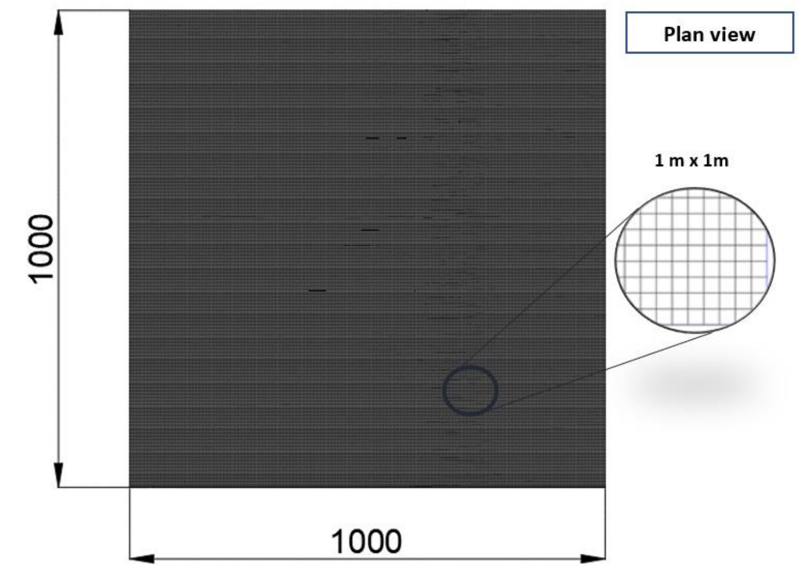

Figure 3.3. Discretization of the area for the model

This total operating cost in a grid cell is:

$$g(x,y) = \sum_{i=1}^{m} w_i[(x-a_i)^2 + (y-b_i)^2]^{1/2} \quad (3.2)$$

Where *g(x,y)* is the total operating cost of the grid cell (x,y); w_i is the weight of the orebody sector i; *(x,y)* is the coordinates of the grid cell; a_i, and b_i are the coordinates of the orebody sector i; and *m* is the number of orebody sectors.

4. Identify sinking cost according to grid cell characteristics

Considering the parameters and characteristics of the grid cell, the sinking cost was calculated. The factors affecting the investment required for the sinking cost are the length and diameter of the shaft, the water, rock mass and weather conditions, and operator skills. Only two of these influential factors are subject to change among grid cells: the water and rock mass conditions. The remaining factors were assumed to remain constant across all grid cells.

5. Create a final model considering total operating cost and sinking cost

The final model considering the total operating and capital costs is as follows:

$$f(x,y) = \sum_{i=1}^{m} w_i[(x-a_i)^2 + (y-b_i)^2]^{1/2} + Inv_{(x,y)} \quad (3.3)$$

Where *f(x,y)* is the global total of the grid cell (x,y) and *Inv(x,y)* is the sinking cost of the shaft in grid cell (x,y).

6. Locate the shaft

For the final step, the grid cell with the lowest total cost is considered the best location for the shaft.

$$Optimal\ position\ of\ the\ shaft = Min[f(x,y)] \quad (3.4)$$

Where *Min[f(x,y)]* is the grid cell with the lowest global cost.

3.2 New Approach of Shaft Sinking Cost Estimation

This research adapts a model developed by Ji et al. (2019) to estimate the cost of shaft sinking (Figure 3.4).

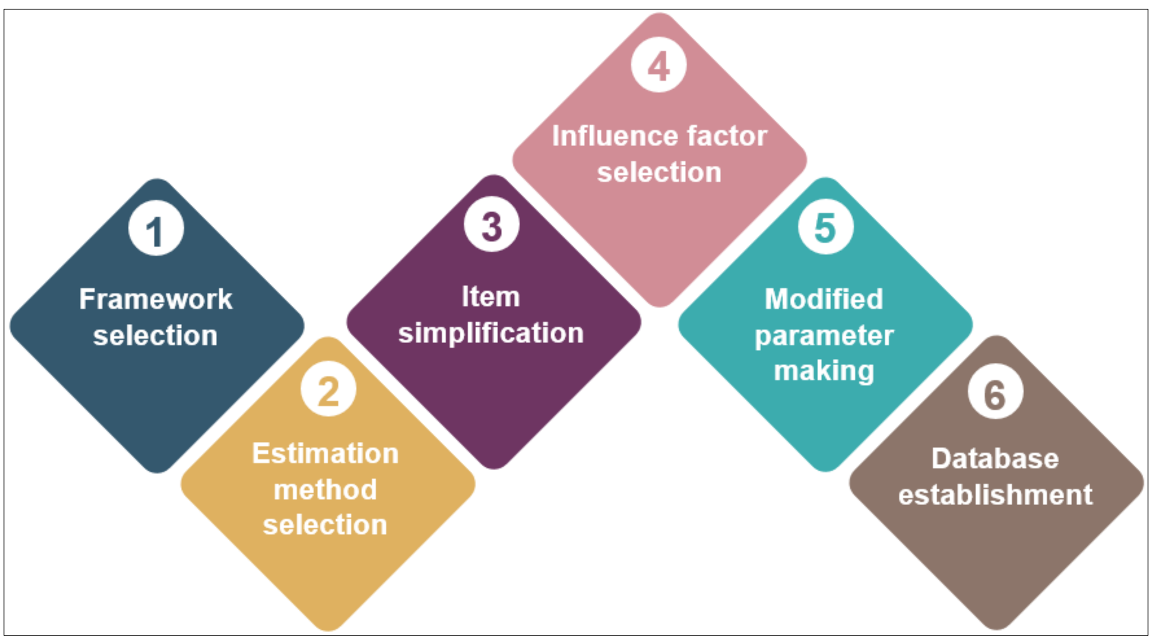

Figure 3.4. Cost model developed process (adapted from Ji et al., 2019)

3.2.1 Framework selection

This thesis will consider a single memory / single agent. The four steps for estimating the cost of shaft sinking with CBR are as follows (Figure 3.5 and Sections I – IV).

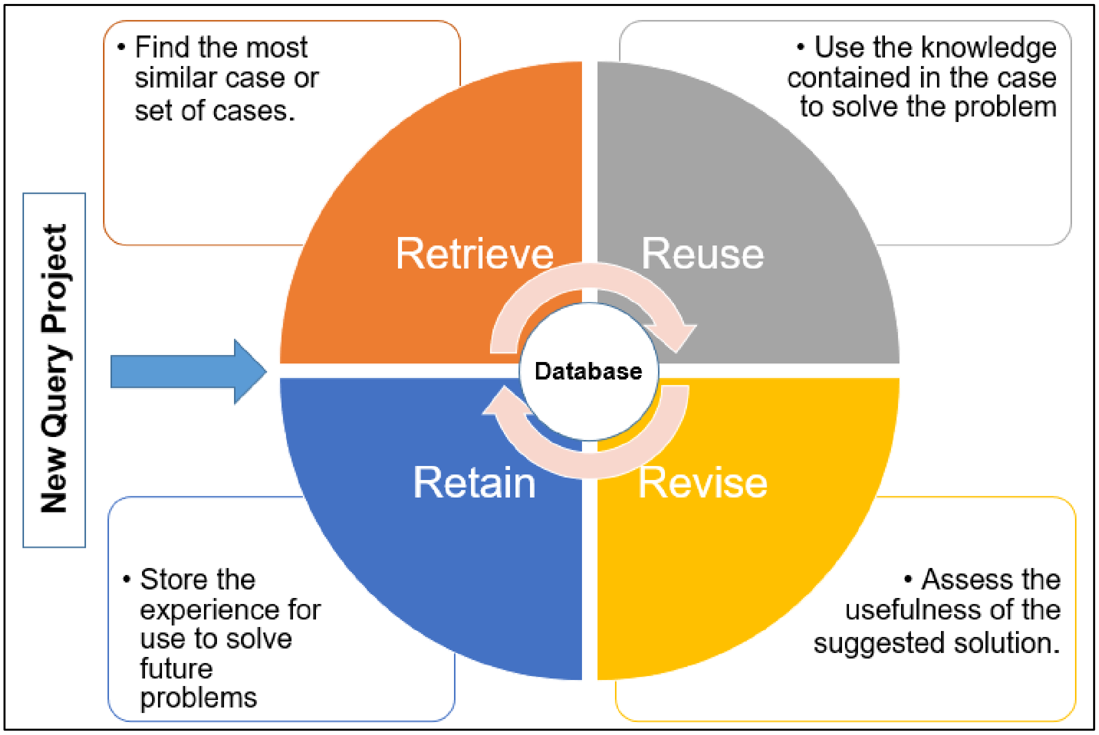

Figure 3.5. Process for the CBR model (adapted from Aamodt & Plaza, 1994)

I. Retrieve

All data related to the shaft sinking cost are collected. It is essential to identify the characteristics or influential factors of the similar cases and then contrast them with the new query project. These influential factors can be represented by a Boolean description (two values), multiple descriptions (more than two values), or a longitudinal description, which is very helpful because some characteristics are exhibited along the axis of the shaft. The data organization used for the thesis was the hierarchical organization, due to the advantages showed in Table 2.3.

The similarity between the new query project and previous projects in the database is assessed by considering the influential factors. The similarity can range from 0 to 1 (equation 3.5).

$$Sim(a, b) = [0,1] \quad (3.5)$$

The similarity assessment comprises two stages. The **first stage** assesses the similarity of two influential factors in the evaluation of two projects (equation 3.6).

$$First\ Stage\ Similarity = Sim\big(P_d(i_n), P_q(i_n)\big) \quad (3.6)$$

Where $P_d(i_n)$ *and* $P_q(i_n)$ are influential factor numbers "n" of the project in the database and the new query project, respectively.

The first-stage similarity is a function of the distance between the influential factors (equation 3.7; Lopez, 2013):

$$Sim\big(P_d(i_n), P_q(i_n)\big) = \frac{1}{1+d\big(P_d(i_n), P_q(i_n)\big)} \quad (3.7)$$

Where $Sim(P_d(i_n), Pq(i_n))$ and $d(P_d(i_n), Pq(i_n))$ are similarity and distance, respectively, of the influential factor "n" between the new query project and a project in the database $d(P_d(i_n)$. The distance should have the following properties:

- Identity: $d\big(P_d(i_n), P_q(i_n)\big) = 0$
- Non-negativity: $d\big(P_d(i_n), P_q(i_n)\big) \geq 0$
- Triangle inequality: $d\big(P_d(i_m), P_q(i_o)\big) \leq d\big(P_d(i_m), P_q(i_n)\big) + d\big(P_d(i_n), P_q(i_o)\big)$
- Symmetry: $d\big(P_d(i_n), P_q(i_n)\big) = d\big(P_q(i_n), P_d(i_n)\big)$

Among the many studies related to the measure of distance, most are defined by the type of influential factor (Lopez, 2013), with the following being most important:

Numeric: $$d\big(P_d(i_n), P_q(i_n)\big) = \big|P_d(i_n) - P_q(i_n)\big| \quad (3.8)$$

Ordinal: Features are ordered by categories such as *good, bad, and normal*. Every category is assigned a number, and the numeric distance is applied.

Nominal: The minor difference between the influential factors generates a zero similarity.

$$Sim\big(P_d(i_n), P_q(i_n)\big) = \begin{cases} 1 & P_d(i_n) = P_q(i_n) \\ 0 & Otherwise \end{cases} \tag{3.9}$$

Structured value: The data belong to a similar ancestor. It is possible to take the distance through the nodes that will be crossed from one datapoint to another.

Heterogeneous: When there are different attributes with different characteristics, it is possible to use a numeric distance or a nominal distance according to the characteristics of the attribute.

Based on the nature of the data, the measure of distance used was numeric and ordinal (heterogeneous). Additionally, one measure of distance was added—the similarity between the axis conditions of the shaft—because some influential factors require this application.

The **second stage** assesses the similarity of the new query project and a previous project in the database:

$$Second\ Stage\ Similarity = Sim\big(P_d, P_q\big) \tag{3.10}$$

Where P_d is a project in the database and P_q is a new query project. The similarity will range from 0 to 1.

$$Sim\big(P_d, P_q\big) = [0,1] \tag{3.11}$$

The second analyzes two projects and determines their similarity as a function of the similarities between their influential factors.

$$Sim\big(P_d, P_q\big) = f\left(Sim\left(P_d(i_1), P_q(i_1)\right), Sim\left(P_d(i_2), P_q(i_2)\right), \dots, Sim\left(P_d(i_n), P_q(i_n)\right)\right) \tag{3.12}$$

Where $Sim(P_d(i_n), P_q(i_n))$ is the similarity of the influential factor "n" between the new query project and a project in the database.

Considering that all the similarities between the influential factor are between 0 and 1, the second stage of similarity is the average of these similarities (Lopez, 2013):

$$Sim(P_d, P_q) = \frac{1}{n} * \sum_{i=a}^{n} Sim\left(P_d(i_i), P_q(i_i)\right) \quad (3.13)$$

Where $Sim(P_d(i_i), Pq(i_i))$ is similarity of the influential factor "i" between the new query project and a project in the database.

The weight of the influential factors is then added to equation 3.13 to represent the impact of the influential factors on the similarity. The weights should sum to 1. The weighted second stage similarity measure is applied when the influential factors have a different impact.

$$Sim(P_d, P_q) = \sum_{i=a}^{n} w_i * Sim\left(P_d(i_i), P_q(i_i)\right) \quad (3.14)$$

$$\sum_{i=a}^{n} w_i = 1 \quad (3.15)$$

Where w_i = weight of the influential factor "i".

This research applies the k-NN procedure to identify the "k" nearest projects to the *new query project*. The principal drawback of the k-NN, is that considers all the parameters with the same weight. To overcome this limitation, El Aoun, Eleuch, Ayed and Aimeur (2009) provided a method to calculate the weights using a reference project and the adjustment of initial aleatory weights. Park, Kim, and Im (2006) used neural networks. Kim and Kim (2010) and Doğan, Arditi and Günaydın (2006) applied genetic algorithms, namely feature counting and gradient descent in the process of determining attribute weights. Wettschereck and Aha (1995), Yan, Shao, and Guo (2014), and Minghai and Huanmin (2010) have shown other methods used for the estimation of the weights in the parameters. The mathematical expression for the weighted k-NN, according to the weights of the influential factors is shown in equation 3.16 (Everitt, Landau, Leese, & Stahl, 2011).

$$Dis(P_d, P_q) = \sqrt{\sum_{i=1}^{n} w_i * \left[dis\left(P_d(i_i), P_q(i_i)\right)\right]^2} \quad (3.16)$$

Where $Dis(P_d, P_q)$ is the distance between the new query project and a project in the database and $dis(P_d(i_i), P_q(i_i))$ is the distance of the influential factor "i" between the new query project and a project in the database.

Using the k-NN process, it is possible to find the similarity between the projects, applying the relationship between the distance and the similarity.

$$Sim(P_d, P_q) = \frac{1}{1 + Dis(P_d, P_q)} \tag{3.17}$$

One problem encountered when measuring similarity was missing data. Figure 3.6 shows the types of missing data and possible solutions. The solution used here was to discard incomplete data.

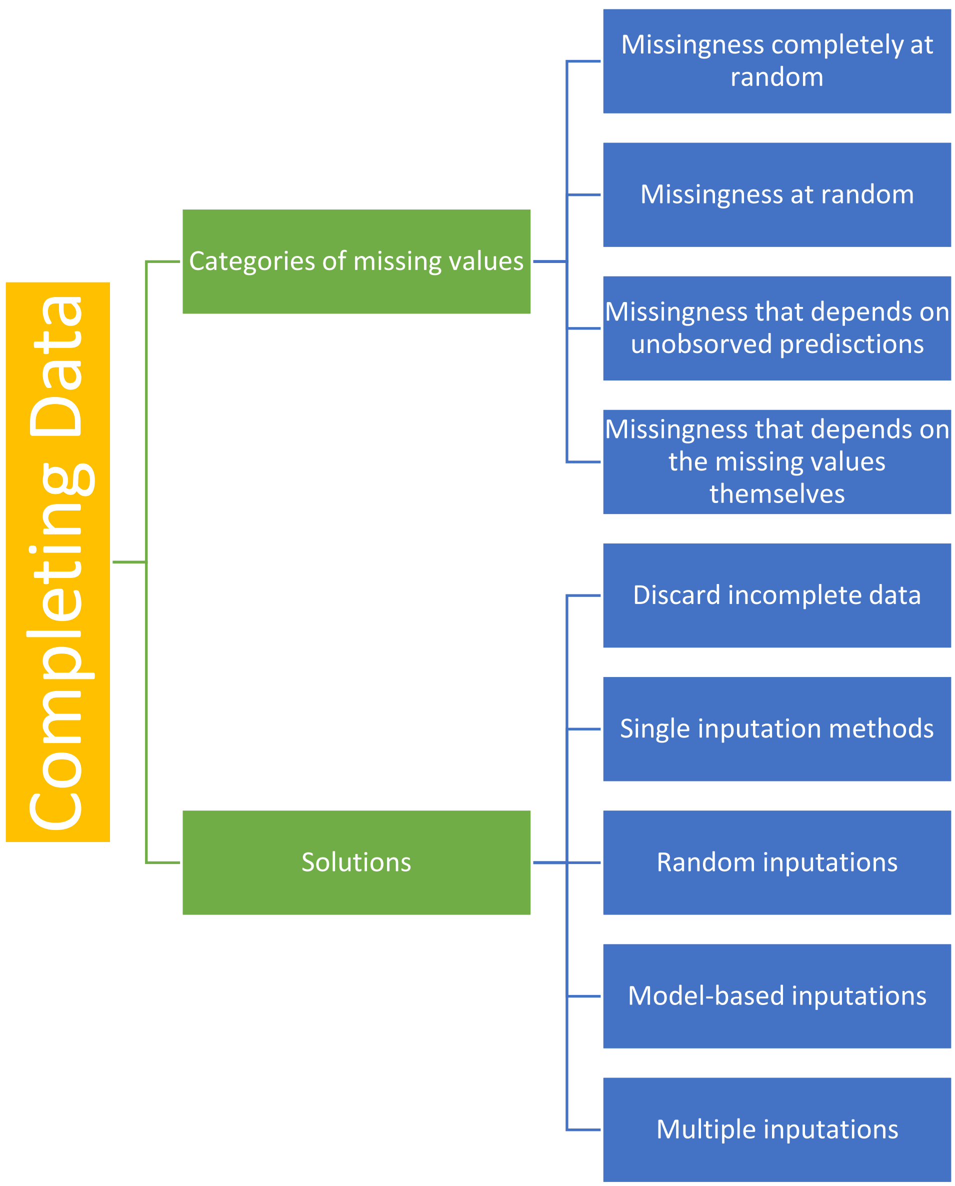

Figure 3.6. Methods to solve the problem of missing data (adapted from Lopez, 2013)

Once the similarity was calculated between the new query project and all the projects in the database, the project in the database with the higher similarity was selected. Given that the weights are crucial in calculating the similarity, the subsequent sections elaborate on the calculation and impact of these weights.

II. Reuse

The reuse stage (see Figure 3.5) uses the solution of the projects in the database to estimate the solution (i.e., values required to estimate the sinking cost of the shaft) for the new query project. The goal is to select a project that has a perfect similarity with the new query project. If there is no perfect similarity, the project with greatest similarity to the new query project is selected.

Adaptation is the next step to improve the accuracy of the estimation. Adaptation can be done via transformation, substitution, or derivational reply. **Transformation methods** modify the influential factors of the project with greater similarity to fit the new query project. They tend to be complex and involved and may require extensive modifications of the influential factors. Transformation methods are generally applied to a wide range of problems because they can make a project more general or more specific. Some examples are the heuristic method and the model-based method. **Substitution methods** replace or modify specific influential factors with greater similarity. They are typically simpler than transformation methods, but more limited in applicability because they focus on specific influential factors. Some substitution methods are parameter adaptation, local search, and memory-based adaptation. **Derivational reply** methods solve problems without using the solutions of the previous project. The adaptation process chosen for this research was transformation using heuristic methods (Figure 3.7).

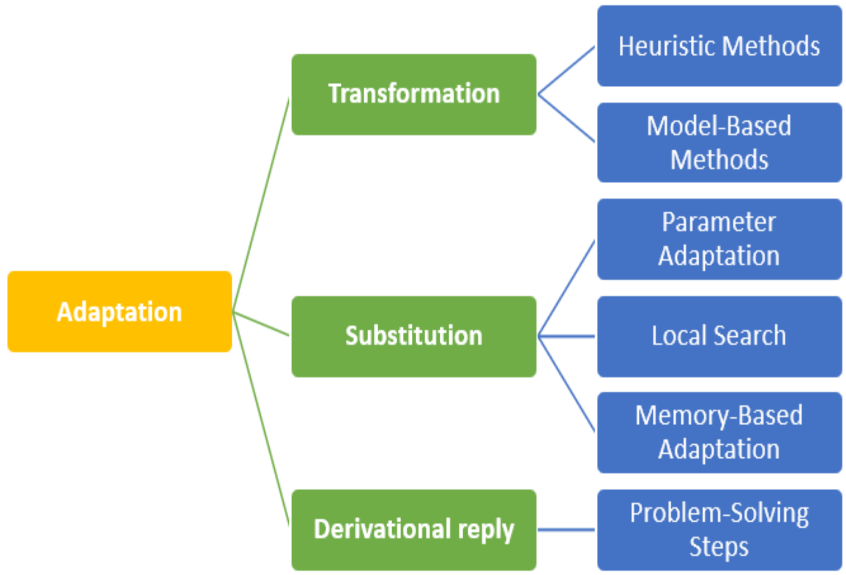

Figure 3.7. Adaptation to improve accuracy of the estimation (adapted from Lopez, 2013)

III. Revise

During the revise stage (see Figure 3.5), solutions obtained in the reuse stage are evaluated in the new query project conditions to determine if they are suitable. If they are not suitable, the reasoning process will return to the retrieve or reuse stage to seek a better solution.

IV. Retain

After revision, the results are "learned" and stored for use in the next estimation (see Figure 3.5), enriching the database.

3.2.2 Estimation Method Selection

This research uses the quantities-based method (quantities × unit cost), due to its multifaceted advantages. For example, the identification and quantification of all the resources needed, such as materials, workforce, and others; the transparency of the estimation by breaking down costs into specific components; the detailing planning and the cost control during the execution of the project, identifying any deviations from the initial estimated quantities.

3.2.3 Item Simplification

All elements and work required for sinking the shaft were grouped by adapting a process for the building industry (Ji et al., 2019; Table 3.1). As the number of elements increase, the level of complexity increases.

Table 3.1. Elements for conventional and mechanical sinking

		Labor	
Foremen	Hoist operators	Food and services	Underground helpers
Miners	Mechanics	Yard workers	Production bonus
Construction workers		Surface crew	Personal protection equipment
		Equipment Operations	
Raise Borer[2]	Winches	Ventilation system	Electricity
Cranes[2]	Air compressor	Parts repair and overhaul	Lubricants
Infrastructure[2]	Installations	Equipment purchase/rental	Drilling and blasting equipment[1]
Surface conditioning	Shotcrete plant	Diesel fuel	
		Drilling and Blasting Supplies[1]	
Explosives	Detonating cord	Drill steel	
Caps	Drill bits		
		Utility Materials	
Water pipe	Electric cable	Skip guides	Temporary hoist ropes
Drainpipe	Ladders	Steel grates	Sinking stage ropes
Compressed air pipe	Conveyors[1]	Hanging bolts	Iron ropes
Ventilation tubing			
		Ground Support Materials	
Cement	Rock bolts	Timber	Sand
Rebar	Mesh	Lagging	Gravel
Structural steel	Chemical additive		
		Electricity	
Energy consumption			

[1]Conventional sinking only
[2]Mechanical sinking only

The unit costs associated with these elements were obtained from the InfoMine Handbook (2021) and Table 3.2 shows the cost ratio associated to each sinking method. No elements estimated by automation (i.e., without quantities) needed to be excluded from the analysis. For this objective, it is necessary to identify the similarities between unit costs. This can decrease the accuracy slightly, but it improves the efficiency of the process. As the number of groups increases, the accuracy increases. The quantities of these group items are the solutions that are estimated using CBR.

Table 3.2. Grouping of conventional and mechanical sinking elements

Group from Table 4	No. elements		Cost ratio (%)	
	Conventional[2]	Mechanical[1]	Conventional	Mechanical
Labor	11	11	55	20
Equipment operations	12	14	23	40
Drilling and blasting	5	0	2	0
Utility materials	13	12	4.5	8
Ground support materials	10	10	8	7
Energy	1	1	7.5	25
Total	**52**	**48**	**100**	**100**

[1] Quantity-based for mechanical
[2] Quantity-based for conventional

3.2.4 Influential Factor Selection

This is an important stage in the construction of the cost model because the quantities of the solutions will change according to the influential factors. Table 3.3 shows the six principal influential factors that the CBR system used for the estimation.

Table 3.3. Influential factors for shaft sinking

Influential factor	Value/Rank	Data structure
Water conditions	1 (dry), 2 (wet), 3 (saturated)	Along axis
Shaft diameter (m)	4.5–7.0	Numerical
Rock mass condition	1 (good), 2 (normal), 3 (poor)	Along axis
Shaft length (m)	500–2,000	Numerical
Operator skill level	1 (expert), 2 (good), 3 (fair), 4 (poor)	Ordinal
Weather	1 (favorable), 2 (normal), 3 (poor)	Ordinal

The water conditions along the axis of the shaft are important to know before shaft sinking, in the event of unfavorable conditions. During recent decades, new technologies have been developed to deal with water issues (e.g., freezing) and to monitor water conditions, though these increase the total cost of the shaft (Farazi, Quamruzzaman & Woobaidullah, 2012). The rock mass condition influences the supports, rate of sinking, and equipment selection and maintenance (e.g., drill bit wear). The parameters used to identify the rock mass rating along the shaft are rock hardness, texture, density, and fracture pattern; the general structure of the formation; and lithology (Singh & Goel, 2011). The three water and rock conditions were compared between two projects (Figures 3.8 and 3.9), then CBR used equation 3.18 to measure the similarity.

$$Sim_{1,2} = \min\left(\frac{length_{1,1}}{length_1}; \frac{length_{1,2}}{length_2}\right) + \min\left(\frac{length_{2,1}}{length_1}; \frac{length_{2,2}}{length_2}\right) + \cdots + \min\left(\frac{length_{n,1}}{length_1}; \frac{length_{n,2}}{length_2}\right) \qquad (3.18)$$

Where $Sim_{1,2}$ is the similarity of the condition between project 1 and project 2; $length_{1,1}$ and $length_{1,2}$ are the lengths of state 1 in project 1 and 2, respectively; $length_1$ and $length_2$ are the lengths of project 1 and 2, respectively; and n = number of possible states.

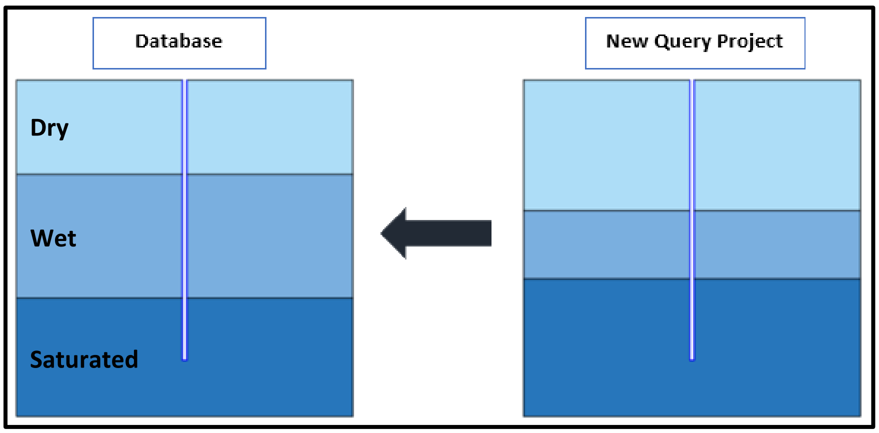

Figure 3.8. Comparison of cases of water conditions

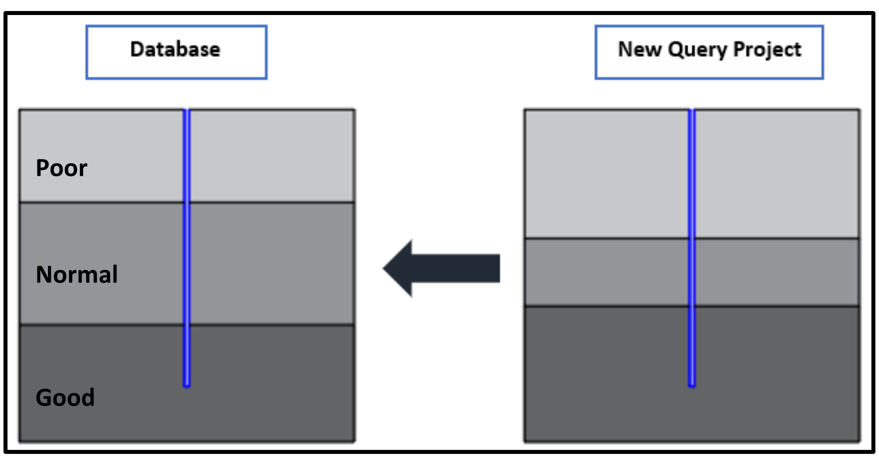

Figure 3.9. Comparison of rock mass conditions

Equation 3.18 measures similarity according to the proportions of the conditions. For example, assume a 500-m project with 250 m each of dry and saturated conditions and a 1000-m project with 500 m each of dry and saturated conditions. The similarity between the two projects from equation 3.18 will be 100% since the proportions of the states are the same.

The two ordinal data types (Table 3.3) affect the rate of advance of shaft sinking: operator skill and weather conditions. Operator skills determine the total time required and the drill bit replacement times. Weather conditions affect the equipment required, especially extreme weather, and the work force requirements.

3.2.4.1 Influential Factor Weighting

The weights of the influential factors reflect their relative power to effect a change. To estimate the weights, the distances between the influential factors and the solution to find the optimal weights were determined using equations 3.19–3.21. Among all the projects in the database, a project was selected as the first *reference project.* Aleatory weights were then assigned to calculate the distance between the reference project and the remaining projects in the database.

$$d_{(P_{ref},p_j)} = \sqrt{\sum_{i=1}^{n} {w_i}^2 * dis(P_{ref(i)}, P_{n(i)})} \tag{3.19}$$

Where $d_{(P_{ref},p_j)}$ is the distance between the reference project and project "j" in the database; w_i is the weight of the influential factor "i"; and $dis\left(P_{ref(i)}, P_{n(i)}\right)$ is the distance in the influential factor "i" between the reference project and the project "j" in the database.

The distance between two projects must be equal to the distance between their solutions. So too should be the sum of the distances between the reference project and the remaining projects in the database and the sum of the distance of the solutions between the reference project and the remaining projects in the database.

$$\sum_{j=1}^{m} d_{(s_{ref},s_j)} = \sum_{j=1}^{m} d_{(P_{ref},p_j)} \tag{3.20}$$

Where $d_{(s_{ref},s_j)}$ is the distance between the solution of the reference project and the project "j" in the database and m = the number of projects in the database. Different CBR system have used this equation to optimize the weights through the generalized reduced gradient nonlinear solving method, a method that Lasdon, Waren, Jain, and Ratner (1978) proved to be “robust and efficient” in the optimization of non-linear programming problems.

This system repeats the process, using all the projects in the database as reference projects, creating different optimized weights according to the reference project used. Finally, the average of all weights is calculated to obtain the final weight for the influential factor.

$$w_{1,(final)} = \frac{\sum_{i=1}^{n} w_{1,i}}{n} \tag{3.21}$$

Where $w_{1,(final)}$ is the final weight of influential factor 1; $w_{1,i}$ is the weight of influential factor 1 estimated in the “i” process; and *n* is the number of estimations made, considering all the projects in the database as a reference project.

In the same way that influential factor 1 was calculated, all the influential factors are calculated. All processes were repeated for every solution.

3.2.5 Modified Parameter Making

A critical part of the CBR model is adaptation because a new query project cannot have perfect similarity with a project in the database. The CBR process uses adaptation to increase the accuracy. Table 3.4 shows an example when a project in the database has all but one of the influential factors (shaft length) in common with the new query project. This CBR system will use a process to adapt this influential factor to the conditions of the new query project.

Table 3.4. Modified parameters for case study

Influential factor	New query project	Database
Water conditions	Conditions along the axis	✓
Shaft diameter (m)	4.5	✓
Rock mass condition	Conditions along the axis	✓
Shaft length (m)	800	✗
Operator skills	2	✓
Weather	2	✓

Ji et al. (2019) proposed an approach to transform a project in the database as follows:

1. Select the projects in the database with the greater similarity without considering the influential factor that will be transformed (Figure 3.10). As the level of similarity increases, the number of projects in the database decreases.

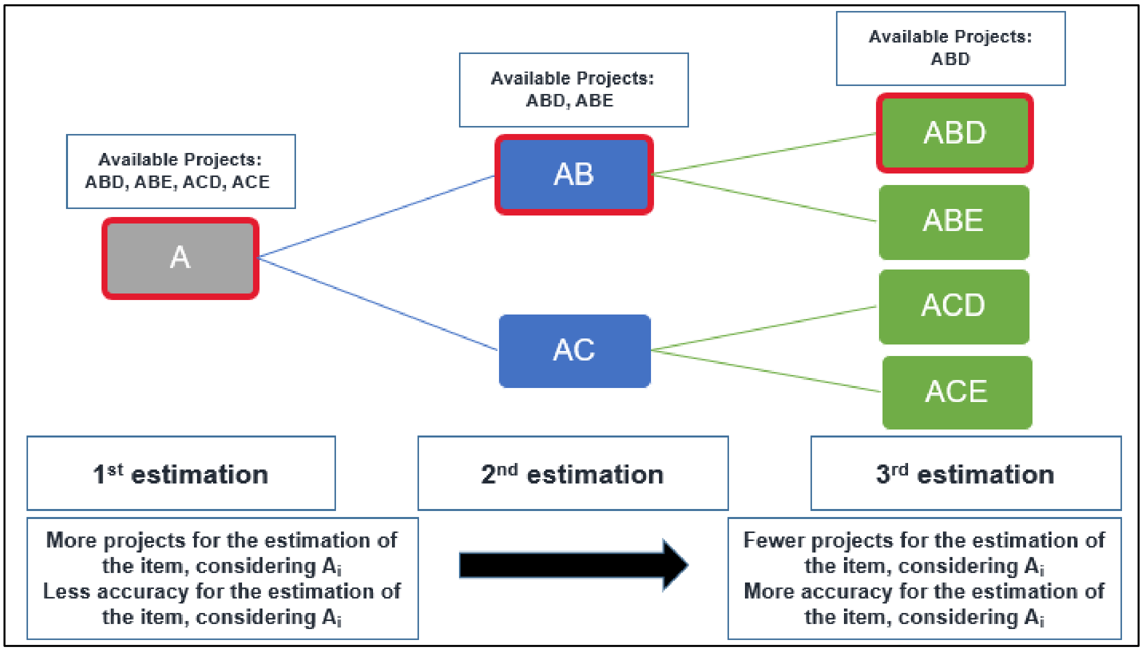

Figure 3.10. Three estimations to adapt the case to the previous cases (adapted from Ji et al., 2019)

2. Using the projects obtained in the step 1, a regression model is applied to estimate the solution with the value of the influential factor that is being transformed to the new query project (Figure 3.11).

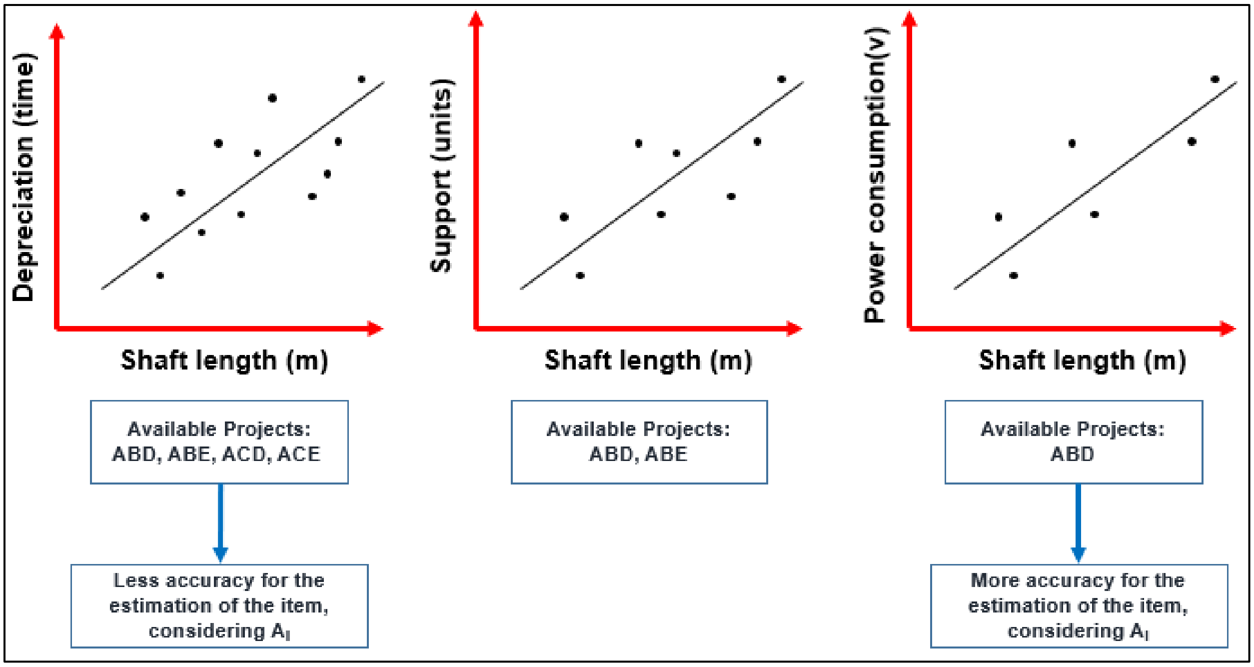

Figure 3.11. Simple regression used to adapt the case using previous information (adapted from Ji et al., 2019)

Two things must be considered when transforming a project in the database.

1. To conduct regression analysis, at least three projects are needed.

2. If more than one influential factor differs between the new query project and the projects in the database:

    - identify and transform the influential factor that has the strongest effect on the difference of the projects; and

    - since no projects have 100% similarity to create the regression, the projects with the higher similarity are used to obtain enough projects to conduct regression analysis. This adjustment will decrease the accuracy, but this will allow the process of transformation of the influential factor selected before.

3.2.6 Database Establishment

The new project is established in the database to be used for a new estimation in future work. In the same way, the CBR system uses all the previous information—influential factors, item quantities, item unit costs, and item cost ratios—for new estimations. Figure 3.12 shows a schematic representation of all the process in the methodology.

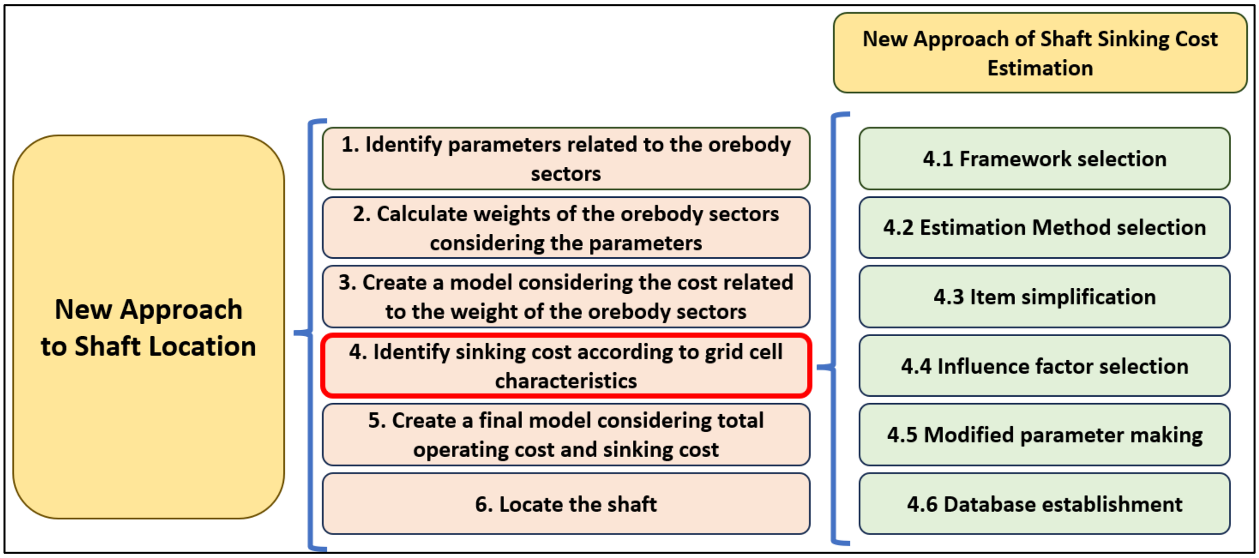

Figure 3.12.- Schematic representation of the methodology

4 Case Study

The case study demonstrates an application of the cost model and the new approach for shaft location using synthetic information. The objective is to identify the location of the shaft for a project, considering a database of investment in previous shaft projects. The steps for the case study are as follows.

4.1 Identify the zones according to the underground conditions

The first step involves an assessment of the underground conditions, among the influential factors identified, two key influential factors could vary within a new query project, the water conditions, and the rock mass condition. Therefore, the division of the surface area into different zones depends on the conditions presented by these two influential factors. In the present case study, four different zones were identified on this criterion. Figure 4.1 shows the division of these four zones in the surface area.

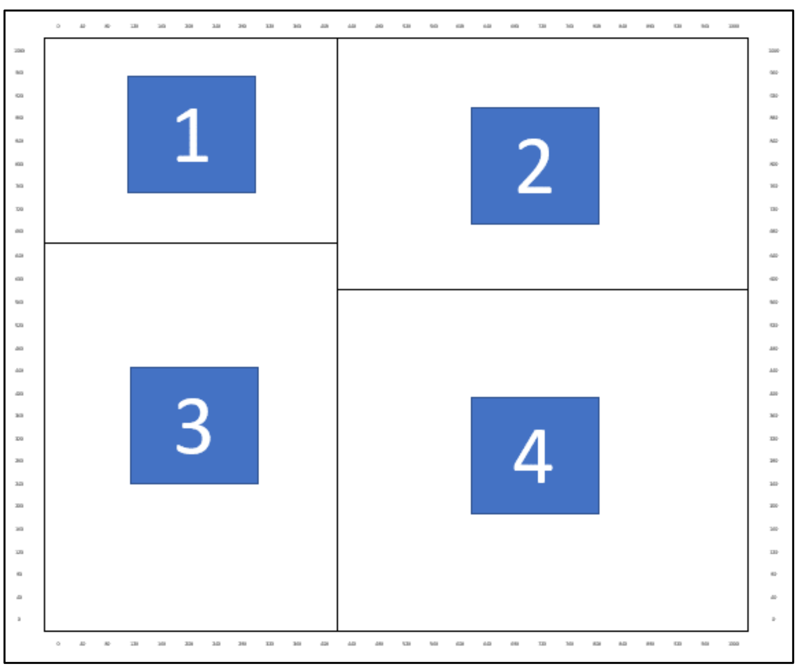

Figure 4.1. Distribution of zones in the case study (plan view)

4.2 Identify parameters to weight orebody sectors and sinking costs

The information for the sinking costs is listed below and presented in Table 4.1. All currency is in US$.

1. Labor: $20/h
2. Equipment operation: $58/h
3. Blasting: $3.11/kg of explosive
4. Blasting supplies: $3.21/unit
5. Drilling supplies: $60/unit
6. Pipes: $50/m
7. Cables: $166.05/m
8. Hoist ropes: $39/m
9. Rock-bolts: $12/bolt
10. Shotcrete: $200/m^3
11. Energy: $0.119/KWh

Three principal orebody sectors were considered for this case study, Table 4.1 shows specific characteristics for each of them used to calculate the weight of the orebody sector, tonnage, location, the cost of excavation from shaft to an orebody sector and movement cost per tonne from an orebody sector to the shaft, last two are going to be the same since the methods used for excavation and movement were same.

Table 4.1. Information used for the case study

Orebody sector	A	B	C
Tonnage (tonnes)	5,000,000	4,500,000	1,800,000
Location (x,y)	(900, 300)	(200, 500)	(700, 800)
Cost of excavation ($/m)	1,800	1,800	1,800
Movement cost per tonne ($/tonne×m)	0.00029	0.00029	0.00029

4.3 Calculate weights of the orebodies sectors

For orebody sectors A, B, and C, the weights were 3,250, 3,105, and 2,322, respectively, based on the formula (3.1) and the numbers in Table 4.1.

Weight_A = 5,000,000*0.00029 + 1,800 = 3,250

Weight_B = 4,500,000*0.00029 + 1,800 = 3,105

Weight_C = 1,800,000*0.00029 + 1,800 = 2,322

4.4 Create model considering costs related to orebody weight

Equation 3.2 was applied to obtain the operating costs in a grid cell (i.e., the discretized area of the mine). Considering only the total operating cost, the optimal location for the new shaft is at x = 640 and y = 520 (Figure 4.2).

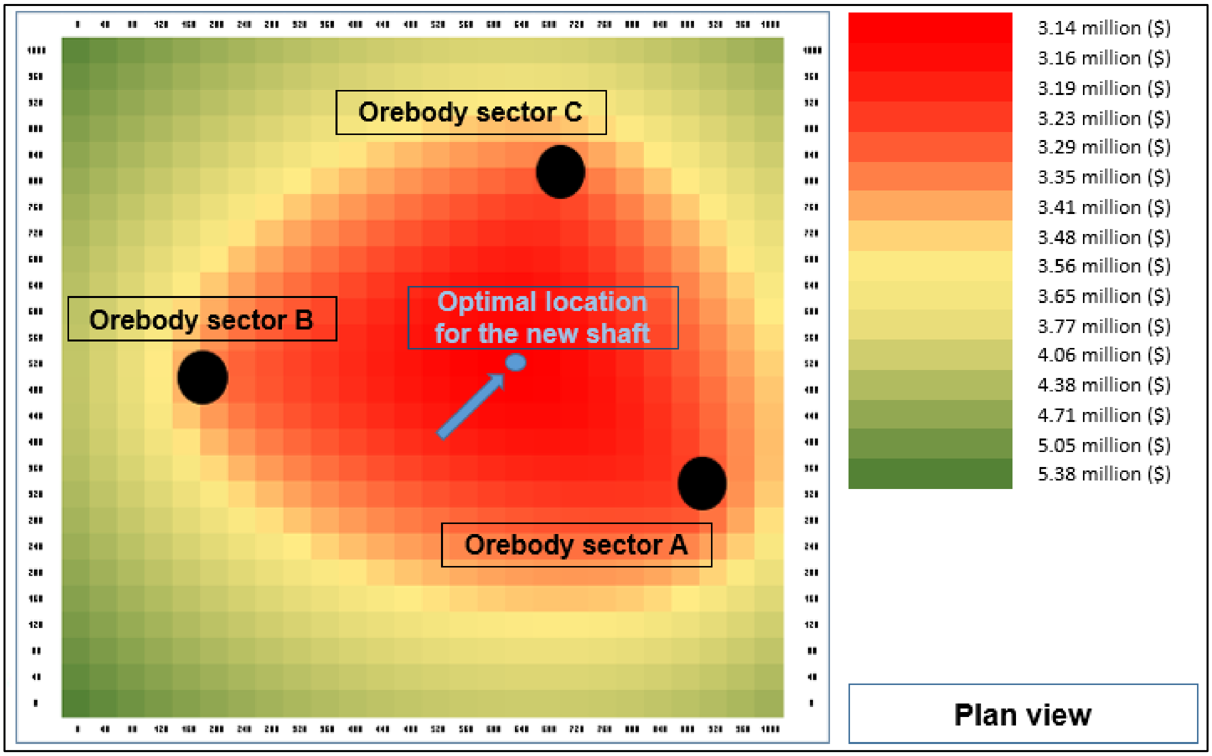

Figure 4.2. Total operating costs for a new shaft in US$

4.5 Identify sinking cost according to grid cell characteristics

The first investment required will belong to zone 1 from Figure 4.1, which was named New Query Project 1 (Table 4.2). The water and rock mass conditions along the axis for this zone are shown in Figure 4.3.

Table 4.2. Influential factors of zone 1 of the case study (New Query Project 1)

Water conditions	Shaft diameter (m)	Rock mass rating	Shaft length (m)	Operator skill	Weather
Along the axis	5.0	Along the axis	650	3 (fair)	2 (normal)

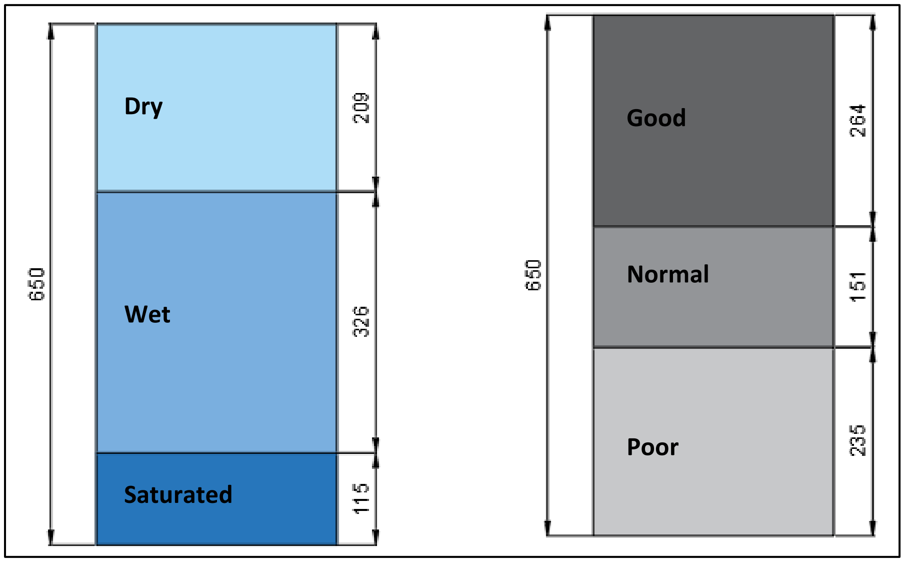

Figure 4.3. Water and rock mass conditions the zone 1 of the case study (New Query Project 1)

The database for the case study is presented in Table 4.3. See Figures 4.4 and 4.5 for the water and rock mass conditions in the database, respectively.

Table 4.3. Influential factors in the database of the case study

Database	Shaft diameter (m)	Shaft length (m)	Operator skill	Weather
P1	5.0	400	1 (expert)	2 (normal)
P2	4.5	600	3 (fair)	3 (poor)
P3	6.0	600	2 (good)	1 (favorable)
P4	5.0	600	3	2
P5	8.5	600	1	1
P6	8.5	650	4 (poor)	2
P7	8.5	700	3	2
P8	5.0	750	3	2
P9	6.5	800	4	2
P10	6.0	800	3	3
P11	7.0	800	4	2
P12	6.5	800	3	2
P13	7.5	850	3	2
P14	7.0	900	3	2
P15	6.5	1,000	4	2

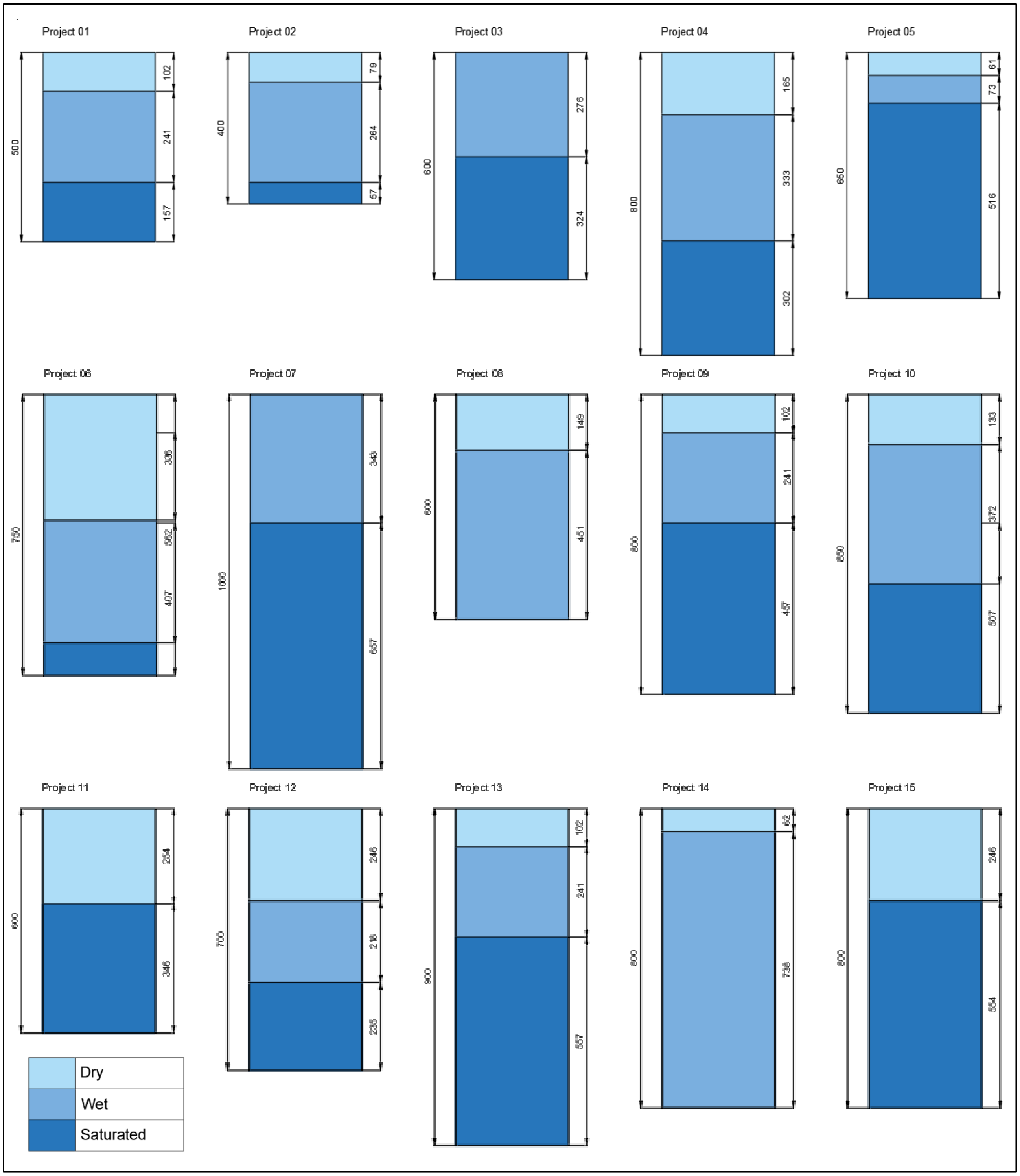

Figure 4.4. Water conditions in the database of the case study

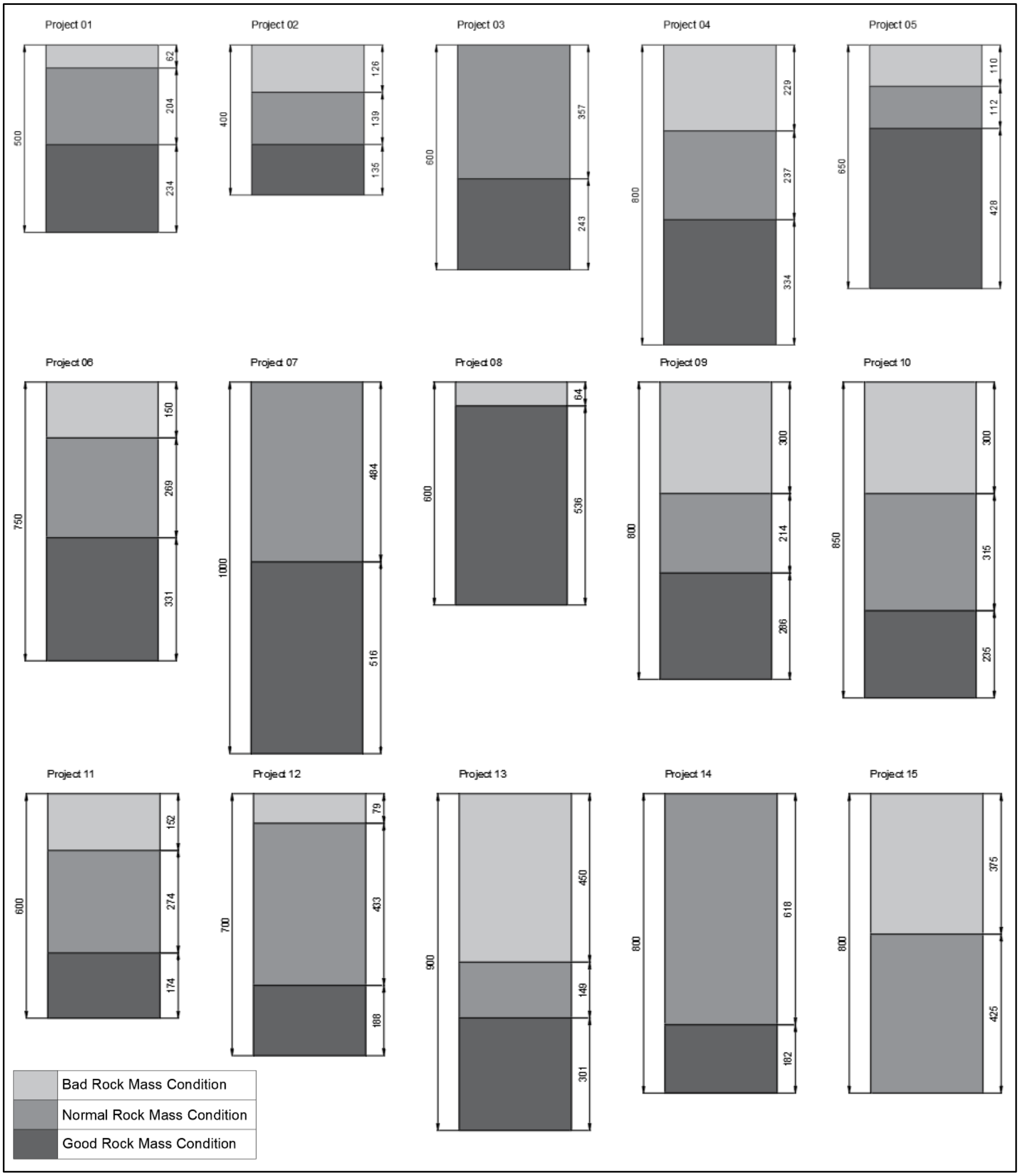

Figure 4.5. Rock mass conditions in the database of the case study

The solutions presented in Table 4.4 represent more accurate information for the estimation than the groups presented in Table 3.1, Chapter 3.

Table 4.4. Solutions of the database in the case study

Database	Labor (h)	Equipment operations (h)	Blasting (kg)	Blasting supplies (units)	Drilling supplies (units)	Utility materials (m)	Ground support materials (units)	Ground support materials (m^3)	Energy (MWh)
P1	180,000	9,300	40,792	13,357	750	894	11,486	736	9,800
P2	266,803	13,762	60,361	19,765	1,110	1,341	16,996	1,089	14,526
P3	276,105	14,289	62,673	20,522	1,152	1,341	17,647	1,131	15,032
P4	267,914	13,842	60,715	19,881	1,116	1,341	17,095	1,095	14,586
P5	294,812	15,255	66,912	21,911	1,230	1,341	18,840	1,207	16,051
P6	317,987	16,429	72,062	23,597	1,325	1,452	20,291	1,300	17,313
P7	340,859	17,611	77,246	25,294	1,420	1,564	21,750	1,393	18,558
P8	337,642	17,445	76,517	25,055	1,407	1,676	21,545	1,380	18,383
P9	372,263	19,234	84,362	27,625	1,551	1,788	23,754	1,522	20,268
P10	369,292	19,057	83,587	27,371	1,537	1,788	23,536	1,508	20,106
P11	375,321	19,392	85,055	27,851	1,564	1,788	23,949	1,534	20,434
P12	374,276	19,338	84,818	27,774	1,559	1,788	23,882	1,530	20,377
P13	402,274	20,784	91,163	29,852	1,676	1,899	25,669	1,645	21,902
P14	421,690	21,787	95,564	31,292	1,757	2,011	26,908	1,724	22,959
P15	460,952	23,816	104,461	34,206	1,921	2,234	29,413	1,884	25,096

The next step is to define the weights that correspond to the solution, “labor”. Therefore, the procedure outlined in Chapter 3 was applied, with the final weights shown in Table 4.5.

Table 4.5. Calculations of the weights for the solution “labor” of the case study

Reference case	Water conditions	Shaft diameter	Rock mass conditions	Shaft length	Operator skill	Weather	Squared sum
1	0.000	0.286	0.000	0.946	0.152	0.000	1.000
2	0.000	0.163	0.000	0.987	0.000	0.000	1.000
3	0.000	0.107	0.000	0.994	0.000	0.000	1.000
4	0.000	0.181	0.000	0.984	0.000	0.000	1.000
5	0.000	0.107	0.000	0.994	0.000	0.000	1.000
6	0.000	0.163	0.000	0.987	0.000	0.000	1.000
7	0.000	0.207	0.000	0.978	0.000	0.000	1.000
8	0.096	0.000	0.136	0.986	0.000	0.016	1.000
9	0.039	0.000	0.000	0.999	0.000	0.000	1.000
10	0.041	0.000	0.000	0.999	0.000	0.000	1.000
11	0.041	0.000	0.000	0.999	0.000	0.000	1.000
12	0.008	0.000	0.000	1.000	0.000	0.000	1.000
13	0.150	0.000	0.000	0.989	0.000	0.000	1.000
14	0.000	0.379	0.000	0.925	0.000	0.000	1.000
15	0.000	0.164	0.000	0.986	0.000	0.000	1.000
Final weight	**0.025**	**0.118**	**0.009**	**0.993**	**0.010**	**0.001**	**1.000**

The same procedure is replicated for all cases. With the weights found, the similarity between the new query project and the projects in the database was calculated, the following the procedures of Chapter 3 (Table 4.6). Project 4 was most similar.

Table 4.6. Similarity between the new query project and the database in the case study

Project	Water conditions	Shaft diameter	Rock mass conditions	Shaft length	Operator skill	Weather	Distance project	Similarity
1	0.000	0.000	0.000	0.171	0.000	0.000	0.414	0.707
2	0.000	0.000	0.000	0.007	0.000	0.000	0.084	0.922
3	0.000	0.001	0.000	0.007	0.000	0.000	0.090	0.918
4	0.000	0.000	0.000	0.007	0.000	0.000	0.083	0.923
5	0.000	0.011	0.000	0.007	0.000	0.000	0.133	0.883
6	0.000	0.011	0.000	0.000	0.000	0.000	0.106	0.904
7	0.000	0.011	0.000	0.007	0.000	0.000	0.132	0.883
8	0.000	0.000	0.000	0.027	0.000	0.000	0.166	0.858
9	0.000	0.002	0.000	0.062	0.000	0.000	0.252	0.799
10	0.000	0.001	0.000	0.062	0.000	0.000	0.250	0.800
11	0.000	0.003	0.000	0.062	0.000	0.000	0.255	0.797
12	0.000	0.002	0.000	0.062	0.000	0.000	0.252	0.798
13	0.000	0.005	0.000	0.109	0.000	0.000	0.339	0.747
14	0.000	0.003	0.000	0.171	0.000	0.000	0.418	0.705
15	0.000	0.002	0.000	0.335	0.000	0.000	0.581	0.632

The next step is to increase the accuracy of the results. The influential factor representing the most distance in the similar project, shaft length, was transformed. Ignoring shaft length, projects 1 and 8 were most similar to the new query project 1 (Table 4.7).

Table 4.7. Similarity between the new query project 1 and the database in the case study if shaft length is ignored

Project	Water conditions	Shaft diameter	Rock mass conditions	Operator Skills	Weather	Distance project	Similarity
1	0.000	0.000	0.000	0.000	0.000	0.004	0.996
2	0.000	0.000	0.000	0.000	0.000	0.017	0.984
3	0.000	0.001	0.000	0.000	0.000	0.034	0.967
4	0.000	0.000	0.000	0.000	0.000	0.007	0.993
5	0.000	0.011	0.000	0.000	0.000	0.104	0.906
6	0.000	0.011	0.000	0.000	0.000	0.106	0.904
7	0.000	0.011	0.000	0.000	0.000	0.103	0.906
8	0.000	0.000	0.000	0.000	0.000	0.006	0.994
9	0.000	0.002	0.000	0.000	0.000	0.046	0.956
10	0.000	0.001	0.000	0.000	0.000	0.033	0.968
11	0.000	0.003	0.000	0.000	0.000	0.059	0.944
12	0.000	0.002	0.000	0.000	0.000	0.046	0.956
13	0.000	0.005	0.000	0.000	0.000	0.075	0.931
14	0.000	0.003	0.000	0.000	0.000	0.061	0.942
15	0.000	0.002	0.000	0.000	0.000	0.049	0.953

Figure 4.6 shows the transformation process to estimate the new value for the "Labor (h)" for the new query project. The solution for "Labor (h)" after transformation is presented in Table 4.8.

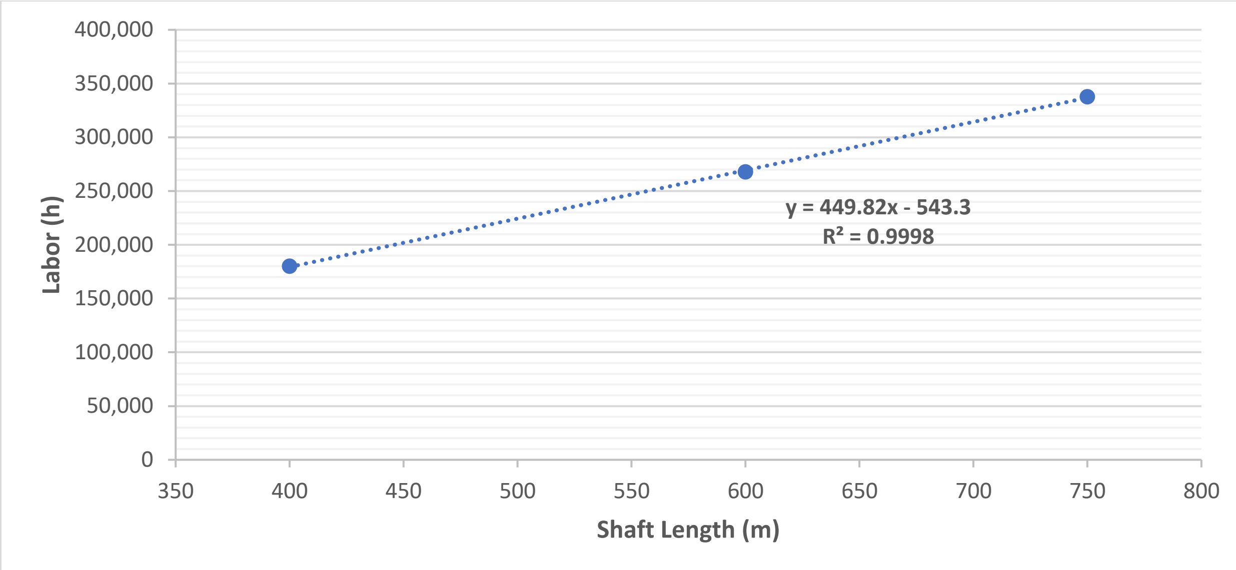

Figure 4.6. Transformation of the solution "labor" for new query project 1 in the case study

Table 4.8. Solution of "labor" after transformation for new query project 1

	Water conditions	Shaft diameter (m)	Rock mass conditions	Shaft length (m)	Operator skill	Weather	Labor (h)
New query project 1	Along the axis	5.0	Along the axis	650	3 (fair)	2 (normal)	291,840

The same procedure was implemented for all solutions. Not all influential factors affected the solutions (Table 4.9).

Table 4.9. Impact of the influential factors on the solutions

Solution	Water conditions	Shaft diameter	Rock mass conditions	Shaft length	Operator skill	Weather
Labor (h)	✓	✓	✓	✓	✓	✓
Equipment operations (h)	✓	✓	✓	✓	✓	×
Blasting (kg)	✓	✓	✓	✓	✓	×
Blasting supplies (units)	✓	✓	✓	✓	✓	×
Drilling supplies (units)	✓	✓	✓	✓	✓	×
Utility materials (m)	×	×	×	✓	×	×
Ground support materials (units)	✓	✓	✓	✓	✓	×
Ground support materials (m^3)	✓	✓	✓	✓	✓	×
Energy (MWh)	✓	✓	✓	✓	✓	✓

With this information, the solutions were obtained using transformation (Table 4.10).

Table 4.10. Solutions for zone 1 after transformation for new query project 1

	Labor (h)	Equipment operations (h)	Blasting (kg)	Blasting supplies (units)	Drilling supplies (units)	Utility materials (m)	Ground support materials (units)	Ground support materials (m3)	Energy (MWh)
New Query Project 1	291,840	15,118	66,309	21,713	1,219	894	18,671	1,196	15,931

The entire procedure was repeated for the four zones in which the project was divided (figure 4.1). Table 4.11 shows the influential factors of the remaining zones that, in most of the projects, will be same. Nevertheless, if they change for any reason, the system can estimate the solution.

Table 4.11. Influential factors for the remaining zones

	Water conditions	Shaft diameter (m)	Rock mass conditions	Shaft length (m)	Operator skill	Weather
New Query Project 2	Along the axis	5.0	Along the axis	650	3 (fair)	2 (normal)
New Query Project 3	Along the axis	5.0	Along the axis	650	3 (fair)	2 (normal)
New Query Project 4	Along the axis	5.0	Along the axis	650	3 (fair)	2 (normal)

The information regarding to the water and rock mass conditions for zones 2, 3, and 4 are presented in Figures 4.7, 4.8, and 4.9, respectively.

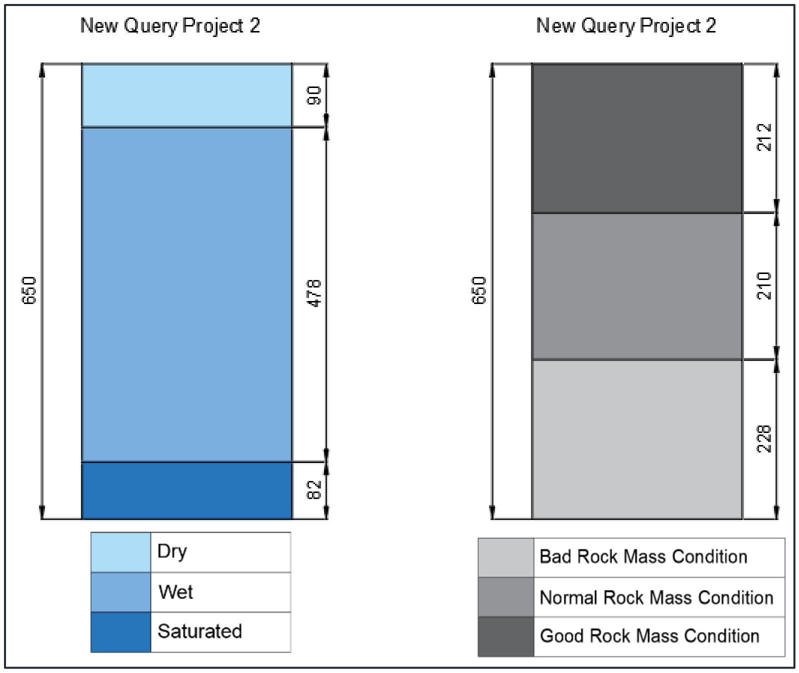

Figure 4.7. Water and rock mass conditions for zone 2 (new query project 2)

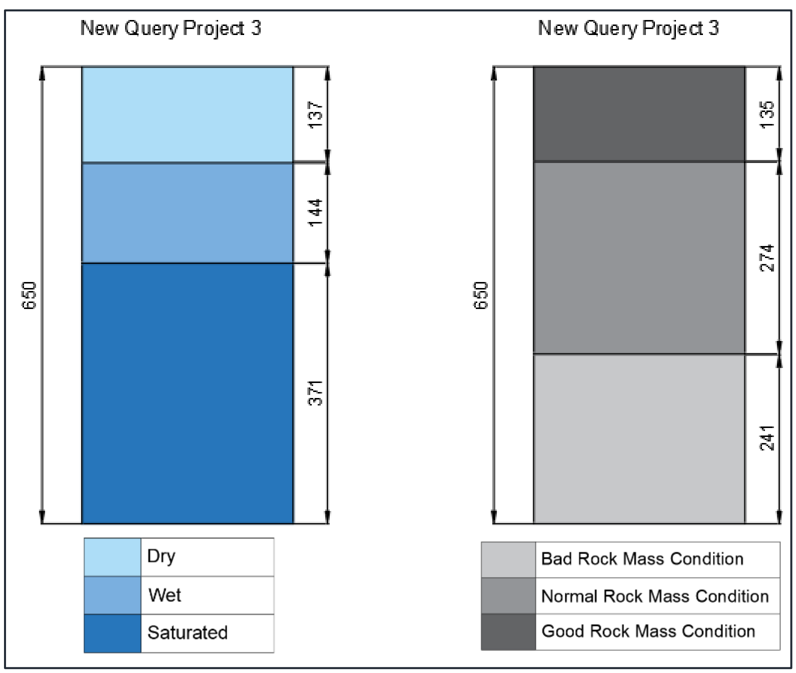

Figure 4.8. Water and rock mass conditions for zone 3 (new query project 3)

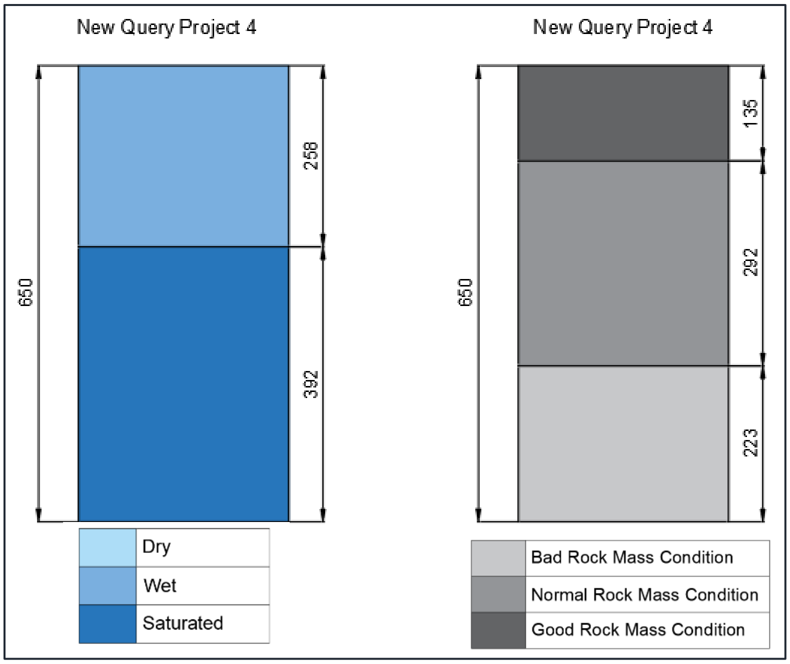

Figure 4.9. Water and rock mass conditions for zone 4 (new query project 4)

With this information of the remaining zones, the solutions are found for each of these zones applying the same process used for the zone 1. The results after transformation process are given in Table 4.12.

Table 4.12. Solutions after transformation in the zones 2–4 in the case study

New query project	Labor (h)	Equipment operations (h)	Blastin g (kg)	Blasting supplies (units)	Drilling supplies (units)	Utility materials (m)	Ground support materials (units)	Ground support materials (m^3)	Energy (MWh)
2	288,504	14,877	65,253	21,367	1,200	894	18,373	1,177	15,707
3	291,157	15,043	65,982	21,606	1,213	894	18,578	1,190	15,852
4	289,892	14,978	65,695	21,512	1,208	894	18,498	1,185	15,783

The investments required for the zones 1, 2, 3, and 4 are $9,664,899, $9,529,486, $9,618,294, and $9,577,515, respectively. These investments were obtained using the unit costs presented in the initial part of the case study and the solution of the Table 4.12 and the Table 4.10.

4.6 Create final model considering total operating cost and the investment

Equation (3.3) was used to generate the final model. The location for the shaft is the grid cell with the lowest final cost: x = 640 and y = 600 (Figure 4.10).

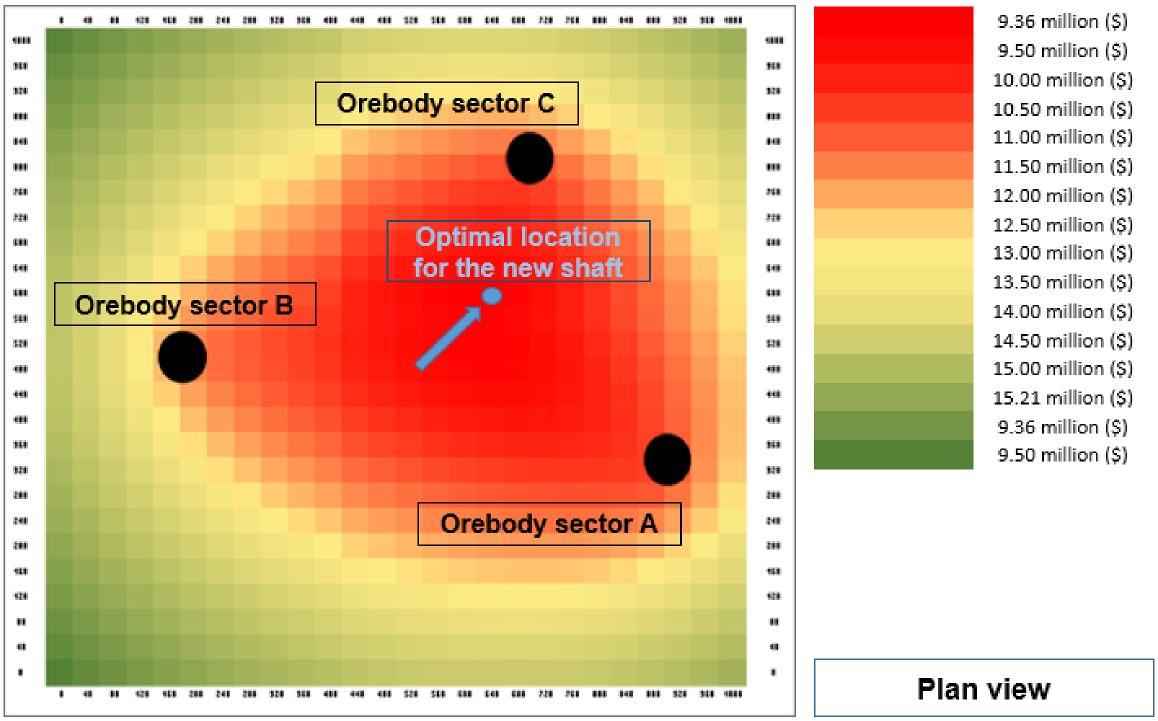

Figure 4.10. Final model, considering the global cost

4.7 Comparison between CBR and multiple regression

The last stage is to compare the CBR model and the multiple regression method in the estimation of the quantities required. The first difference is the way the data are managed. While in the CBR model the data maintains their own characteristics, in the multiple regression method the rock mass condition and water conditions are converted to a numerical parameter.

$$Water\ or\ Rock\ Mass\ Condition = \frac{1 \times Length_1 + 2 \times Length_2 + 3 \times Length_3}{Total\ Length} \qquad (4.1)$$

Where $Length_1$, $Length_2$, and $Length_3$ are lengths of states 1, 2, and 3 in the shaft, respectively; and *Total Length* is the total length of the shaft.

It is also important to check for multicollinearity for the multiple regression method using the row-wise method. Table 4.13 shows the results of the correlation between the influence factors and the solutions of Labor. Figure 4.11 shows the shaded ellipses for the correlations showed in the Table 4.13. A similar analysis is conducted for the remaining solutions and their corresponding influencing factors. It's important to note that all these factors need to be transformed into numerical parameters for the analysis.

Table 4.13. Correlations between the influential factors and the result for "Labor"

	Water conditions	**Shaft diameter**	**Rock mass conditions**	**Shaft length**	**Operator skill**	**Weather**	**Labor**
Water conditions	**1.0000**	0.3726	-0.1308	0.3927	0.2158	-0.0588	0.4103
Shaft diameter	0.3726	**1.0000**	-0.2076	0.2538	0.1137	-0.4022	0.3818
Rock mass condition	-0.1308	-0.2076	**1.0000**	-0.2131	0.2413	-0.0556	-0.2280
Shaft length	0.3927	0.2538	-0.2131	**1.0000**	0.6758	0.1770	0.9150
Operator skill	0.2158	0.1137	0.2413	0.6758	**1.0000**	0.4171	0.5525
Weather	-0.0588	-0.4022	-0.0556	0.1770	0.4171	**1.0000**	0.0231
Labor	0.4103	0.3818	-0.2280	0.9150	0.5525	0.0231	**1.0000**

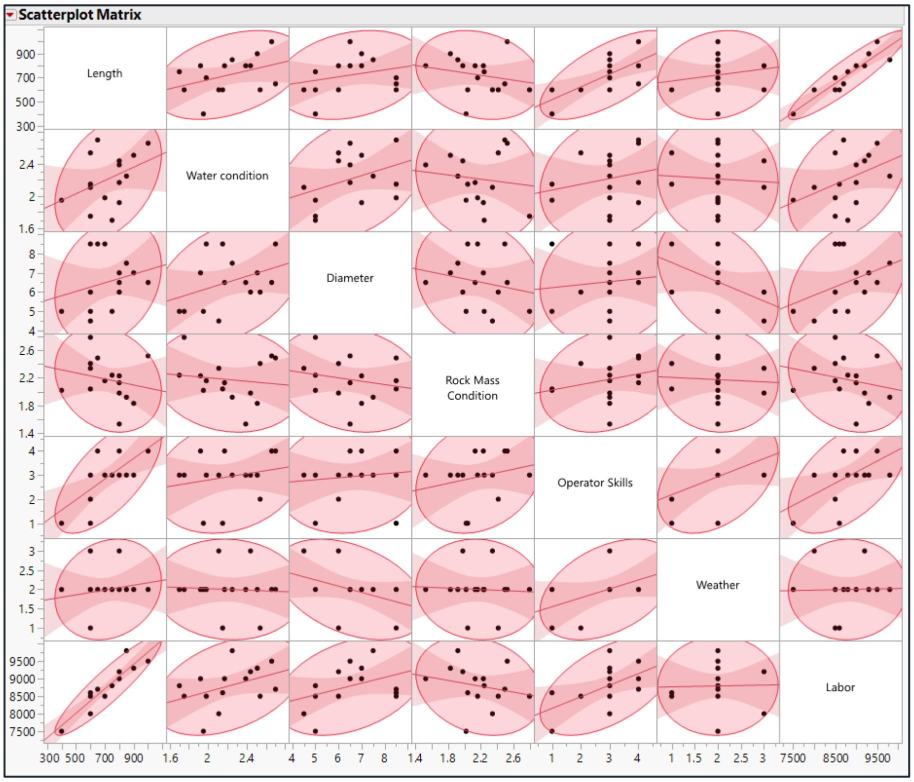

Figure 4.11. Shaded ellipses for correlations between the influential factors and the solution "Labor"

With this information in the database, the coefficients were estimated (Table 4.14). The same process was applied to all the solutions required to estimate the investment cost (Table 4.15).

Table 4.14. Multiple regression analysis results for "Labor" in new query project 1

	Length	Water conditions	Shaft diameter	Rock mass conditions	Operator skills	Weather	Labor
New Query Project 1	650	1.86	5.0	1.96	2	2	293,320

Table 4.15. Results of all solutions applying multiple regression analysis to new query project 1

Labor (h)	Equipment operations (h)	Blasting (kg)	Blasting supplies (units)	Drilling supplies (units)	Utility materials (m)	Ground support materials (units)	Ground support materials (m^3)	Energy (MWh)
293,320	15,155	66,472	21,766	1,222	1,452	18,717	1,199	15,970

Then the process was applied to zones 2–4 in the mine (Table 4.16).

Table 4.16. Multiple regression analysis results for zones 2–4

	Labor (h)	Equipment Operation (h)	Blasting (Kg)	Blasting supplies (units)	Drilling Supplies (units)	Utility Materials: pipes, cables, hoses (m)	Ground Support Materials (units)	Ground Support Materials (m3)	Energy (MWh)
New Query Project 2	290,907	15,030	65,925	21,587	1,212	1,452	18,563	1,189	15,838
New Query Project 3	294,702	15,226	66,786	21,869	1,228	1,452	18,805	1,205	16,045
New Query Project 4	289,995	14,983	65,719	21,520	1,208	1,452	18,504	1,186	15,789

The results of the solutions were utilized to obtain the investment of the shaft sinking in each zone. Table 4.17 shows the investment for the four zones, next to the result obtained using CBR process. After conducting a comparison between these two models, it was observed that, on average, there is a difference of 2.00% in the investment of the shaft sinking.

Table 4.17. Investment for the four zones calculated from case-based reasoning (CBR) and multiple regression analysis

	Investment (US$)		
Zone	**CBR model**	**Multiple regression**	**Difference (%)**
1	9,664,899	9,830,536	1.68
2	9,529,486	9,752,705	2.29
3	9,618,294	9,875,116	2.60
4	9,577,515	9,723,299	1.50

The 2.00% advantage observed in favor of the CBR model underscores an enhancement in the cost estimation process. Although this percentage might not appear substantial within the present case study, it's important to recognize its potential to grow under varying conditions and project scopes. Another significant benefit lies in the adept handling of data by the CBR model, considering the own conditions and nature of them. This aspect holds particular significance in the mining industry.

5 Uncertainty Analysis for Shaft Localization

The previous chapters described and demonstrated a new approach to select shaft location; however, they did not consider the uncertainty associated with the parameters. The estimated mineral content of the orebody creates uncertainty in one of these parameters: production from the orebody sectors (Dominy, Noppé, & Annels, 2002). Figure 5.1 shows an example of how drillholes obtain information about the orebody sectors.

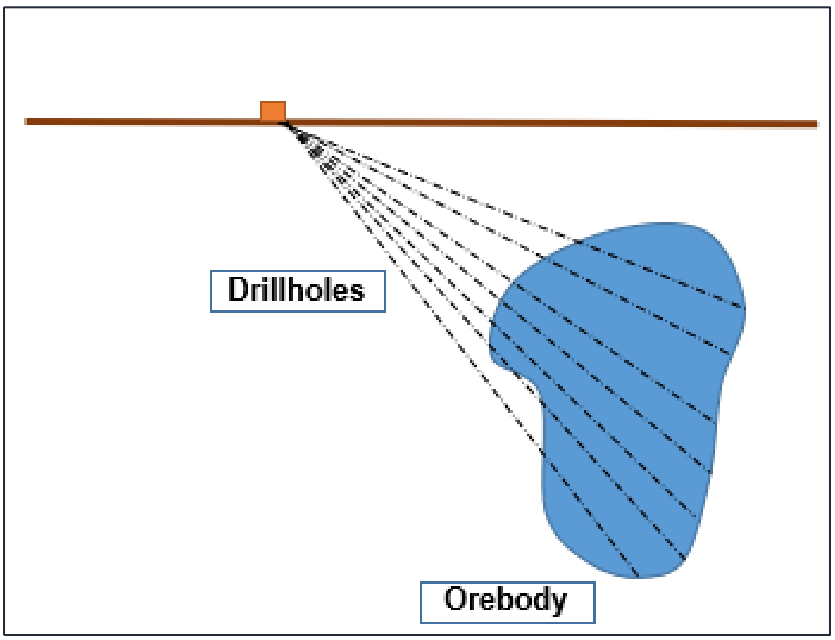

Figure 5.1. Example of the drillholes in an orebody that generate uncertainty in the estimation

Drillhole data make it possible to determine the probability density function (PDF) of the production from the orebody sector. Probabilities can follow normal, lognormal, or other distributions. When one of the parameters is a PDF, a joint probability distribution is applied to select the shaft location. The joint probability distribution is a statistical process that represents the probability of occurrence of two variables in the same space (Feller, 1957). It measure the probability of grid cell (x,y) being the best option, considering coordinates (x,y) as the two variables in the same space.

$$f_{XY}(x, y) = P(X = x, Y = y) \tag{5.1}$$

Where $f_{XY}(x,y)$ is the probability that the best position of the shaft is at coordinates (x,y), X represents the variable of the coordinate "x" in space, and Y represents the variable of the coordinate "y" in space.

Monte-Carlo simulations were used to generate random samples for the production of the orebody sectors on a Pert distribution fitted to production rates. Then the new approach described in Chapter 3 was applied to every simulation.

5.1 Case Study

The parameters used in the case study in Chapter 4 were used except the production of the orebody sectors was considered a PDF. For structures A, B, and C, the information in Table 4.1 was used. The distributions are shown in Figures 5.2–5.4.

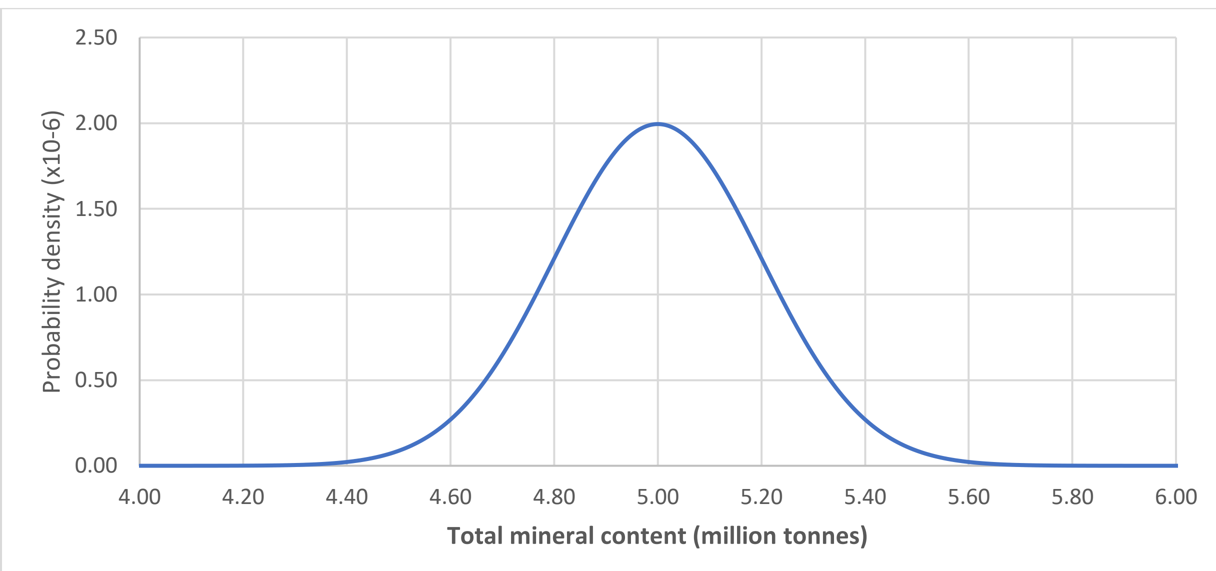

Figure 5.2. Probability distribution of total minerals in orebody sector A

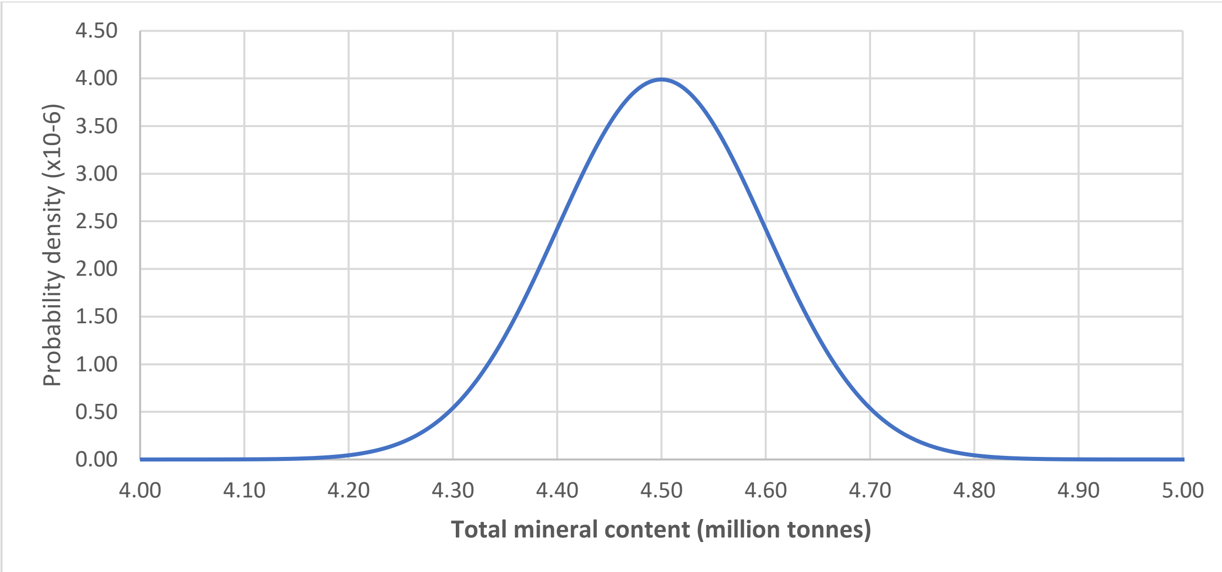

Figure 5.3. Probability distribution of total minerals in orebody sector B

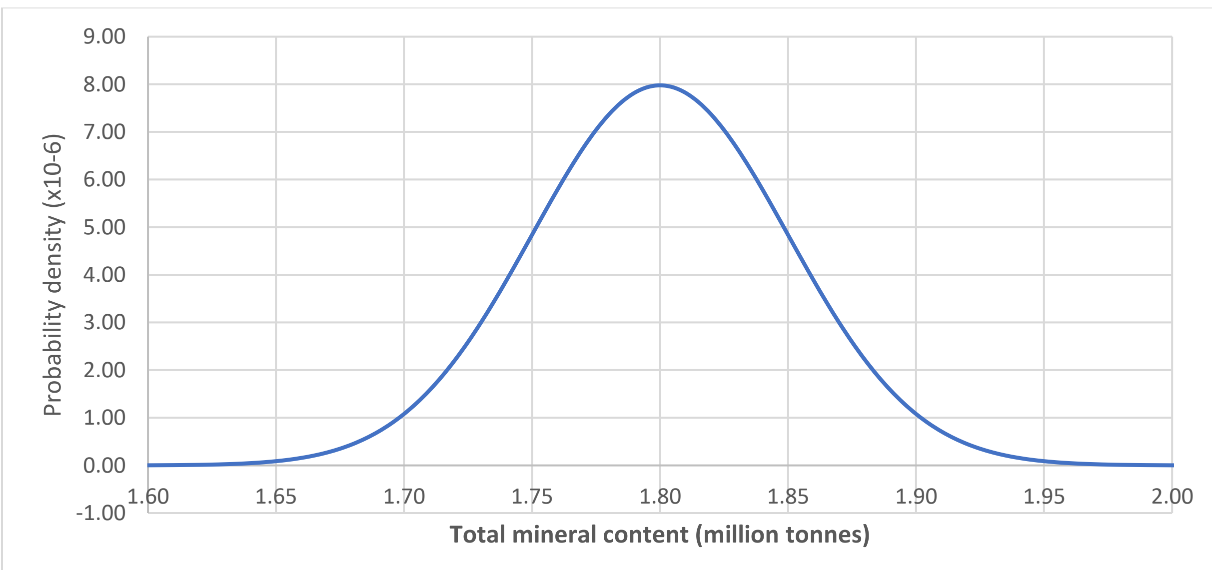

Figure 5.4. Probability distribution of total minerals in orebody sector C

Table 5.1 shows the results of 10,000 simulations of the mineral content of the three orebody sectors. The best shaft locations were then obtained using the new approach.

Table 5.1. Monte-Carlo simulations for mineral production from three orebody sectors and their grid cell coordinates for the best shaft location

	Total mineral content (tonnes)				
Simulation	Structure A	Structure B	Structure C	x	y
1	4,925,109	4,343,671	1,793,543	693	421
2	4,967,417	4,538,295	1,831,792	664	434
3	4,917,627	4,613,904	1,768,229	646	440
4	5,225,227	4,439,959	1,751,572	740	392
5	5,350,204	4,511,151	1,833,103	743	392
6	5,296,550	4,588,010	1,866,554	712	409
7	4,934,266	4,359,853	1,784,321	692	421
8	4,743,482	4,474,114	1,823,594	639	447
9	4,876,048	4,455,442	1,838,911	663	437
10	5,058,722	4,459,327	1,764,301	699	415
11	5,274,055	4,404,375	1,846,449	748	391
12	4,988,398	4,511,146	1,699,962	680	422
13	5,010,176	4,593,679	1,814,298	663	433
14	4,739,747	4,453,117	1,781,448	643	444
15	4,903,508	4,658,109	1,745,619	637	442
16	5,282,371	4,540,294	1,792,230	726	400
17	4,659,726	4,631,115	1,824,369	602	460
18	5,020,989	4,537,807	1,792,357	676	427
19	4,974,344	4,398,003	1,777,343	693	419
20	5,127,939	4,515,506	1,861,638	694	420
…	…	…	…	…	…
10,000	4,871,214	4,517,129	1,815,763	653	440

The optimal location associated with each simulation is presented in Table 5.2, along with their corresponding probabilities based on the frequency of occurrence after the simulation. The results shown that one hundred eighty-seven possible locations for the shaft were obtained.

Table 5.2. Probabilities coordinates for the location of the shaft

N`	X	Y	Probability
1	651	440	0.0077
2	652	439	0.0092
3	653	438	0.0075
4	654	438	0.0082
5	655	438	0.0082
6	656	438	0.0100
7	657	437	0.0114
8	658	437	0.0092
9	659	436	0.0117
…	…	…	…
287	660	436	0.0105

Using the information generated above, the joint probability distribution of the final location of the shaft was created. Figure 5.5 shows the plane in (x,y) coordinates and the probability that the shaft will be in every grid cell, considering the PDF of the production of the orebody sectors. The grid cell with the highest probability to be the best location for the shaft is at x = 680 and y = 530.

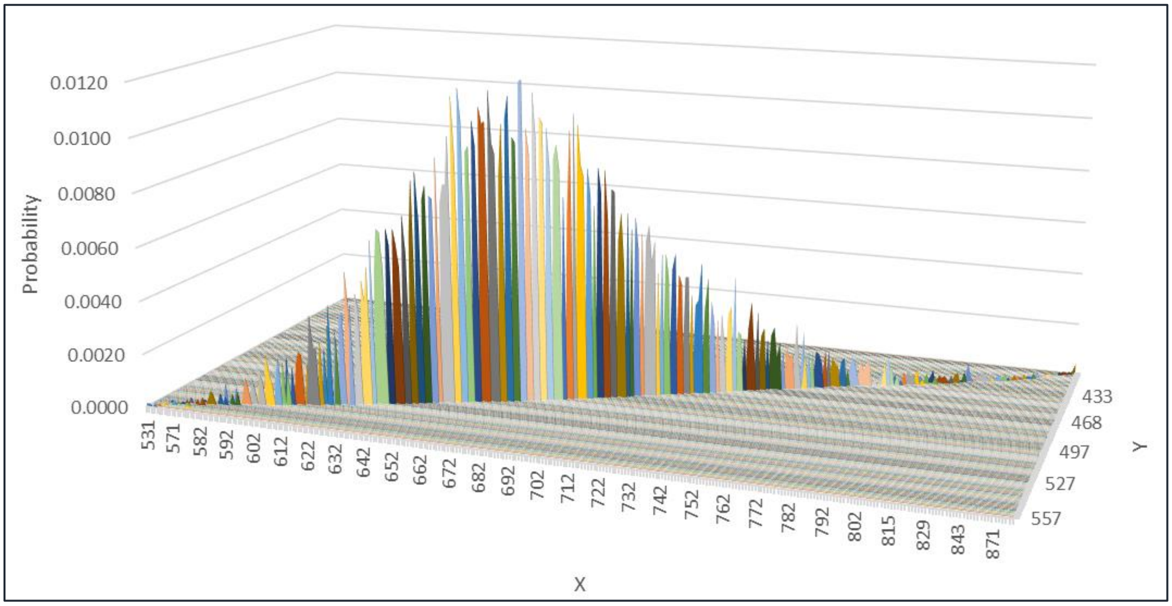

Figure 5.5. Joint probability distribution of the shaft location

6 Conclusions and Future Work

The locations of facilities in the mining industry holds significant importance in economic and design decision-making processes for new mining projects. It significantly affects operating costs. While past research studies generally used the similarities between different projects. Among all facilities, the shaft is one of the most crucial infrastructures in underground mining operations, and determining its optimal location carries substantial implications for project viability. First if all, shaft is the most expensive capital of a mining project. The shaft is an infrastructure that allow the movement of ore and waste from the mine to the surface and the workforce and materials from the surface to the mine, this infrastructure sometimes represents the major access to the mine and stands for all the life of the mine.

Investment requirement as a parameter in the selection of the location selection is often overlooked. The shaft infrastructure represents a substantial and costly investment within underground mining operations. The different conditions encountered in the mine can impact the necessary investment.

The current research presented a new approach to select the shaft location, considering the investment required for sinking the shaft. Most of the models involved the operating cost, nevertheless the present thesis added the initial investment to improve the models. Given that shaft sinking is one of the most expensive investments of an underground mining operation.

A new cost model based on CBR was developed to estimate the cost of shaft sinking. The use of influential factors is a clear advantage of the CBR. They affect the quality of the solution (the cost). Also, they allow the CBR to use a wide range of data, such as the rock mass and water conditions along the shaft axis. In other words, managing the influential factors produces a better way to find the similarity between projects. Another advantage is the possibility of extrapolating the cost for projects that are higher or lower than the range of the database using linear regression.

For cost estimation, another consideration was finding the quantities required for the new project. To avoid problems with inflation or differing prices among countries, the cost is found indirectly, first via the quantities of the principal materials required and then multiplying by the unit cost in the country where the shaft is developed. For different regions, inflation and cost adjustments should be made.

Once the method of the shaft sinking is defined, the surface of the mining zone is divided in grid cells, the operating cost and the cost of shaft sinking is calculated for each grid cell, creating a model for the total cost. The best location for the shaft was the grid cell with the lowest total cost.

This research also assessed the uncertainty in parameters and its impact on shaft location selection. The uncertainty was analyzed for production from the orebody sectors. Production is related to the mineral content of the orebody, which is based on uncertain estimates (e.g., drillhole data). Using a PDF of the orebody sector production, the location of the shaft was defined such that this uncertainty was considered. Monte-Carlo simulations of production from the orebody sectors were made, the new approach was applied, and a group of possible locations were generated. With these results, a joint probability distribution was generated, where the coordinates (x,y) are the two variables in the same space, and the joint probability represents the probability that each grid cell (x,y) is the best position for the shaft. The grid cell with the greatest probability is the best location.

The present research demonstrated that the investment in the shaft sinking and the consideration of the uncertainty in the parameters affect the selection of the shaft location significantly. Table 6.1 shows how the location selection was influenced by these factors in the case study. Furthermore, the research study highlights the suitability of CBR for the cost estimation of shaft sinking. CBR considers the different parameters and the own conditions presented in the mining industry and performs an accurate estimation. To improve the accuracy of the cost estimation the research study incorporates the k-NN algorithm, a machine learning method, to enhance the search of the similar projects, a crucial stage in the process. A comparison was performed between CBR and multiple regression techniques, yielding similar (~2.0%) results in the case study conducted.

Table 6.1. Comparison of the case study results

Best shaft location	Considering operational cost	New approach	With uncertainty analysis
x (m)	640	640	680
y (m)	520	600	530

Although previous research considered the investment required for the location of mining facilities, in the case of the shaft location, this parameter has been omitted. Moreover, considering the uncertainties presented in the selection of facilities locations has not received the appropriate attention. On the other hand, CBR is an estimation process that has gained a good acceptation among the cost assessment, specially in the construction sector. Nevertheless, its potential in the mining industry remains unexplored.

Future research should consider increase the groups of items for cost estimation, the present thesis considers seven principal groups of items according to their unit ratio, a higher number of group items will increase the accuracy of the estimation. A limitation of the present thesis is the number of influence factors that affect the sinking cost of the shaft (two influence factor considered), according to the own conditions of different projects, this number could increase, leading to greater complexity of the process. Regarding the uncertainty analysis, future research studies should consider the impact of the uncertainty through more advanced simulation techniques. Finally, this thesis considered the transformation of one influential factor to increase the accuracy; future research studies should consider the transformation of two or more influential factors to increase the accuracy. Also, quantitative methods and stochastic optimization techniques can be considered.

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