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DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK (ANN) MODEL FOR ESTIMATING CEMENTED PASTE BACKFILL PERFORMANCE

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RÉSUMÉ

L'utilisation de la technologie des remblais miniers en pâte cimenté est devenue une pratique courante dans les opérations minières modernes. Cependant, l'optimisation de la recette est capitale pour satisfaire les contraintes techniques d'exploitation (propriétés mécaniques) et en même temps pour garantir une utilisation économique et sécuritaire de tels matériaux. Par ailleurs, cette optimisation de recette se fait souvent sur la base de batteries de tests expérimentaux en laboratoire qui sont couteux, demandent du temps et quelque fois difficiles à mettre en œuvre. Dans ce travail, les réseaux de neurones artificiels (RNAs) sont testés afin de développer un modèle prédictif pour l'estimation des résistances ciblées. Les RNAs se basent sur des paramètres d'entrée qui sont dans notre cas la granulométrie, le teneur en sulphate dans l'eau de mélange, la recette de liant et le temps de cure. Plus de 600 échantillons on été nécessaire pour mener a bien une batterie de tests laboratoire utilisant la silice broyée comme rejet minier. Ceci dans le but de bien contrôler les principaux paramètres affectant la résistance mécanique. Le travail a permis d'obtenir un modèle global et l'approche développée et testée montre que la corrélation entre les valeurs prédites et celles obtenues est excellente

Mots-clés : Environnement minier, remblai cimenté en pâte, compression uniaxiale, réseaux de neurones artificiels.

ABSTRACT

Paste backfilling becomes a world wide attractive technology used by most modern underground mining industries. However, optimizing the recipe of paste backfill is of utmost importance to reach the technical requirements (the needed mechanical properties) and at the same time it ensures that the safeness and economical purposes are satisfied. Moreover, achieving this optimization on the basis of the only experimental laboratory testing could be expensive, time consuming and in some cases difficult to succeed. In addition, these studies are often affected by subjectivity. In this work, Artificial Neural Networks (ANNs) are tentatively applied for developing predictive models to estimate needed strength values. The ANNs are based on the input parameters of grain size distribution, sulphate content, binder recipe and curing time. In this work, to provide the input data for the neural networks, more than 600 samples were carried out by using silica as artificial tailings. Silica was used in this work to well control the main tailings properties effects on the UCS and to obtain a global model. The approach developed and tested in this study shows that the correlation between the predicated and achieved strength of the paste backfill is excellent.

KEYWORDS: Mining environment, cemented paste backfill, unconfined compressive strength, artificial neural networks.

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Introduction

In the practice of underground mining, cemented backfill has become more important with the development of large scale bulk mining methods. In wet mill tailings, cement and water are mixed and delivered into underground stop opening by pipelines. The cured fill then may support the rock walls when an adjacent pillar is recovered (Potvin et al, 2005). Stability of mine backfill is necessary for maximum ore recovery, for safe working conditions and for underground and environmental concerns. The mechanical and rheological properties of cemented paste backfill depends on physical, chemical, and mineralogical properties of the mine tailings, binder types and their proportions, and chemistry as well as proportion of type mixing water (Benzaazoua et al, 2002).

Generally, backfill stability increases with the binder proportion. Thus, a more stable backfill can be obtained by adding more binder (Hassani et Archibald, 1998). However, due to the fact that backfill cement costs are a significant part of the operating costs in large underground mines, the use of cement should be minimized. A high quality backfill should use minimum binder and be capable of maintaining its stability during the mining process of adjacent pillar recovery (Fall et al, 2007). In many practical cases, mine engineers have to choose the best recipe, which provides the desired Unconfined Compressive Strength (UCS) with optimum cost, out of a number of alternatives. Usually, this number is significant; the decision should be based on an indirect estimation by empirical equations. If it is small, the decision may be based on the comparison analysis. Both methods are time consuming, expensive, and allocated. Then, it has been necessary to apply machine learning methods to optimize the recipe and predict the performance.

Few different ways are available to determine some mechanical parameters such as modulus of elasticity (E) and unconfined compressive strength (UCS) of cemented paste backfill(CPB). For example, Regression- Causal methods have been previously developed for UCS forecasting (Wang et al, 2007). Thus, based on a battery of experimental tests, the authors have established a multiple linear regressive model for fill strength prediction with the help of Matlab software. Moreover, artificial neural networks have been employed for developing predictive models to estimate the needed parameters (Rankine and Sivakugan, 2005).

An artificial neural network (ANN), often called "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons that processes information using a connectionist approach to computation. In most cases, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase (Haykin, 1994).

Rankine and Sivakugan (2005) proved that the correlations between the predicted and achieved strength of the paste for both Cannington mine and paste fill worldwide using ANNs was excellent. The authors stated that the use of ANNs as part of an integrated planning tool for the design of backfills is very pertinent.

The main objective of this study is to develop an ANNs model to predict the paste backfill performance and study the effects of some physical and chemical parameters on the mechanical behaviors of cemented backfill by using artificial tailings. The direct use of mine tailings proves to be hard to study, especially when an individual wants to study few specified parameters among all of them. For this reason, silica powder is used in this research. It gives the power to control and minimize the effects of other mineral compounds presented in the real tailings. The main assumption allowing that tailing grains are not reactive in the condition of paste backfilling. This is well demonstrated by previous works where sulphide oxidation has been demonstrated as negligible (Ouellet et al, 2005). The methodology of this work is based on two stages: an experimental study which may illustrate the effect of the main chemical and physical properties of tailings (particle size), mixing water (sulphate content) and binder by using silica as simulated tailings. In the second part, the obtained results in terms of unconfined compressive strength (UCS) are used to train and test the implemented neural networks. Then, the obtained network can act as a computer tool to predict the unconfined compressive strength of cemented paste backfill.

The reminder of this work is organized as follows. In chapter 1, a literature review on the backfill is presented. Chapter 2 provides background information on the optimization and prediction models and methods applied for cemented paste backfill. In chapter 3, the experimental apparatus and procedures as well as experimental results are presented. Also, in chapter 3, it is shown that the constructed ANN model exhibits a high performance for predicting UCS.

CHAPTER 1. Literature review on the backfill

1.1. Introduction

During the last decade, technological advances in ore processing has increased. As a result of the continual extraction of high grade ore deposits in the earth's crust and development in ore processing, a large volume of waste products including tailings and waste rocks are produced during mining operations.

On the other hand, increasing environmental legislations dictate that waste materials must be treated in an appropriate way. Therefore, the use of cemented paste backfill as an appropriate waste management approach has increased in the most mines all around the world (Benzaazoua et al, 2004).

Traditionally, mine tailings were deposited as dilute slurries in large dams. However, it is well known that dams are at risk of failure due to leakage, instability and liquifaction. To overcome these problems, the best solution is to use dry or half dry disposal methods such as dry stacking, thickened tailings disposal and mine backfill.

Mine backfill refers to any material that is used to fill mine openings for stability, environmental and other economic reasons. Backfilling provides several useful functions in the mining cycle. For example, backfill is used to improve safety and to increase productivity. In terms of safety, it is used as an engineered structural product to control subsidence, to provide pillar support and to improve ground conditions in deep mines or stressed zones. In other words, backfilling provides an adequate working floor for workers and mine equipment, and also increases productivity by controlling ore dilution (Aitchison et al, 1973). In mining operation, backfilling provides a mean of disposing large quantities of waste products underground away from the surface. Backfill is also used to improve mine ventilation. In a more unique role, backfill is used to establish new mining methods (Annor et al, 1988).

In this chapter, we deal with the identification of potential properties of backfill and we present a comprehensive review of backfill materials, properties, and behaviors from the literature.

1.2. Why mine fill?

As mentioned before, the disposal of tailings is a controversial environmental problem. Early methods such as discharging tailings into rivers and streams or dumping of coarse dewatered tailings on land are not acceptable anymore.

The best way to deal with tailings is to use them in positive ways such as reprocessing in order to recover additional value or return the coarser fraction of mill tailings underground. Back filling has been used since the beginning of the century in South African mines (Stradling, 1988).

The use of different types of fill and their specific functions greatly depends on mining methods, mining strategies and mining sequence.

Brady and Brown (2004) proposed a subdivision of mining methods according to three main categories, Figure 1:

- Unsupported methods; where the voids created are meant to be continuously self-filling with caving material as mining progresses. These include block caving methods where orebodies are undercut to induce caving of the ore. They also include sublevel caving methods where the hanging wall progressively caves to fill voids produced by ore extraction.
- Naturally supported methods; where pillars are left in place as the main way of controlling the stability of extracted areas. This includes room and pillar methods, often employed in low dipping orebodies. Shrinkage and some variations of open stop mining can also rely on naturally supported methods, by using crown and rib pillars to separate stoping blocks. This approach generally yields lower ore recovery and is often practiced in low grade orebodies where the increases in ore recovery does not justify the cost of fill.
- Artificially supported methods; where fills are used to limit voids exposure so as to not exceed critical stable dimensions. This includes variations of cut and fill and open stope mining methods. As underground extraction reaches deeper levels, stable void exposure becomes smaller, and reliance on an efficient fills delivery.

Mine fill is generally applicable to artificially supported methods. There are three kinds of back filling: rock backfill, hydraulic backfill and cemented paste backfill (CPB).

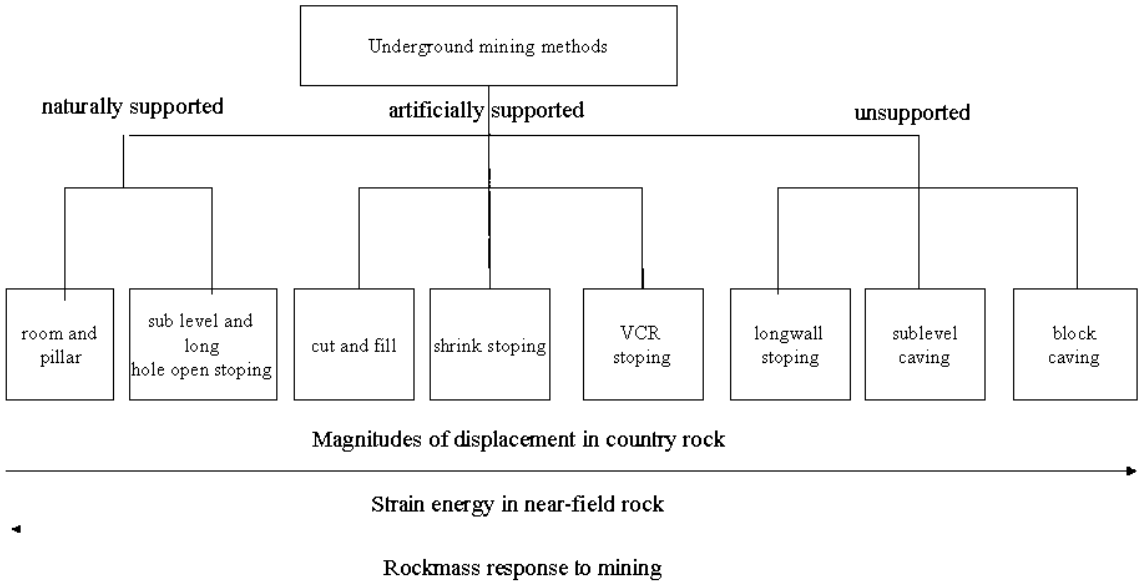

Figure1: Diagram showing a breakdown of mining methods according to the mine regional support system used, Brady and Brown (2004)

1.2.1. Waste disposal

Disposal of mining processing wastes, whether land based or into bodies of water, is usually considered as an undesirable consequence of meeting society's needs for metals and minerals. Environmental disasters associated with the discharge or storage of such wastes can have very important consequences (Aitchison et al, 1973). Then, environmental standards and mine closure requirements are gradually transforming the economics of mine waste disposal. Filling of underground voids is proven to be an environmentally friendly vehicle as well as a cost saving option to permanent disposal of mine waste.

1.2.2. Excavation exposure

The stability of underground excavation is a function of a set of variables including spans, time, and ground conditions. Then, uncovered and large excavations have an increasing risk of collapsing with time. Fill can be used to eliminate this problem. In this method, fill acts as a bulking agent and its function is simply to occupy the mining void. If the excavation becomes unstable, loosening material from the excavation boundary is kept in place by fill, and the rockmass failure is stopped.

As explained before, the application of filling depends on the mining methods. For extraction sequence progressing upward, the fill mass in the stope below will act as a working floor for the stope above. For extraction sequences such as undercut-and-fill moving downward, fill may be used as a replacement roof. This is especially appropriate when the ground conditions in the back are deemed unsafe and leaving crown pillars separating stopes is not an option.

The use of fill to limit excavation exposure can lead to very productive and flexible mining sequences, particularly when mining massive orebodies of reasonable grade.

In deep mining conditions, where the in situ stress field is high, the sequence of stope extraction becomes one of the main strategic control measures for managing the effects of mine induced critical stress.

1.2.3. Sulphide reactivity limitation and metal fixation

The mining of certain minerals like gold and nickel is associated with acid drainage problems that can cause long-term impairment to waterways and biodiversity. Also, some effluents generated by the metal mining industry contain large quantities of toxic substances, such as cyanides and heavy metals, which cause serious health and environmental impacts.

Acid Mine Drainage (AMD) is formed by uncontrolled bioleaching reactions. Bioleaching is a series of complex geochemical and microbial reactions that occurs when water comes into contact with pyrite (iron disulfide minerals) for example in coal, refuse, or in the overburden of a mine operation.

Laboratory studies have shown that sulfuric acid is produced when sulfide minerals are exposed to oxygen and water, but scientists have found that the rate of generation is so slow and it would take decades to oxidize a significant proportion of sulfide. Observations of AMD and other natural systems clearly demonstrate that acid production occurs in a short time period, from months to years. This is caused by some common strains of bacteria present in almost all environments that increase the reaction rate by orders of magnitude.

Once the acid is formed, it leaches to other metals, such as copper, zinc, cadmium, nickel, arsenic, lead, and mercury, from the mineralized vein. High concentrations of these metals are dissolved by the acid and carried away in solution. As the acid solution flows away from the mine, the pH changes and affects the chemistry of the solution and causes different metals to begin to precipitate out of solution.

The underground disposal of tailings is a significant way to reduce the production of AMD. Ouellet et al (2005) proved that the physical and mineralogical characterization of the CPB and the pore water quality evolution result into deduction in the oxidation rate, which can be related to the high degree of saturation maintained in the paste backfill material.

1.3. Backfill performance and Measurement of mechanical strength

Shear strength is one of the most important properties for cemented fills. How a fill mass will behave when it is exposed during the extraction of the adjacent stope depends on the shear strength of fill. As explained before, backfill strength is directly attributed to the physiochemical properties such as particle size, binder type, PH, sulpate content and soil mechanic relationships. In uncommented fills, an apparent (C) results from surface tension forces in pore water that disappears when the fill is fully dry or fully saturated. In cemented fills, the cementation between particles results in the development of cohesion between particles. If there is no cohesion in a fill mass, it is not possible to have unsupported vertical faces of fill mass. However, backfill develops shear resistance through the following mechanisms:

- Frictional resistance between fill particles
- Interlocking of fill particles
- Cohesion or any cementing of fill particles at the surface or at contact point

The total shear resistance of a fill material can be effectively represented by the Mohr-Coulomb theory. Mohr-Coulomb theory is a mathematical model describing the response of brittle materials such as concrete, or paste backfill to shear stress as well as normal stress. Most of the classical engineering materials somehow follow this rule in at least a portion of their shear failure envelope. Generally the theory applies to materials for which the compressive strength far exceeds the tensile strength (Juvinal, R. and Marshek, K. 1991).

As mentioned above, the total shear resistance of a fill material can be effectively represented by the Mohr- Coulomb failure strength equation

$$\tau = \sigma_n \tan\phi + C \quad (1)$$

The cohesion intercept in a typical Mohar-Coulomb envelope arises due to our representation of the shear stress versus normal stress relationship by a straight line. C is graphically generated and may not be a direct measurement of the strength of cemented bonds as shown in Figure2.

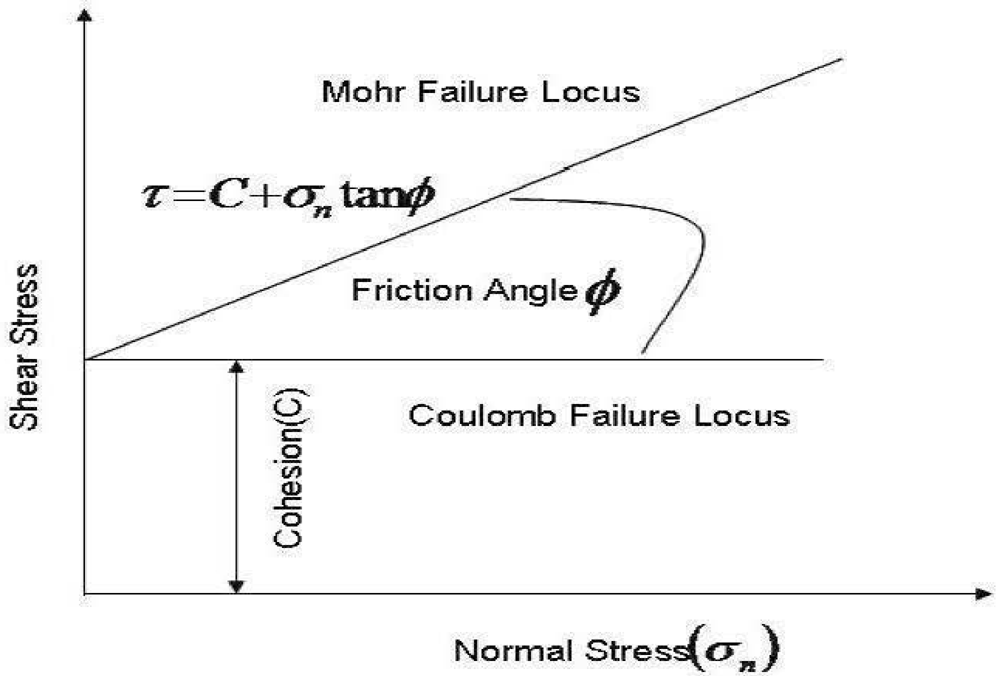

Figure 2: Mohr Failure Locus

In this work, unconfined compression testing is used to define the compressive strength of the samples. By definition, the compressive strength of a material is that value of uniaxial compressive stress reached when the material fails completely. A cylindrical sample is subjected to a confining stress and axially loaded until failure in uniaxial testing. In an unconfined compressive strength test, the sample is subjected to axial loading without any confining pressure applied.

During the test, the axial load and the sample vertical displacement are recorded as is the pore water pressure induced in the sample is also recorded. The results are plotted in a deviator stress versus vertical compressive strain plot (Potvin et al, 2005). It has been proven that the obtained results in the lab are different from the reality. It is really hard to maintain the same physical and mechanical conditions found in an underground stope. Then, the experimental data obtained from mine sites is very important for understanding back fill behavior as a ground support. Much research has been launched to investigate the backfill behavior in the mine site (Ouellet and Servant, 2000), (Belem et al, 2000) and (Belem et al, 2004). These results are also necessary to develop design criteria for mine fill. For example, many scientific works demonstrated that the backfill stresses distribution in the horizontal and vertical directions are not equal and strongly depend on the geometry and span of the stope (Aubertin et al, 2003), (Hassani et al, 2004) and (Ouellet and Servant, 2000). Few researchers have tried to investigate the applied pressure of paste backfill. However, they have divided the applied pressure in two different categories (Potvin et al, 2005):

- Backfill acting as a local support would have a pressure less than 10 MPa,
- Backfill acting as regional support with a pressure exceeding 100 MPa.

1.4. Types of backfill used in underground mines

There are three kinds of back filling, rock backfill, hydraulic backfill and cemented paste backfill (CPB). The use of backfill can bring some advantages:

- To reduce the amount of sulphide-rich tailings on the mine-site surface, reducing potential environmental problems.
- To increase the available ore reserves by acting as secondary pillars support and providing mine stability for equipment.
- To reduce mine operating costs.
- To increase the safety of mine operators.

Mines choose the most suitable backfill system among different types of back filling systems based on:

- Availability and supply of fill materials.

- Fill preparation procedure.
- The use of alternative cementing agents.
- Backfill transportation and placement.
- Desired stability and consolidation.

Mining at greater depths (Canadian mines) are demanding high density backfill and related backfill technologies. These demands have presently resulted in a growth of usage for cemented back fill. Then, in the following subsection, we present an overview of the types of backfill.

1.4.1. Hydraulic fill

Hydraulic fill is the name given to the class of mine fill types that are delivered as high-density slurry through boreholes and pipelines to the underground workings. The name is derived from the water-borne delivery method. This may be produced directly from coarse sand and/or mill tailings, or by desliming finer tailings with hydrocyclones to meet a nominal standard of $<10\%$ passing 10μ. This widely accepted rule of thumb usually produces an acceptable permeability that ensures a free draining fill. Target permeabilities of $3\times10^{-6}ms^{-1}$ or percolation rates of 60 to 100 $\frac{mm}{hr}$ are usually achieved with these sizing targets. Hydraulic fills should be placed at the highest possible solid density to minimize the amount of the excess transported water that must be drained and pumped to the surface. This is usually in ranges between 70% to 75% solids by weight.

Slurry fill technology has been widely used in mining operations but its efficient application may be limited in modern backfill design. In the following, we review some of the advantages and disadvantages of slurry fill (Hassani et Archibald, 1998).

Advantages:

- Relatively simple to operate and to install with a minimum technical supervision required.
- All constituents are controlled at the fill station which secures the fill quality and the mixture density.
- Pumping can normally be avoided by optimizing the pipeline lay-out.

Disadvantages:

- Binder washout.
- Excess water needs to be recovered from stopes and pumped to surface; the placed backfill permeability character is a critical design criterion.

1.4.2. Rockfill

Dry rock fill is rock waste, surface sands, gravels, or dried tailings. The fill is either dropped down a raise, or tipped into an open stope by a Load Haul Dump (LHD) or dump trucks. The dry rock fill is most suited for cut and fill mining. While slurry fill or paste fill can be used to fill voids and achieve tight filling within stopes, rockfill continues to provide the best strength support and for this reason, it is unlikely to be totally replaced by other types of fill. In the following, we review some of the advantages and disadvantages of rockfill (Hassani et Archibald, 1998).

Advantages:

- Simple preparation system.
- Reduction of waste disposal on surface.
- High strength can be relatively attained when waste rock is consolidated with cement.

Disadvantage:

- High production and transportation cost.
- Coning of placed rockfill when placed in the stope results in the segregation of coarser material to stope sides and reduces the ability to tight fill stopes.
- Any tailings produced are only partially utilized. Surface disposals must be considered.

The rock fill can be modified to suit the mining requirement by:

- Optimization particle size using inclusion of fines or blending materials.
- Adding binder such as cement.
- No fines concrete – cement slurry rock fill.
- Tailings paste added rock fill that can be reticulated through boreholes and pipe lines as a true rocky paste fill.

In the following, we briefly review different types of rockfill:

- RF (Rockfill). Rockfill is made by sized or unsized waste rock, obtained either from surface or underground sources, which is normally placed without the use of consolidating materials into underground stopes. Then, regarding the fact that RF remains unconsolidated, it provides limited ground support.
- CRF (Consolidated Rockfill). It consists of sized rockfill aggregate mixed with cement, 5% to 6% by weight of aggregate at a pulp density of 50% to 60%. With use of consolidated rockfill, there is usually no drainage problem, and high fill quality can often be achieved if materials are placed properly.
- CSRF (Consolidated Sand Rockfill). CSRF is a combination of CRF and sand. It requires higher cement additions in the range of 5-10% by weight. With the use of consolidated sand rockfill, raise layouts become less critical as, CSRF material has relatively good mobility and it provide less segregation potential than CRF.
- CSWF (Consolidated Sand Waste fill). CSWF is a rockfill. Rock waste can be left into stopes as ore is mined and consolidated by pouring a cement/sand slurry mixture on top to percolate through the rockfill.

Finally, it is proven that by reducing the porosity of the rock fill the strength of fill increasing, for the same level of binder content.

1.4.3. Paste backfill

Paste fill is prepared, retaining more fine particles and dewatered to toothpaste-like consistency. The resulting paste does not drain. To eliminate the risk of subsequent liquefaction and remobilization paste backfill is typically placed at 75% to 80% solid by weight via high pressure boreholes and/or pipelines. Sufficient shear yield stress is required to remobilise paste backfill. Note that the longer the paste is left idle, the greater becomes the yield stress to reinitiate flow. If this yield stress is high, and if there is insufficient energy available to remobilise the paste, the line will become plugged (Revell, 2002).

The non-segregation behavior of paste materials offers a number of operational and management advantages as an underground filling material such as:

- Providing a shorter mining cycle due to the earlier development of higher compressive strength.
- Reducing binder consumption for equivalent or better slurry backfill strengths.
- Disposing of mining waste materials.
- Creating a fresh working surface.

Disadvantages:

- The need for developed dewatering equipment.
- The presence of increased pipeline pressure

It is proven that not all tailings may be used to create paste fill (Landriault et al, 1996). A paste is a granular material which is mixed with sufficient water to fill the interstices between the particles so that the material behaves as a fluid. In order to form a paste, the water must be retained between the particles and not separated from the mix. Collodial electrical particle charges will bond solid particles to water molecules to achieve this, but the colloidal of the granular material must retain enough water to form a paste. The colloidal properties of a material are strongly ruled by particle size. As explained before, in the paste backfill tailings must have at least 15wt% of fine particles in order to form paste. However, granular materials with insufficient fines will not be able to retain enough water to form a paste, and will separate into two distinct phases.

A comparison between the properties of slurry fill, rock fill and paste fill is presented in Table 1 (Landriault et al, 1996).

In summary, paste backfill can be used as a substitute for all other types of underground mine fills. The choice between alternative fills is therefore based on financial and environmental impact.

Table 1: Property Comparison of the Principal Backfilling Methods

Properties	Slurry fill	Paste fill	Rock fill
Placement state	60% to 75% solids	75% to 85% solids	Dry
Underground transport system	Borehole/pipeline via gravity	Borehole/pipeline via gravity, can be pumped	Raise, mobile equipment, separate cement system
Binder application	Cemented or uncemented	Cemented only	Cemented or uncemented
Water to cement ratio(w/c)	High w/c ratio, low binder strength	Low to high w/c ratio. Low to high binder strength	Low w/c ratio, higher binder strength
Placement rate	100 to 200 tonne/hr	50 to 200 tonne/hr	100 to 400 tonne/hr
Segregation	Slurry settlement and segregation, low strength development	No segregation	Stockpile and placement, reduced strength and stiffness
Stiffness	Low stiffness	Low or high stiffness	High stiffness if placed correctly
Tight filling	Cannot tight fill	Easy to tight fill	Difficult to tight fill
Binder quantity	Requires large quantity of binder	Usually lower quantity of binder required	Moderate binder quantities
Barricades	expensive	inexpensive	Not necessary
Water runoff	Excessive water runoff	Negligible water runoff	No water runoff
Capital costs	Low capital cost	Higher than slurry fill	Moderate capital costs
Operational costs	Low distribution costs;	Lowest cost for a cemented fill	High operation costs

1.5. Basic paste backfill material

The use of cemented paste backfill improves ground support by reducing the amount of tailings that have to be sent to surface disposal facilities. These are some of the reasons why CPB is currently receiving more attention than ever before. A survey conducted on

32 mines showed that 44% of surveyed underground mines in North America and Australia use CPB as backfilling technology (Benzaazoua et al, 2005).

Then, in this subsection, we try to investigate the properties that affect backfill behaviors, rheological strength and hardened strength. Unfortunately, these properties are often affected by subjectivity and influenced by several parameters that can be classified into two main types (Benzaazoua et al, 2002).

- Macroscopic parameters, which include all phenomena occurring at the scale of a stope filled with paste fill and its interaction with the adjacent rock;
- Intrinsic parameters, which include all the parameters related to the three main paste backfill components and their changes during curing process.

As explained before, the strength development within paste backfill depends upon:

- The physical, chemical and mineralogical characteristics of tailings;
- Chemistry and the amount of water;
- Binder type and proportion.

In the following, we focus on the intrinsic parameters and review some of work that demonstrated their effects on the backfill performance.

1.5.1. Tailings

Tailings consist of ground rock and process effluents that are generated in a mine processing plant. Mechanical and chemical processes are used to extract the desired product from the mine ore, and produce a waste stream named as tailings. This process of product extraction is never 100% efficient, nor is it possible to reclaim all the reusable and expanded processing reagents and chemicals. Even the milling process may add other materials to the tailings stream: cyanide, lime, acid and various agents used to assist in the separation of values from gangue. In addition, other deleterious substance in the tailings stream, for instance sulphides, arsenic and other heavy minerals, may as a result of the processing become unstable. The implication of which should be fully considered in any form of tailing disposal, including use in fill.

Tailings can range from fine sand to clay-sized particles. The final sizing depends on the level of grinding carried out during processing. The most common means of presenting the sizing is in the form of a cumulative distribution. Particle size of tailings has direct impact on the micro-structural properties of the CPB. Porosity of CPB has a direct relation with the particle size, which means that fine particle size leads to high porosity and vice versa.

In other words, many researchers demonstrated that porosity, void ratio and degree of saturation is not only related to particle size, but also related to drainage and consolidation conditions. Consolidated and drained CPB leads to lower porosity, void ratio and degree of saturation than unconsolidated and undrained CPB.

Benzaazoua et al, (2002), Hassani and Archibald, (1998) and Fall et al, (2005) presented that coarse and medium tailings produce better strength and stability than fine tailings due to less pore size and porosity. Also, coarse tailings require less water than medium or fine tailings to reach the same pulp density.

The particle size of tailings is not only an important factor in backfill performance, but is also in terms of backfill transportation, from the backfill plant to the stope, and through the pipelines. It is proven that fine particles less than 20 μm act as lubricant along the pipe wall, which reduces flow resistance. In fact, coarse particles are naturally forced to the center of the flow (Verkek and Markus, 1998).

The comminution process, for most minerals, produces particles that are angular shaped, and that yield a dense and competent mass. However, some minerals produce elongated or platy particles. This can influence some properties, such as permeability, density and strength. Flat mineral particles will generally settle more slowly than rounded particles of equal specific gravity and drainage time, in the case of hydraulic fill. However, particle shape affects the size of void and connection paths available for holding and transporting fluids (Herget and Korompay 1978). Table 2 presents the relationship between the particle shape and friction angles, and packing density.

Table 2: Effect of Particle Shape

Shape and grading	Friction angle (φ)	
	Losse packing	Dense packing
Rounded, uniform	30°	37°
Rounded, well graded	34°	40 °
Angular, uniform	35°	43 °
Angular, well graded	39°	45 °

There are two different methods available to determine the particle size distribution of fill materials. The first method uses a set of sieves of different apertures, and a set of cyclones. The second method, applied here, uses optical imaging and laser light.

Finally, it is difficult to choose the dividing particle size that will define the fine filling applications. In this work, we apply 20 μm as the dividing particle size for coarser and finer fractions of tailings.

The chemical and mineralogical properties of tailings have a great impact on the retention, settling and strength development of CPB. Different ore type with different mineral assemblage can result in different fill properties.

As explained, the mineralogy of tailings can also affect the final strength of paste backfill by influencing chemical reactions that promote strength or produce additional chemical reactions. Other examples of mineralogy affecting fill properties include:

- Specific gravity of minerals which will determine the density of the fill.
- Silica minerals as it can be very abrasive and result in the high pipeline wear.
- Sulphides which may results in the breakdown of the hydrated cement in the fill over time.

In terms of chemical properties, mill tailings contain pyrites, which is the main source of sulphides. When sulphur is exposed to water and oxygen, it begins to oxidize, generating sulphuric acid and heat. This oxidation is evident as a change of colors, indicating rusting of the particles. In other words, the pyrite oxidizes and breaks down into ferrous and ferric iron, hydrogen ions and sulphate ions. The sulphide ions can combine with existing hydrated NPC to form gypsum and ettringite (Kesimal et al, 2005) and (Ouellet and Hassani, 2002).

It is proven that sulphides may cause the dissolution of calcic phase of binder in CPB. Also, it is shown that high amount of sulphides in the tailings lead to CPB failure, even though they are made with a relatively high proportion of sulphate-resistance binder.

Note that a certain amount of sulphides has a positive effect on the paste backfill performance. This positive effect may be related to tailings' density and sulphate precipitation.

1.5.2. Water

Many studies have demonstrated that water has great impact on the cemented paste backfill performance. For example, Benzaazoua et al (2004) presented that the water ratio is very important, because it controls all of the hydration and precipitation reaction. This controls all of the hardening processes within paste fill materials. Benzaazoua et al (1999) also launched a series of experimental tests. They produced many mixtures for a constant binder type ratio, with a same ratio of municipal (tap) water, lake water and process water. It was observed, over a 28 day curing period, that the paste backfill made by municipal water produced a higher mechanical strength than lake and process water. It was also proven that a decrease in strength (UCS) occurred with an increase in the water content. Mechanical strength development in the paste back fill is related to appearance of hydrated phase that form the binder matrix of the fine grains from tailings.

The presence of salt in sufficient concentration can also affect the strength development of cemented fill. During the curing process, large amount of the salt crystallises. The growth of such crystals may inhibit the strength gain of paste backfill by reducing the dispersion of cement.

Laboratory studies by Wang and Villaescusa, (2000) demonstrated that for both tailings and aggregate based fills, increases in salinity leads to deduction of fill strengths.

1.5.3. Binder

Another significant factor in the mechanical behavior of paste backfill is the type of binder, for both short and long term. Normally, cement, pozzolans, or a mixture of both is used in mines.

The most widely used cements are hydraulic cements, which include a fine powder that reacts with water to bind particles together as aggregates, by hardening from a flowable plastic state to a solid. Mitchell and Smith, (1979) reported that the addition of small quantities of cement to classified hydraulic backfill does not alter the initial porosity significantly.

The relationship between strength of backfill and binder content is not linear. Laboratory testing is necessary to define their relationship.

Swan, (1985) determined that the unconfined compressive strength for any given fill material is related empirically to cement content by:

$$UCS \alpha (C_v^{2.36}) \tag{2}$$

Henderson and Lilley, (2001) found that the following relationship fits better to aggregate fills:

$$UCS \approx 63\left(\frac{c}{n}\right)^{1.54} \tag{3}$$

C_v is the volume of cement particles, c is the cement content weight, and n is the porosity.

Pozzolans are defined as materials which contain constituents that will combine with lime at normal temperatures in the presence of water, to form stable insoluble compounds that show cementing properties.

- Coal Ash: Coal ash is a waste derived from the combination of coals in thermal power generation plants. Coal ash consists of fine particles known as fly ash that flow with flue gases and coarser particles, called bottom ash. They are collected at the bottom of the boiler (Hassani et Archibald, 1998). Chemically, fly ash is predominantly oxides of silicon, aluminum and iron, with small amounts of calcium and alkalis. The mean value of particle size distribution of fly ash is around 10 to 15 μm. There are two types of fly ash: type C, which is produced from the burning of lignite or sub-bituminous coal and has high lime content, and type F, which is produced from the burning of anthracite or coal and has lower lime.

- Slag: Blast furnace slag is a by-product that results from the fusion of fluxing limestone with coke ash and siliceous, and aluminious residues remaining after the separation of the metal from ore. Note that the granulated slag is the glassy, non- crystalline, granular material resulting from the rapid quenching of molten slag with water.

The selection and use of an alternative binder for mine backfill consolidation is largely controlled by material availability, cost and technical performance with a particular mine's fill aggregate.

Benzaazoua and et al (2002) presented that for high sulphide tailings, neither the slag-based binder nor fly ash based binders is effective. However, the sulphate resistance based binder gives good long term strength. In other words, the slag based binder provides the best strength for low and medium sulphide tailings. The two other types of binder produce unacceptable results.

Many studies proved that there is no universal recipe for all mines to get good performance for their paste backfill. Finally, Benzaazoua et al, (1999) launched other series of tests with sulphide rich tailings to find the binder recipe. The study proved that a mixture of cement type 10 and cement type 50 gives good UCS values, but the best UCS was obtained by cement type 10 and slag. It is important to mention again that the proportion of binder has a sub-linear relationship with the obtained mechanical resistance.

Finally, the mining operations used to obtain useful minerals from the earth's crust inevitably create fairly huge amount of waste materials, waste rock, and tailings, of which the mine companies must dispose in an acceptable manner. Mine fill is a new part of the mining operation that provides a safe working environment for mine operators and that stores mill tailings in underground mine openings. In this chapter, the main concepts of backfill have been presented. In order to understand the mechanical behaviours of back fill, we reviewed the physiochemical properties of its constituent materials, and their interactions. Some well-known types of backfill were presented as well.

In the following chapter, we discuss applied methods that optimize the recipe and/or predict the performance of cemented backfill.

CHAPTER 2. Optimization and predictive methods for backfill properties

2.1. Introduction

Currently, nobody can explain all the phenomena contributing to pastefill hardening. Then, it seems important for mines to do recipe optimization to find the optimal recipe to satisfy technical, environmental and economical constraints before each of the backfill operations (Benzaazoua et al, 2004).

Considering the interaction between the backfill parameters, an integrated design methodology is essential in order to meet the requirements of mining operations involving backfill. Computers are widely used during the planning and design stages of mining operations. However, there has been little standardization of hardware and software, and most tasks are covered by individual programs. Usually, a general purpose numerical simulation program is used for the modelling of underground mining activities and these programs can only handle one aspect of the design process. Figure 3 shows a flow chart of Bieniawski (1986) which generalizes design charts for underground mines.

Gunduz (1992) developed an integrated hydraulic backfill transport simulation module which utilized most of the backfill characteristics data evaluated by material characterisation modules. Figure 3 shows the structure of the system analysis software developed by Gunduz (1995).

FLAC has been used to develop a model capable of demonstrating the excavation, filling, lateral, and vertical earth pressure and loading measures on the backfill (Rankine, 2001) and (Li et al, 2003). Also SEEPW was used to evaluate the flow conditions (Godbout et al, 2004).

Analytical modeling, same as limiting equilibrium analysis, the Overburden method and the Marston were also used for resembling the stress of backfill stope (James et al, 2004).

Most of the studies focused on the optimization of CPB properties (Archibald et al, 1995), (Hassani and Archibald, 1998) and (Amaratunge and Yaschyshyn, 1997).

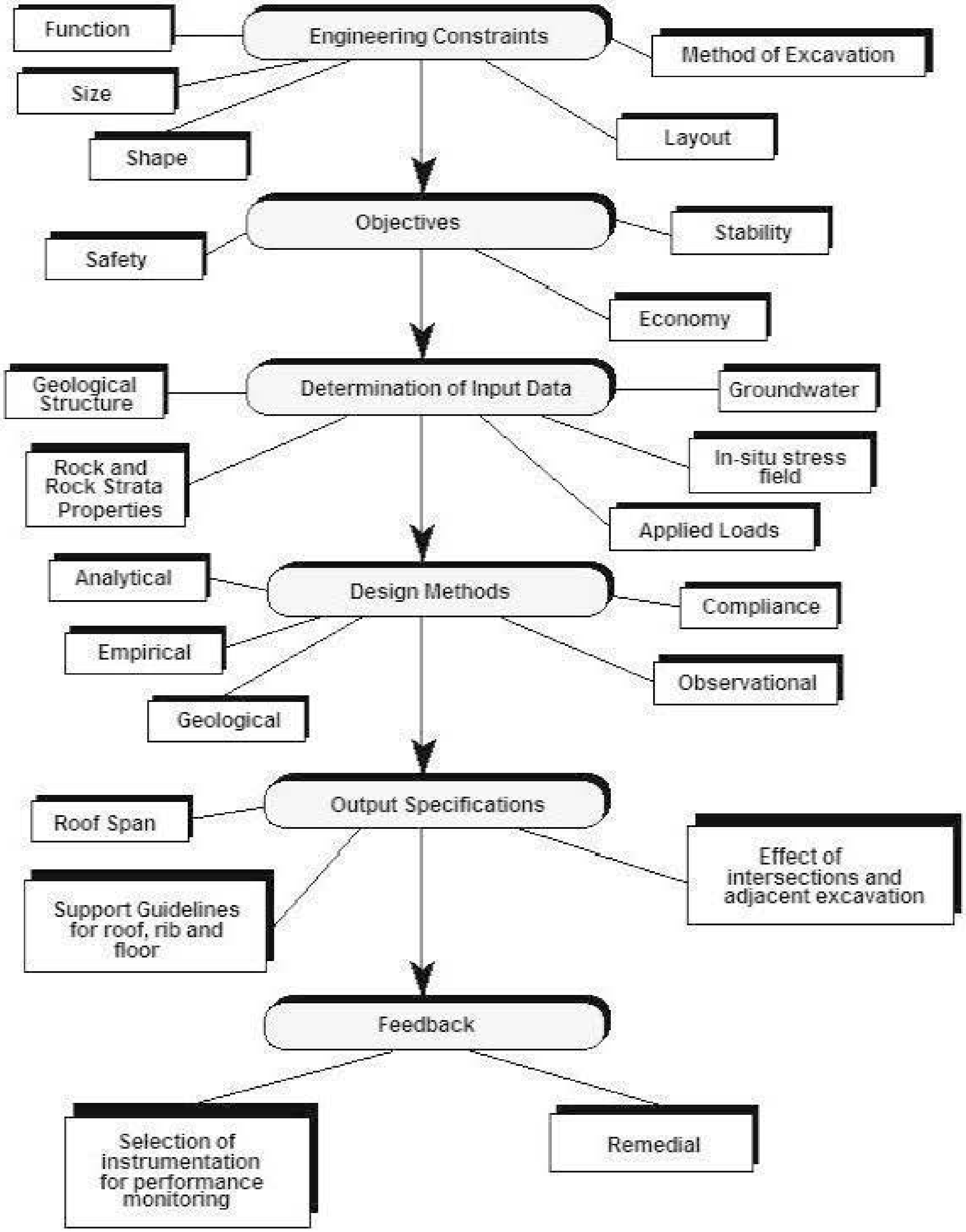

Figure 3: The flow chart showing a simplified design chart for underground mine design

In order to propose an indirect estimation of CPB properties by empirical equations, the statistical methods are traditionally used (Berry, 1980), (Saliba, 1996) and (Swan, 1985).

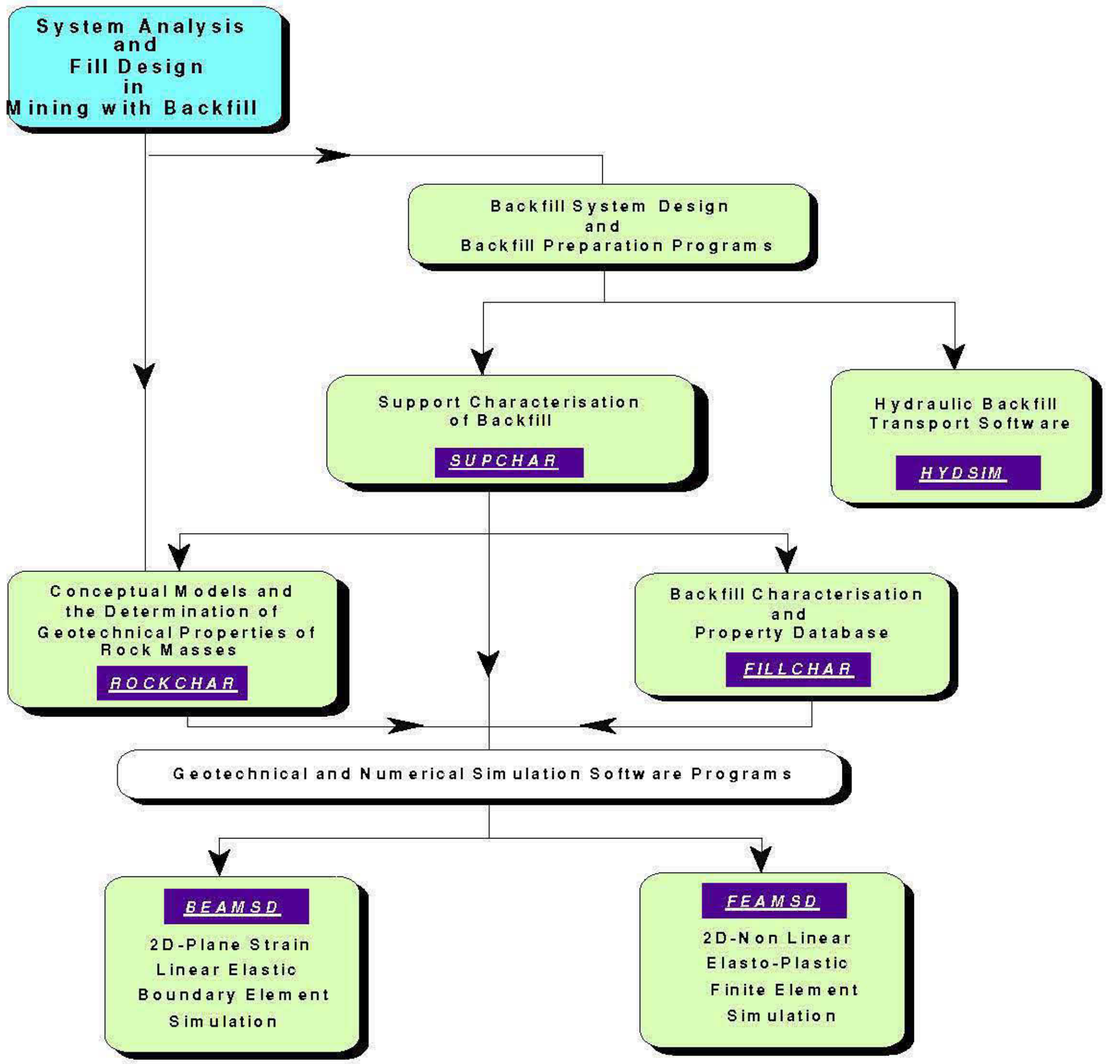

Figure 4: The structure of the system analysis software developed by Gunduz (1992)

In recent years, new techniques have been applied for developing predictive models to estimate the needed parameters.

For example, Fall et al (2007) applied the response surface methods based modeling to predict the technical and economical performance properties of the CPB and analysis the interactions between the main components of CBP and their effect on its properties. Wang et al (2007) developed a multiple linear regressive model for fill strength forecasting by using Matlab software. They carried out many tests for the ShiZhu Yuan non-ferrous metal mine. The samples were prepared with different ratio of paste backfill material same as binder ratio, mass fraction and curing time. The residual examination proved that the multi-factor regression result is reasonable and reliable. Rankine and Sivakugan (2005) used artificial neural networks (ANNs) to predict and optimize the cost. Applied ANN was based on the input parameters of cement content, solid content, curing time and grain size distribution.

They collected data from various sources and trained the Network by two sets of Data from Cannington mine (PFCAN) and the world wide (PFVAR) samples. To prepare the network two subdivided data were used for modelling and validation respectively.

The obtained coefficient of determination, r^2 between the predicted and measured data by this work is 0.901 for world wide model.

In this chapter, we present an overview of the definition of statistical techniques, predictive analytics, types of predictive analytics, and artificial neural network.

2.2. Statistical methods

Statistics is a mathematical science pertaining to the collection, analysis, interpretation or explanation, and presentation of data. It is applicable to a wide variety of academic disciplines, from the natural and social sciences to the humanities. Statistics are also used for making informed decisions in governments and businesses.

In applying statistics to a scientific, industrial, or societal problems, one begins with a process or population to be studied. This might be a population of people in a country, of crystal grains in a rock, or of goods manufactured by a particular factory during a given period. It may instead be a process observed at various times; data collected about this kind of "population" constitute what is called a time series.

For practical reasons, rather than compiling data about an entire population, one usually studies a chosen subset of the population, called a sample. Data is collected about the sample in an observational or experimental setting. The data is then subjected to statistical analysis, which serves two related purposes: description and inference.

- Descriptive statistics can be used to summarize the data, either numerically or graphically, to describe the sample. Basic examples of numerical descriptors include the means and standard deviation. Graphical summarizations include various kinds of charts and graphs.

- Inferential statistics are used to model patterns in the data, accounting for randomness and drawing inferences about the larger population. These inferences may take the form of answers to yes/no questions (hypothesis testing), estimates of numerical characteristics (estimation), descriptions of association (correlation), or modeling of relationships (regression). Other modeling techniques include time series and data mining.

The concept of correlation is particularly noteworthy. Statistical analysis of a data set may reveal that two variables (that is, two properties of the population under consideration) tend to vary together, as if they are connected.

2.2.1. Experimental studies

A common goal for a statistical research project is to investigate causality, and in particular to draw a conclusion on the effect of changes in the predictors or independent variables on response or dependent variables. There are two major types of causal statistical studies, experimental studies and observational studies. In both types of studies, the effect of differences of an independent variable (or variables) on the behavior of the dependent variable are observed. The difference between the two types are how the study is actually conducted.

An experimental study involves taking measurements of the system under study, manipulating the system, and then taking additional measurements using the same procedure to determine if the manipulation modified the values of the measurements. In contrast, an observational study does not involve experimental manipulation. Instead data is gathered and correlations between predictors and the response are investigated. The basic steps for an experiment are to (Lindley, 1995):

- Plan the research including determining information sources, research subject selection, and ethical considerations for the proposed research and method.

- Design the experiment concentrating on the system model and the interaction of independent and dependent variables.
- Summarize a collection of observations to feature their commonality by suppressing details (descriptive statistics).
- Reach consensus about what the observations tell us about the world we observe (statistical inference).
- Document and present the results of the study.

2.2.2. Design of experiments

Design of experiments includes all of information-gathering exercises where variation is present, whether under the full control of the experimenter or not (the latter situation is usually called an observational study). Often the experimenter is interested in the effect of some process or intervention (the 'treatment') on some objects (the 'experimental units'), which may be people. Design of experiments is thus a discipline that has very broad application across all the natural and social sciences.

The first statistician to consider a formal mathematical methodology for the design of experiments was Sir Ronald A. Fisher. As an example, he described how to test the hypothesis that a certain lady could distinguish by flavor alone whether the milk or the tea was placed first in the cup. While this sounds like a frivolous application, it allowed him to illustrate the most important means of experimental design:

1. **Comparison**: In many fields of study it is hard to reproduce the exact measured results. Comparisons between treatments are much more reproducible and are usually preferable. Often, one compares against a standard or traditional treatment that acts as a baseline.
2. **Randomization**: There is an extensive body of mathematical theory that explores the consequences of making the allocation of units to treatments by means of some random mechanism such as tables of random numbers, or the use of randomization devices such as playing cards or dice. Provided the sample size is adequate, the risks associated with random allocation (such as failing to obtain a representative sample in a survey, or having a serious imbalance in a key

characteristic between a treatment group and a control group) are calculable and hence can be managed down to an acceptable level. Random does not mean haphazard, and great care must be taken that appropriate random methods are used.

3. **Replication**: Where measurement is made of a phenomenon that is subject to variation, it is important to carry out repeat measurements, so that the variability associated with the phenomenon can be estimated.
4. **Blocking**: is the arrangement of experimental units into groups (blocks) that are similar to one another. Blocking reduces known but irrelevant sources of variation between units and thus allows greater precision in the estimation of the source of variation under study.
5. **Orthogonality**: Orthogonality concerns the forms of comparison (contrasts) that can be legitimately and efficiently carried out. Contrasts can be represented by vectors and sets of orthogonal contrasts are uncorrelated and independently distributed if the data are normal. Because of this independence, each orthogonal treatment provides different information to the others. If there are treatments and orthogonal contrast, all the information that can be captured from the experiment is obtainable from the set of contrasts.
6. **Use of factorial experiments instead of the one-factor-at-a-time method**. These are efficient at evaluating the effects and possible interactions of several factors (independent variables).

2.2.3. Plan of experience based methods (Taguchi)

Taguchi methods are statistical methods developed by Genichi Taguchi to improve the quality of manufactured goods (Taguchi, 1986). The Taguchi method of experimental design (TMED) is a powerful approach to optimizing designs for performance, quality and cost. Taguchi differentiates online and offline quality control methods within the quality engineering system. Offline quality control refers to all activities that take place during the product planning, design and development stages, and includes the phases system designs, parameter designs and tolerance designs. In contrast, online quality control refers to all the activities that take place during the production stage and includes measurement, feedback and adjustment, prediction and correction. Taguchi introduced his strategy of experimental design (ED) for application in the following areas:

- Designing products and processes so that they are robust to environmental conditions.
- Developing products and processes so that they are robust to manufacturing variation.
- Developing products so that they are robust to component variation.
- Reducing variation in processes around a specified target value.

Taguchi's parameter design has proven to be the most powerful stage for process optimization. It involves maximization of performance and quality at minimum cost. This is fundamentally achieved by determining the best setting of those designs or process parameters which influence the product performance variation and by fine tuning the designs or process parameters which influence the average performance. There are ten steps in a systematic approach to use of taguchi's parameter design methodology:

1. **Problem recognition and formulation**. To establish a good understanding of the problem and the objective of the experiment.
2. **Select quality characteristic**. Select the appropriate quality characteristics to measure the experimental results.
3. **Select design or process parameters**. Identify the design or process parameters which are believed to influence the quality characteristic of interest.
4. **Classify design parameters into control**. Control parameters are those which can be controlled fairly easily under standard conditions. Noise factors are those which cannot be controlled or are expensive to control during normal or standard conditions.
5. **Determine levels of design or process parameters**. Determine the number of test levels for the design or process parameters
6. **Identify interactions**. Determine which, if any, design parameter interactions should be studied or analyzed.

7. **Choose appropriate Orthogonal Array** (OA). Select the most suitable OA from standard OA designs and assign design parameters and their interactions to various columns of the chosen OA.
8. **Conduct experiments**. Execute the experiment based on pre-prepared experimental layouts showing all the experimental trial conditions.
9. **Perform statistical analysis**. Determine the best design parameters setting, predict the optimal condition, and establish confidence intervals for the predicted response or quality characteristics.
10. **Perform a confirmatory experience and implement results**. A confirmatory experience is performed to verify the optimal setting of design parameters to see whether or not the optimal condition derived by the experiment actually yields an improvement in product quality, yield, or performance. If the results from the confirmatory experiment are conclusive, a specific action on the product or process must be taken for improvement. On the other hand, if unsatisfactory results are obtained, further investigations of the problem may be required.

2.3. Predictive modeling and Regression techniques

Predictive analytics encompasses a variety of techniques from statistical and data mining that analysis current and historical data to make prediction about the future events. Such predictions rarely take the form of absolute statements, and are more likely to be expressed as a value that corresponds to the odds of a particular event or behavior taking place in the future. The core of predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting it to predict the future outcomes.

Although predictive analytics can be put to use in many applications, we outline a few examples where predictive analytics has shown positive impact in recent years.

- **Direct marketing**: product marketing is constantly faced with the challenge of coping with the increasing number of competing products, different consumer preferences and the variety of methods available to interact with each consumer.

Efficient marketing is a process of understanding the amount of variability and tailoring the marketing strategy for greater profitability. Predictive analytics can help identify consumers with a higher likelihood of responding to a particular marketing offer. Models can be built using data from consumers past purchasing history and past response rates for each channel. Additional information about the consumers demographic, geographic and other characteristics to make more accurate predictions. Targeting only these consumers can lead to substantial increase in response rate which can lead to a significant reduction in cost per acquisition. Apart from identifying prospects, predictive analytics can also help to identify the most effective combination of products and marketing channels that should be used to target a given consumer.

- **Underwriting**: many businesses have to account for risk exposure due to their different services and determine the cost needed to cover the risk. For example, auto insurance providers need to accurately determine the amount of premium to charge to cover each vehicle and driver. A financial company needs to asses a borrower's potential and ability to pay before granting a loan.

  For a health insurance provider, predictive analytics can analyse a few year of past medical claims data, as well as lab, pharmacy and other records where available, to predict how expensive an enrolee is to be in future. Predictive analytics can help underwrite these quantities by predicting the chances of illness, default, bankruptcy, and etc. They can streamline the process of customer acquisition, by predicting the future risk behaviour of a customer using application level data. Proper predictive analytics can lead to adequate pricing decisions, which can help mitigate future risks of default.

The approaches and techniques used to conduct predictive analytics can be broadly grouped into regression and machine learning techniques. In the following subsections we will represent the basic concepts of regression techniques and artificial neural net work, which both apply to predict the performance of paste backfill.

However, regression models are the mainstay of predictive analytics. The focus lies on establishing a mathematical equation as a model to present the interactions between the different variables in consideration. Depending on the situation, there is a wide variety of models that can be applied while performing predictive analytics. Some of them are briefly discussed here (Menard, 1995).

Linear Regression Model:

The linear regression model analyzes the relationship between the response or dependent variable and a set of independent or predictor variables (Agresti, 1996). This relationship is expressed as an equation that predicts the response variable as a linear function of the parameters. These parameters are adjusted so that a measure of fits is optimized. Much of the effort in the model fitting is focused on minimizing the size of the residual, as well as ensuring that it is randomly distributed with respect to the model predictions.

A simple linear regression model is a summary of the relationship between a dependent variable *Y* and an independent variable *X*. *Y* is assumed to be a random variable while, even if *X* is a random variable, we condition on it. Essentially, we are interested in knowing the behavior of *Y*. However, we know that $X = x$.

A multiple regression model is a summary of the relationship between a dependent variable Y and multiple independent variables X. Y is assumed to be a random variable,

$$X_1 = x_1, X_2 = x_2, ..., X_n = x_q \tag{4}$$

In simple linear regression, the population regression line is given by:

$$E[y|x] = \mu_{y|x} = \alpha + \beta x \tag{5}$$

and the full linear regression model is:

$$y = \alpha + \beta x + \varepsilon \tag{6}$$

Where ε is normally distributed random variable with zero mean and variance of σ^2, α is the constant of the equation and β is the coefficient of the predictor variable. In multiple regressions, the population regression line is given by:

$$E[y|x_1, x_{2,} ..., x_q] = \mu_{y|x_1, x_2, ..., x_q} = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_q x_q \tag{7}$$

The full linear regression model is:

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_q x_q + \varepsilon \quad (8)$$

Again ε is a normally distributed random variable with mean 0 and variance of σ^2. Finally, the model predicts the dependent variable based on the value of independent variables which can be assessed by using the R^2 statistic.

Logistic Regression:

In a classification setting outcome probabilities to observations can be achieved through the use of a logistic model, which is a method that transforms information about the binary dependent variable into an unbounded continuous variable and estimates a regular multivariate model.

The dependent variable in logistic regression is usually dichotomous; the dependent variable can take the value 1 with a probability of success θ, or the value 0 with probability of failure $1-\theta$. This type of variable is called a "Bernoulli variable". Although not as common and not discussed in this chapter, applications of logistic regression have also been extended to cases where the dependent variable is of more than two cases, known as multi-nominal or polytomous (Tabachnick and Linda, 1996).

As previously mentioned, the independent or predictor variables in logistic regression can take any form. Logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related, or of equal variance within each group. The relationship between the predictor and response variables is not a linear function in logistic regression. Instead, the logistic regression function is used, which is the log transformation of θ:

$$\theta = \frac{e^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i)}}{1 + e^{(\alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i)}} \quad (9)$$

Where α is the constant of the equation and β is the coefficient of the predictor variables.

An alternative form of equation (8) is given as:

$$Log\left[\theta(x)\right] = \log\left[\frac{\theta(x)}{1-\theta(x)}\right] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i \tag{10}$$

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most parsimonious model. To accomplish this goal, a model is created that includes all predictor variables that are useful in predicting that response variable. Several different options are available during the model creation. Variables can be entered into the model in the order specified by the researcher or logistic regression can test the fit of the model after each coefficient is added or deleted, called "stepwise regression".

Stepwise Regression:

Stepwise regression is used in the exploratory phase of research however it is not recommended for theory testing (Menard, 1995). Theory testing is the testing of a prior theories or hypotheses of the relationships between variables. Exploratory testing makes no prior assumptions regarding the relationship between variables, thus the goal is to discover relationships. The process by which coefficients are tested for significance for inclusion or elimination from the model involves several different techniques. The most commonly used one will be mentioned below.

Likelihood-Ratio Test: this test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likehood function for the simpler model (L_0).

The likelihood-ratio test statistic equals:

$$-2\log\left(\frac{L_0}{L_1}\right) = -2\left[\log(L_0) - \log(L_1)\right] = -2(L_0 - L_1) \tag{11}$$

This log transformation of the likelihood functions yields a chi-squared statistic. This is the recommended test statistic to use when building a model through backward stepwise elimination.

2.4. Artificial Neural Networks

According to Cross et al. (1995), an artificial neural network consists of a set of processing units (nodes) which simulate neurons and are interconnected with a set of weights in such a way that allows signals to travel through the network in parallel as well as in series. The nodes are very simple computing elements and are based on the observation that a neuron behaves like a switch: when sufficient neurotransmitter has accumulated in the cell body, an action potential is generated. Neuron behavior has been mathematically modeled. Each node is initially weighted which this weight is equal to sum of all incoming signals to a node, and it is compared with a threshold. If the threshold is exceeded, the nodes fire, otherwise, it remains quiescent or inactive. Computational power in each node derives not from the complexity of each processing unit (as in conventional computers) but from the density and complexity of the interconnections. In further contrast with conventional computers, memory in a neural network is distributed through its structure and modified by experience.

The most widely used network model, the multi-layer perceptron, is represented in Figure 5. It has layers of nodes, represented as circles, joined by connection through which signals may be transmitted. On the top are input nodes for data. On the bottom are output nodes, which indicate the network's assessment of the likelihood of an order classification. The input and output nodes are linked by hidden layers of nodes; every node in a layer is connected with every node in the adjacent layer.

Each node sums the weight of signals which it receives from its input, thus mimicking the way that incoming nerve impulses are aggregated in biological neuron which will fire if these signals exceed the activation threshold (Fu, 1994).

As explained, each of the neurons receives inputs and delivers a single output. The input can be raw data or the output of some other neuron. The output can be the final output or it can be used into next neurons.

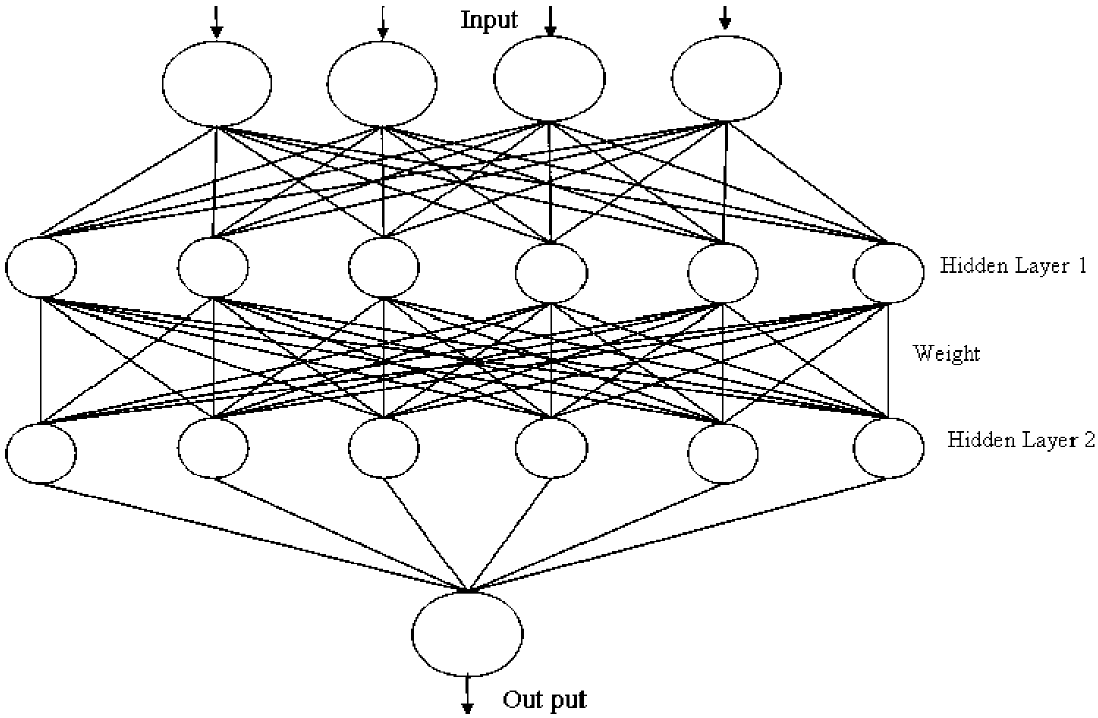

Figure 5: Structure of multi-layered type artificial neural network

2.4.1. Inputs

Each input corresponds to single attribute. Each attribute must be represented as a numeric value in order to be used as an input as neural network can process only numbers. If a problem-solving attempt included qualitative data or pictures, these must be converted to a type of numerical scale. Qualitative data can be converted to numeric with questions such as "How strongly did the respondent feel about this subject on a scale from one to ten". An interesting problem arises when some of neural network inputs are represented as pictures. Pictures must be converted to numeric data and a significant challenge is the design of suitable coding system so that the data can be used.

2.4.2. Transformation functions with weight and summations

Weights express the relative strength of the input data and attempt to describe the connection between layers. The weights are a mathematical attempt to establish and identify the relative importance of each input in determining the output. Weights are crucial as they store learned patterns of information through repeated adjustments. It is through the repeated adjustments that the network learns. The neural network is constantly changing and adjusting these weights as experience accumulates. The summation function computes the weighted sum of all the input elements entering the processing elements. This quantifies the impact that multiple neurons could have on a single processing element. This quantifies the impact that multiple neurons could have on a single processing element. The transformation function defines the relationships between the inputs and the final output. This relationship can be linear or non-linear and the selection of this mathematical equation can have an impact on the accuracy of the network. The sigmoid transfer function has been shown to work reliably and is the standard used in neural networks, but other transformation functions have been developed for specialized applications (Caudill, 1987).

2.4.3. Learning

The neural network learning process is when the software identifies patterns in the data that lead to certain outputs. The actual learning process starts with the setting of some values for the weights, either by known rules or randomly. The software then begins to compare the output using the initial weight against the desired output for the given set of inputs. The objective is to minimize the difference between the produced and the desired output by adjusting the weight on all the inputs. This learning process is usually accomplished on a set of data known as "training data". Training data is a collection of known inputs and outputs that represent the correct solution to the problem. Several iterations of the complete training data are required to produce a consistent set of weights (Principe et al, 2000).

Having the neural network with both known inputs and outputs is referred to as supervised learning. However, one of the strengths of neural network is its ability to do unsupervised learning. In unsupervised learning, only input data are shown to the work. The network becomes self-organizing; it organizes itself internally so that each processing element is optimized and responds to different sets of inputs. No knowledge is supplied about which outputs are correct and those that the network derives may or may not have meaning.

2.5. Conclusion

Finally, predictive analytics, into regression techniques and machine learning techniques, adds great value to a mining and filling engineering decision making capabilities by allowing it to formulate smart policies on the basis of predictions of future outcomes. A broad range of studies and techniques are available for this type of analysis. As previously mentioned different studies such as fall et al (2007), Wang et al (2007) and Rankine & Sivakugan (2005) applied the new techniques to optimize paste backfill recipe or predict paste backfill performance. However, the works which focused on the backfill are largely affected by subjectivity. In other words, all the mentioned studies used real tailings as a part of their experimental testing and it is proven that tailings from one area are different form another area.

In this chapter we presented the basic concept of predictive analytics and statistical techniques. In the next chapter, the application of the methodology developed is given in the form of a case study as well as obtained results and the main conclusions of this research.

CHAPTER 3. Problem statement, results, interpretation and discussion

3.1. Introduction

Paste backfill is a relatively new technology in some producing mines. Paste technology is gaining importance because of its economic and environmental advantages. Paste backfill is a pumpable and non Newtonian fluid consisting generally of mine tailings and cement. It is prepared from dilute slurries of tailings by using filters. Backfill with a paste consistency is prepared by mixing dewatered tailings with cement and water to obtain the desired consistency of medium slump concrete.

During the backfill design production, operational and closure health are important but the most important factor is to ensure the stability of the underground mine opening and to maximize the safe recovery ore. The technical design has to satisfy sufficient compression strength, technical consistency and high solid concentration with the optimal cost (Fall et al, 2007). These costs depend on the binder consumption and can be up to 80% of the total cost of cemented paste backfill.

Studies on the cemented backfill properties are still based on the traditional experimental methods. It is also proven that the strengths measured in laboratory for CPB are at least two to four times lower than the real values in mines (Belem et al 2002). Even in some mine design cases, the mine operators do not have either the facility or the finance to carry out all the site investigations and tests to obtain the input data required to run the computer programs developed. These lacks of engineering approach for defining the proportions of paste backfill are related to the mechanical properties of CPB placed underground. It means these properties are often affected by subjectivity and influenced by physical and chemical properties of cemented paste backfill ingredients (Benzaazoua et al, 2004):

As explained before, some methods same as Regression- Causal methods and Artificial Neural Network (ANN) are used to predict the performance of paste backfill.

In this work, the main objective is to propose a global machine tool by using neural network to predict the cemented paste backfill's UCS. Also, we study the effects of some physical and chemical parameters on the mechanical behaviors of cemented backfill by using artificial tailings for the first time.

In this chapter, we present the material and method, experimental procedure, applied artificial neural net work, obtained results, and at the end, the discussion on the results.

3.2. Material

The disposal of mill tailings is a major environmental problem which is becoming more serious with increasing social concerns. Tailings can be stored underground in the voids made by mining activities. The backfill tailings are generally mixed with a binder on the surface, and then transferred underground to fill voids and help support an underground mine. Note that the nature of tailings varies widely and it is hard to study a few specified parameters among all of them and obtain a global prediction tool. It is the main reason why we use silica as tailings in this study.

The methodology of this work contains two stages: experimental study which is illustrating the effect of the important chemical and physical properties of tailings, particle size and sulfate content, mixing water and binder by using silica as artificial tailings (Benzaazoua et al, 2004) and (Fall et al, 2007).

In the second part of this work, the obtained results, uniaxial compressive strength (UCS), are used to train and test the implemented neural networks. The obtained network can act as a computer tool to predict uniaxial compressive strength of cemented paste backfill.

The most important work in view of building an ANNs model is the selection of input variables (e.g., Kandil et al., 1999). In order to construct an artificial neural network model, the data set is obtained by a series of laboratory tests on the CPB samples. This work just considers few parameters among many that influence the mechanical resistance of backfill. Some of the other parameters are considered as fixed values. These parameters are the tailings density, the binder proportion which is 4.5 wt% of total mass of dry tailings, and the mixing water content, which is 24.35% and corresponding to a water-to-cement ratio of 7.5 for all the prepared batches. Also, no extra additive is used and no changes in temperature are considered here. However, more than six hundred samples were necessary to be prepared for the work purposes. The experimental program includes the preparation of 600 cemented paste backfill cylinders, each one with a 5.08 cm diameter and 10.16 cm heights. The preparation of each batch is done after the calculation of each ingredient's proportions to be used in the mixture. It has to be mentioned that all the calculations are based on the mass proportions. The quantity of silica powder is calculated based on its density, and the number of moulds per batch. Normally, tailings contain water which is necessary to consider during the preparation process. However, in this case, the silica is initially dry. The quantity of binder used for the recipe corresponds to the mass of used tailings. Here, the rate of binder equals to 4.5% of the total mass of the solid. By defining the total solid mass in the backfill, the only remaining term is the water quantity. The next step is to load the moulds and label them individually. Each label describes the recipe of the sample. Then, all the samples are transferred to the wet chamber. The wet chamber's temperature is around $25^{\circ}C$, and its humidity is 70%. These conditions are relatively close to the underground conditions.

After curing, the samples were subjected to Unconfined Compressive Strength tests (UCS). Each UCS value is the average strength obtained from three different moulds. It provides the opportunity to minimize the statistical error.

3.2.1. Tailings like material

The physical nature of the particles and the way they fit with each other and with binder hydrates influence the final mechanical properties of the paste backfill. The presence of fine particles can increase the UCS of paste backfill by filling the voids, increasing inter-particle connections, affecting the porosity and permeability (Hassani and Archibald, 1998).

As mentioned in the previous subsection, the parameters related to the tailings are considered as fixed values. To be able to study the influence of particle size distribution of tailings, two types of pure silica (Quartz) are used in this work:

- The SIL-CO-SIL 106 is used because its particle size distribution corresponds to the average particle size distribution of nine mines tailings in the Abitibi sector.
- The BARCO F110 has coarser particle size than SIL-CO-SIL 106.

In addition to their physical characteristics, these products have chemical characteristics which are appropriate for this study.

The particle size distribution of the tailings is the only parameter related to tailings, which is considered here. Four different particle size distributions are taken into account (G1, G2, G3 and G4) for the current work. These particle sizes cover a wide range of particle distributions observed for tailings produced by hard rock polymetallic mines. The G1 sample contains 72% of minus 20 µm grains (fine), G2 contains 45% of fine, G3 contains 32.5% of fine, and G4 contains 25% of fine. All the particle size characteristics are summarized in Table 3. The D_{50} vary between 8.4 µm (for the finer tailings G1) and 63.5 µm (for the coarser tailings G4).

Table 3: Particle Characteristic of Silica Powder

Particles	D_{10}	D_{30}	D_{50}	D_{60}	D_{90}	Cu	Cc
G1	0,94	3,10	8,40	11,00	38,00	**11,70**	**0,93**
G2	1,85	9,20	21,00	30,50	85,00	**16,49**	**1,50**
G3	2,70	18,05	40,50	58,00	160,00	**21,48**	**2,08**
G4	3,50	26,00	63,50	90,00	205,00	**25,71**	**2,15**

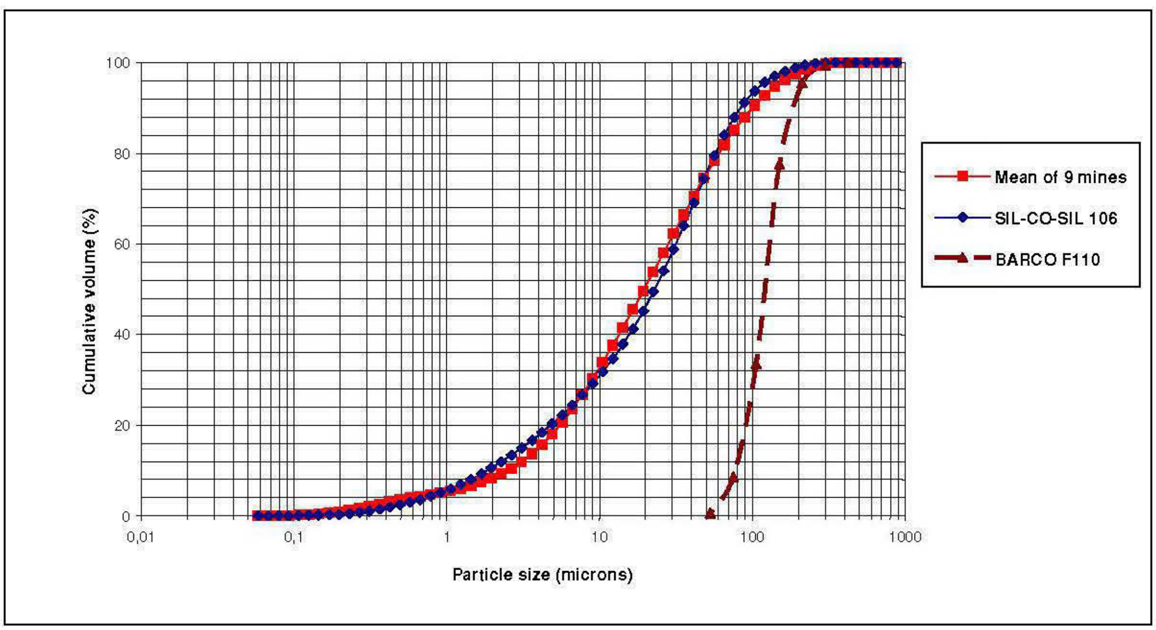

Figure 6: Particle size distribution of the silica products

Figure 6 and Figure 7 represent the particle size distribution curves, obtained by using the laser particle measurement instrument, and percentage for each diameter, respectively. Figure 8 shows the histogram of particle size distribution of used silica powder.

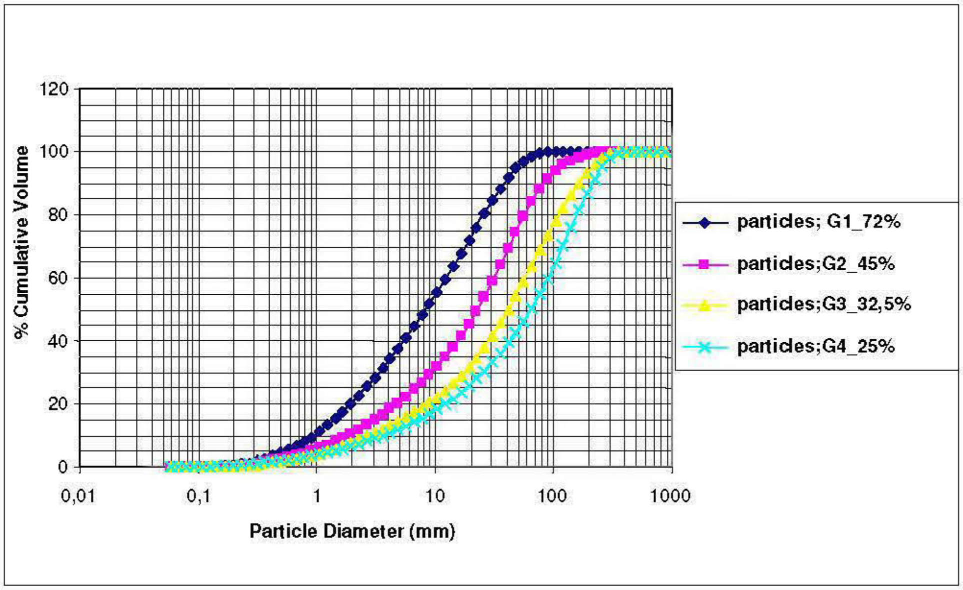

Figure 7: Particle size distribution curves

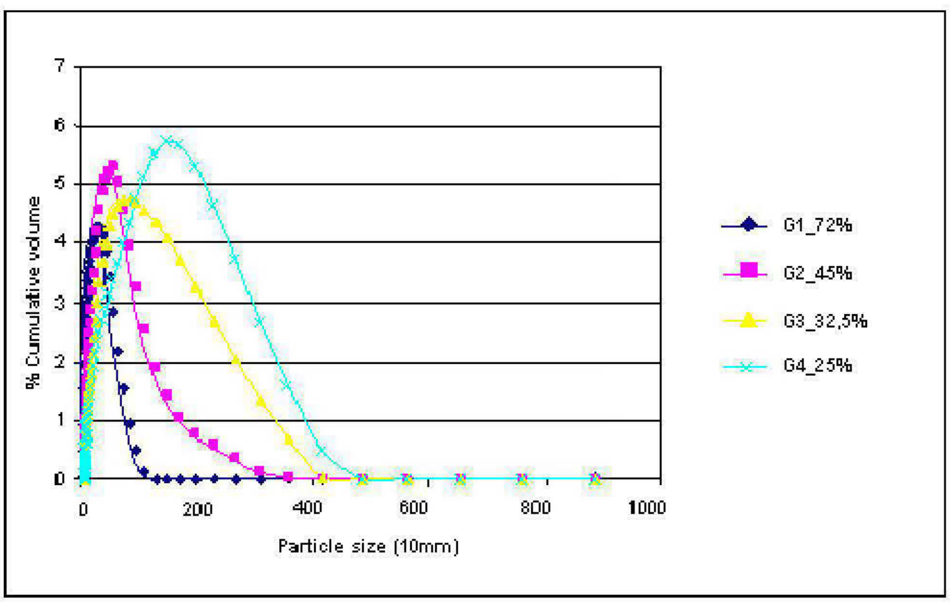

Figure 8: Histogram of Particle size distributions of the silica powder

3.2.2. Binding agent

The use of Portland cements and slag into mine backfill brings some advantages such as increasing the level interval, stope dimensions, and developing of bulk mining methods (Fall et al, 2005). The binders used in this work are standard Portland cement Type10 (CP 10), standard Portland cement Type 50 (CP50) and blast furnace slag. All binders are supplied by Lafarge Canada. The CP10 is the most common used binder in the mines, because of its effect on short term resistance and relatively low costs. The sulphates resistance property of CP50 is the main reason why this binder is chosen by those mines suffering from the reactivity of their tailings due to sulphates presence (Benzaazoua et al., 2004). The last but not the least one is slag based cements, which gives good long term resistance. It is popular for sulphidic mines as well. The two recipes that are used in this research project are:

- Standard Portland cement Type 10 and Standard cement Portland type 50 (50:50);
- Standard Portland cement Type 10 and slag (20:80);

3.2.3. Mixing water

Usually, within gold and polymetallic source tailings, there are a lot of sulphides. Two abundant sulphide minerals that have received the most attentions are pyrite and pyrrhotite. These minerals can react during the ore processing and produce sulphates (sulphide oxidation) that remain in the pore water after tailings filtration. It is also frequent, in the case of gold ore treated by cyanidation, that soluble sulphates concentration increases as the residual cyanide within tailings are often destroyed by SO_2 addition before backfilling (Benzaazoua et al., 2004).

Important volume of the mixing water during paste backfill preparation usually contains sulphates. The mixing water used in this research is pure distilled water where various concentrations of sulphate are added. It helps to obtain the mixing water with desired value of sulphate content. Sulphate effects on the backfill are very important due to their interferences with cement hydration processes (Benzaazoua et al., 2004).

The following sulphate contents were used in this work: 0ppm (representing the reference free sulphate water), 2500ppm, 5000ppm, 10000ppm and 15000ppm (representing the extreme sulphated water). These ranges of sulphate content also cover all the sulphate range usually present in the tailings. The desired rate of sulphate was obtained by adding $FeSo_4,7H_2o$ in the water, Table 4.

Table 4: Sulfate Concentration and Related Mass of $FeSo_4,7H_2o$

Sulfate concentration (PPM)	Mass of $FeSo_4,7H_2O$ gr
2,500	11.95
5,000	23.91
10,000	47.80
15,000	71.72

3.2.4. Artificial paste backfill preparation

Curing time is a key factor in terms of mechanical resistance development. It is all about studying the evolution of mechanical resistance of the backfill during curing time. The following curing times were chosen in this study: 7days, 28 days, 56 days, 90 days and 180 days. Note, that the short term mechanical resistance of paste backfill is important to design bulkheads and estimate the mine cycle's duration (Hassani and Archibald, 1998).

Finally, the preparation of each experimental batch is done after the calculation of each ingredient's proportions used in the mixture. It has to be mentioned that all the calculations are based on the mass proportions. The quantity of silica powder is calculated based on its density, and the number of moulds per batch. Normally, tailings contain water which is necessary to consider during the preparation process. However, in this case, the silica is dry. The quantity of binder used for the recipe corresponds to the mass of used tailings. Here, the rate of binder equals 4.5% of the total mass of the solid. By defining the total solid mass in the backfill, the only remaining term is the water quantity. The mass proportions of all ingredients used in the composition of backfill are carefully and separately prepared in the laboratory.

The mass of tailings for each mixture is 4911 gr;

The mass of hydraulic binder for each mixture is 221 ; gr

The volume water used for each sample is 1652 cm^3;

When all the parameters are defined, a series of experiments were designed for various mixtures to obtain the expected results. For this study, a total of 40 batches were prepared and there are a total number of 600 moulds, Table 5. Figure 9 presents all the parameters used in this work.

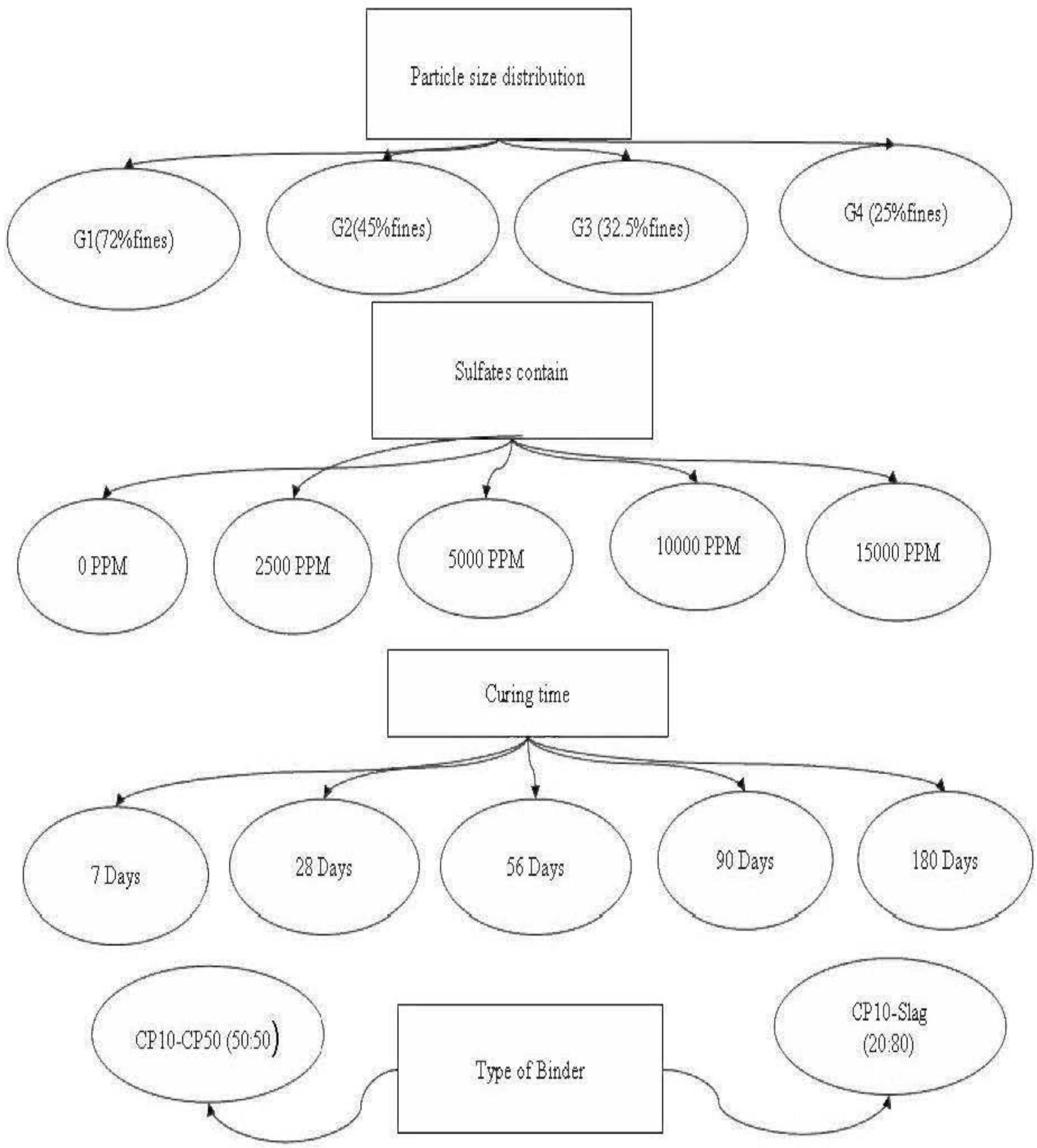

Figure 9: Chemical and physical factors which were considered to prepare laboratory samples

Table 5: Mixture Applied in this Work

Name of the mixture	Tailings	Binder	% Fine	Sulfates contain (ppm)
Silica G1-0ppm-CP10/CP50 (50/50)	G1 (72%)	CP10 -CP50	72%	0
Silica G1-2500ppm-CP10/CP50 (50/50)	G1 (72%)	CP10 -CP50	72%	2500
Silica G1-5000ppm-CP10/CP50 (50/50)	G1 (72%)	CP10 -CP50	72%	5000
Silica G1-10000ppm-CP10/CP50 (50/50)	G1 (72%)	CP10 -CP50	72%	10000
Silica G1-15000ppm-CP10/CP50 (50/50)	G1 (72%)	CP10 -CP50	72%	15000
Silica G1-0ppm-CP10/Slag (20/80)	G1 (72%)	CP10 - Slag	72%	0
Silica G1-2500ppm-CP10/Slag (20/80)	G1 (72%)	CP10 - Slag	72%	2500
Silica G1-5000ppm-CP10/Slag (20/80)	G1 (72%)	CP10 - Slag	72%	5000
Silica G1-10000ppm-CP10/Slag (20/80)	G1 (72%)	CP10 - Slag	72%	10000
Silica G1-15000ppm-CP10/Slag (20/80)	G1 (72%)	CP10 - Slag	72%	15000
Silica G2-0ppm-CP10/CP50 (50/50)	G2 (45%)	CP10 -CP50	45%	0
Silica G2-2500ppm-CP10/CP50 (50/50)	G2 (45%)	CP10 -CP50	45%	2500
Silica G2-5000ppm-CP10/CP50 (50/50)	G2 (45%)	CP10 -CP50	45%	5000
Silica G2-10000ppm-CP10/CP50 (50/50)	G2 (45%)	CP10 -CP50	45%	10000
Silica G2-15000ppm-CP10/CP50 (50/50)	G2 (45%)	CP10 -CP50	45%	15000
Silica G2-0ppm-CP10/Slag (20/80)	G2 (45%)	CP10 - Slag	45%	0
Silica G2-2500ppm-CP10/Slag (20/80)	G2 (45%)	CP10 - Slag	45%	2500
Silica G2-5000ppm-CP10/Slag (20/80)	G2 (45%)	CP10 - Slag	45%	5000
Silica G2-10000ppm-CP10/Slag (20/80)	G2 (45%)	CP10 - Slag	45%	10000
Silica G2-15000ppm-CP10/Slag (20/80)	G2 (45%)	CP10 - Slag	45%	15000
Silica G3-0ppm-CP10/CP50 (50/50)	G3 (32,5%)	CP10 -CP50	32,5%	0
Silica G3-2500ppm-CP10/CP50 (50/50)	G3 (32,5%)	CP10 -CP50	32,5%	2500
Silica G3-5000ppm-CP10/CP50 (50/50)	G3 (32,5%)	CP10 -CP50	32,5%	5000
Silica G3-10000ppm-CP10/CP50 (50/50)	G3 (32,5%)	CP10 -CP50	32,5%	10000
Silica G3-15000ppm-CP10/CP50 (50/50)	G3 (32,5%)	CP10 -CP50	32,5%	15000
Silica G3-0ppm-CP10/Slag (20/80)	G3 (32,5%)	CP10 - Slag	32,5%	0
Silica G3-2500ppm-CP10/Slag (20/80)	G3 (32,5%)	CP10 - Slag	32,5%	2500
Silica G3-5000ppm-CP10/Slag (20/80)	G3 (32,5%)	CP10 - Slag	32,5%	5000
Silica G3-10000ppm-CP10/Slag (20/80)	G3 (32,5%)	CP10 - Slag	32,5%	10000
Silica G3-15000ppm-CP10/Slag (20/80)	G3 (32,5%)	CP10 - Slag	32,5%	15000
Silica G4-0ppm-CP10/CP50 (50/50)	G4 (25%)	CP10 -CP50	25%	0
Silica G4-2500ppm-CP10/CP50 (50/50)	G4 (25%)	CP10 -CP50	25%	2500
Silica G4-5000ppm-CP10/CP50 (50/50)	G4 (25%)	CP10 -CP50	25%	5000
Silica G4-10000ppm-CP10/CP50 (50/50)	G4 (25%)	CP10 -CP50	25%	10000
Silica G4-15000ppm-CP10/CP50 (50/50)	G4 (25%)	CP10 -CP50	25%	15000
Silica G4-0ppm-CP10/Slag(20/80)	G4 (25%)	CP10 - Slag	25%	0
Silica G4-2500ppm-CP10/Slag (20/80)	G4 (25%)	CP10 - Slag	25%	2500
Silica G4-5000ppm-CP10/Slag (20/80)	G4 (25%)	CP10 - Slag	25%	5000
Silica G4-10000ppm-CP10/Slag (20/80)	G4 (25%)	CP10 - Slag	25%	10000
Silica G4-15000ppm-CP10/Slag (20/80)	G4 (25%)	CP10 - Slag	25%	15000

3.3. Method

3.3.1. Unconfined compression tests

A mechanical resistance test is applied to all the samples to obtain UCS (unconfined compressive strength) at each specified curing time. To determine the UCS, a mechanical press MTS 10/GL is used at 1 mm/min deformation rate. As explained before, to avoid possible errors, each outcome is the average of three related UCS tests.

Figure 10 is a simplified representation of the unconfined compression test. Before the test, for each cylinder, the mass is recorded as well as the size of the sample. At the end, the wet mass of the mould is stored, which helps to compute the water content of samples. The next step is to dry the samples. They are placed in the drying oven at 45°C for a period of seven days.

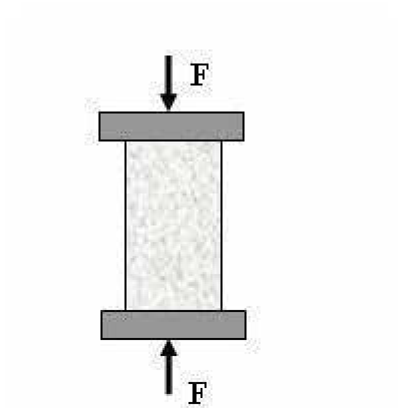

Figure 10: Simplified diagram of unconfined compression test to obtain UCS value

3.4. Model development of Artificial Neural Networks (ANNs)

ANNs have been developed as a generalization of mathematical models of human cognition biology. However, the most powerful super-computer of today can not match a human brain in terms of connectivity and complexity. Therefore, an ANN is considered as an extremely simplified biological neural system model.

3.4.1. Artificial Neuron (node)-Mathematical aspects

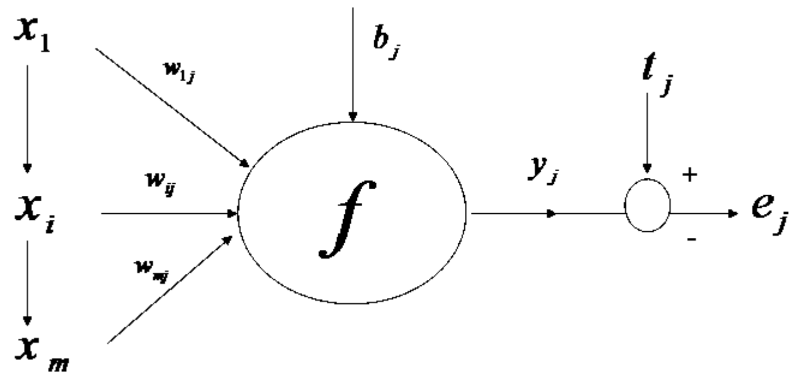

Figure 11: Mathematical model of an ANN neuron.

A node is a fundamental component of an artificial neural network. The schematic diagram of a typical $j-th$ node is displayed in Figure 11 (Chen et al, 2001). The inputs to such a node may come from system causal variables or outputs of other nodes, depending on which layer the node is located in. These inputs form an input vector $X=(x_1,...,x_i,...,x_m)$. The sequence of weights leading to the node form a weight vector $W_j=(w_{j1},...,w_{ji},...,w_{jm})$ where w_{ji} represents the connection weight from the $i-th$ node in the preceding layer to this node. The output of node j, y_j is obtained by computing the value of nonlinear function $f(\bullet)$ with respect to the inner product of vector X and W_j minus b_j,where b_j is the threshold value, also called the bias, associated with this node. A bias is often used to offset the total input to a neuron. The following equation defines the operation:

$$y_j = f(X \times W_j - b_j) \qquad (12)$$

If neuron j is the output layer, its output is compared to the target values t_j to evaluate the corresponding error $e_j=(t_j-y_j)$, which will be used in training procedure.

The function $f(\bullet)$ is called an activation function. Its functional form determines the response of a node to the total input signal it receives. The most commonly used form of $f(\bullet)$ is sigmoid function given as:

$$f(t) = \frac{1}{1+e^{-t}} \tag{13}$$

The sigmoid function is a bounded, monotonic, non-decreasing function that enables the network to map a nonlinear process. However, sigmoid function used as activation function here and Input parameters are particle size, sulphate content, binder type and curing time. Other parameters are set as a part of programming steps.

3.4.2. Structure of Multi-Layered perception type ANN

Multi–layered percepton (MLP) artificial neural networks consist of several layers; one input layer, one or more hidden layers, and one output layer as depicted in Figure 5. Neurons in a layer are interconnected generally to all the neurons in adjacent layer. Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer.

Input variables were obtained from a series of lab tests corresponding to the factors that affect the UCS. The outputs are the desired forecasting results. The number of inputs, the number of hidden nodes, transfer function, and training methods, affect the performance of network needed to be chosen carefully.

3.4.3. Network training

For a neural network, learning is acquiring ability to generalize a relationship from input-output vector pairs. In order for an ANN to generate an output vector $Y = (y_1, y_2, ..., y_p)$, that is as close as possible to the target vector $T = (t_1, t_2, ..., t_p)$, a training algorithm is designed to find optimal weight matrices W and bias vectors B, that minimize a pre-determined error function that usually has the form:

$$\varepsilon = \frac{1}{N} \sum_{N} \left(\frac{1}{2} \sum_{p} e_j^2 \right) \tag{14}$$

$$e_j = t_j - y_j$$

Here t_j is the component of desired output, y_j is the corresponding ANN output, p is the number of output nodes, N is the number of training patterns and e_j is the output error for neuron j. During training, the connection weights of an ANN are modified in an iterative fashion to minimize the error function.

Back-propagation is perhaps the most popular and fundamental algorithm for training ANNs. Back propagation is also used here as the training method, which is an iterative procedure that has three steps during each iteration (Chen et al, 2001):

1. Forward: the outputs are calculated for given inputs
2. Backward: the error at the output layers are propagated backwards toward the input layer, with the partial derivatives of the performance with respect to the weights and biases calculated in each layer
3. Weight adjustment: a multivariate nonlinear numeric optimization algorithm finds the weight that minimizes the error based on the gradient.

The training process is stopped when no appreciable change is observed in the values associated with the connection links or some termination criterion is satisfied. The delta rule postulates that the amount of weight adjustment is proportional to the rate of the total error change. However, instead of applying the steepest descent method characterized by slow convergence and long training time, an approximation of Newton's method called Levenberg-Marquardt algorithm is used here. The following equations explain the mathematical notation of Levenberg-Marquardt algorithm (Kandil et al, 1999):

$$E(\underline{W} + \Delta\underline{W}) = E(\underline{W}) + \frac{\partial E}{\partial W}\Delta\underline{W} + (higherterms) \qquad (15)$$

$$E(\underline{W} + \Delta\underline{W}) = E(\underline{W}) + \underline{J}^t\Delta\underline{W} + (higherterms) \qquad (16)$$

$\underline{W}$ is a vector containing all the weights in the net-work, and $\underline{J}$ is the Jacobian vector of derivative of the error to each weight.

Considering only the first derivative and by dropping higher terms, the error may be given by:

$$E(\underline{W} + \Delta\underline{W}) = E(\underline{W}) + \underline{J}^t\Delta\underline{W} \qquad (17)$$

The goal is to eliminate this error then:

$$E(\underline{W}+\Delta\underline{W}) = E(\underline{W}) + \underline{J}^t\Delta\underline{W} = 0 \tag{18}$$

$$\underline{J}^t\Delta\underline{W} = -E(\underline{W}) \tag{19}$$

Multiplying both side of equation (18) by $\underline{J}$ and solving for $\Delta\underline{W}$ gives:

$$\Delta\underline{W} = -\left[\underline{J}\,\underline{J}^t\right]^{-1}\underline{J}E(\underline{W}) \tag{20}$$

The problem here is that the matrix $\left[\underline{J}\,\underline{J}^t\right]$ is singular and has no inverse, however the singularity may be eliminated and a solution can be found by:

$$\Delta\underline{W} = -\left[\left[\underline{J}\,\underline{J}^t\right] + \mu[I]\right]^{-1}\underline{J}E(\underline{W}) \tag{21}$$

Where μ is scalar and $[I]$ is the unity matrix (Kandil et al, 1999).

3.5. Experimental Results

3.5.1. Database obtained

As explained before more than six hundred samples were prepared for this study in the URSTM lab. All the obtained results (UCS), by using press MTS 10/GL, for the experimental batches are recorded and presented in Table 6 to Table 10.

Table 6: UCS for 7 Days, 4.5% binder and 75,65% solid

	Recipe	Binder type	E/C	% Fine	Sulfate (ppm)	UCS (kPa)
Particle Size G1	Silice G1-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	0	872.9
	Silice G1-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	2500	918.9
	Silice G1-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	5000	964.3
	Silice G1-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	10000	1172.6
	Silice G1-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	15000	1182.0
	Silice G1-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	72	0	659.4
	Silice G1-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	2500	561.1
	Silice G1-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	5000	45.0
	Silice G1-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	10000	41.0
	Silice G1-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	15000	36.9
Particle Size G2	Silice G2-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	0	289.6
	Silice G2-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	2500	387.5
	Silice G2-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	5000	403.8
	Silice G2-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	10000	364.1
	Silice G2-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	15000	246.0
	Silice G2-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	45	0	675.7
	Silice G2-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	2500	830.3
	Silice G2-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	5000	589.2
	Silice G2-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	10000	73.0
	Silice G2-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	15000	45.0
Particle Size G3	Silice G3-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	0	330.1
	Silice G3-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	2500	360.0
	Silice G3-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	5000	529.0
	Silice G3-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	10000	376.7
	Silice G3-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	15000	180.4
	Silice G3-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	32.5	0	712.0
	Silice G3-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	2500	816.8
	Silice G3-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	5000	434.8
	Silice G3-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	10000	65.8
	Silice G3-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	15000	42.4
Particle Size G4	Silice G4-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	0	222.5
	Silice G4-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	2500	453.3
	Silice G4-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	5000	357.6
	Silice G4-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	10000	182.3
	Silice G4-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	15000	97.4
	Silice G4-0ppm-CP10/Slag(50/50)	CP10 - Slag	7.47	25	0	480.5
	Silice G4-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	2500	877.0
	Silice G4-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	5000	792.1
	Silice G4-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	10000	136.0
	Silice G4-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	15000	41.8

Table 7: UCS for 28 Days, 4.5% binder and 75,65% solid

	Recipe	Binder type	E/C	% Fine	Sulfate (ppm)	UCS (kPa)
Particle Size G1	Silice G1-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	0	1969.97
	Silice G1-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	2500	2352.89
	Silice G1-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	5000	2403.16
	Silice G1-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	10000	2747.05
	Silice G1-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	15000	2331.58
	Silice G1-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	72	0	1942.06
	Silice G1-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	2500	1589.84
	Silice G1-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	5000	800.00
	Silice G1-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	10000	232.88
	Silice G1-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	15000	77.05
Particle Size G2	Silice G2-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	0	488.15
	Silice G2-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	2500	858.69
	Silice G2-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	5000	883.85
	Silice G2-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	10000	884.48
	Silice G2-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	15000	978.90
	Silice G2-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	45	0	961.09
	Silice G2-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	2500	1377.70
	Silice G2-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	5000	1922.88
	Silice G2-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	10000	670.37
	Silice G2-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	15000	196.57
Particle Size G3	Silice G3-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	0	550.00
	Silice G3-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	2500	749.16
	Silice G3-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	5000	803.35
	Silice G3-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	10000	845.51
	Silice G3-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	15000	727.56
	Silice G3-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	32.5	0	933.94
	Silice G3-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	2500	1390.58
	Silice G3-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	5000	1657.60
	Silice G3-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	10000	723.99
	Silice G3-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	15000	272.71
Particle Size G4	Silice G4-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	0	373.82
	Silice G4-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	2500	750.43
	Silice G4-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	5000	676.42
	Silice G4-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	10000	548.65
	Silice G4-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	15000	460.55
	Silice G4-0ppm-CP10/Slag(50/50)	CP10 - Slag	7.47	25	0	809.68
	Silice G4-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	2500	1336.03
	Silice G4-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	5000	1843.81
	Silice G4-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	10000	913.81
	Silice G4-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	15000	388.32

Table 8: UCS for 56 Days, 4.5% binder and 75,65% solid

	Recipe	Binder type	E/C	% Fine	sulfates (ppm)	UCS (kPa)
Particle Size G1	Silice G1-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	0	2527.2
	Silice G1-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	2500	3369.5
	Silice G1-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	5000	3335.8
	Silice G1-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	10000	3541
	Silice G1-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	15000	3225.6
	Silice G1-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	72	0	2476.6
	Silice G1-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	2500	2070
	Silice G1-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	5000	1261
	Silice G1-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	10000	144.3
	Silice G1-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	15000	211.5
Particle Size G2	Silice G2-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	0	772.3
	Silice G2-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	2500	1150
	Silice G2-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	5000	1235
	Silice G2-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	10000	1500
	Silice G2-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	15000	1600
	Silice G2-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	45	0	1208
	Silice G2-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	2500	1846
	Silice G2-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	5000	2591
	Silice G2-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	10000	1105.6
	Silice G2-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	15000	447.3
Particle Size G3	Silice G3-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	0	690
	Silice G3-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	2500	947
	Silice G3-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	5000	1107.3
	Silice G3-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	10000	1252
	Silice G3-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	15000	1272.8
	Silice G3-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	32.5	0	1128
	Silice G3-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	2500	1702
	Silice G3-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	5000	2210
	Silice G3-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	10000	1155.5
	Silice G3-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	15000	489.8
Particle Size G4	Silice G4-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	0	500
	Silice G4-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	2500	900
	Silice G4-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	5000	851.3
	Silice G4-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	10000	723.6
	Silice G4-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	15000	651.6
	Silice G4-0ppm-CP10/Slag(50/50)	CP10 - Slag	7.47	25	0	994.9
	Silice G4-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	2500	1600
	Silice G4-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	5000	2400
	Silice G4-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	10000	1321.6
	Silice G4-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	15000	144.3

Table 9: UCS for 90 Days, 4.5% binder and 75,65% solid

	Recipe	Binder type	E/C	% Fine	sulfates (ppm)	UCS (kPa)
Particle Size G1	Silice G1-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	0	3000
	Silice G1-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	2500	3647.8
	Silice G1-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	5000	3466.3
	Silice G1-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	10000	3776
	Silice G1-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	15000	3000
	Silice G1-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	72	0	2650
	Silice G1-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	2500	2105.3
	Silice G1-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	5000	1696
	Silice G1-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	10000	160
	Silice G1-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	15000	228
Particle Size G2	Silice G2-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	0	923.3
	Silice G2-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	2500	1464.3
	Silice G2-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	5000	1588.6
	Silice G2-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	10000	1890
	Silice G2-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	15000	1983
	Silice G2-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	45	0	1466.3
	Silice G2-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	2500	2079
	Silice G2-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	5000	2925.6
	Silice G2-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	10000	1376.75
	Silice G2-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	15000	600
Particle Size G3	Silice G3-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	0	822.6
	Silice G3-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	2500	1150
	Silice G3-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	5000	1371
	Silice G3-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	10000	1590
	Silice G3-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	15000	1620.3
	Silice G3-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	32.5	0	1151
	Silice G3-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	2500	1922.8
	Silice G3-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	5000	2350
	Silice G3-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	10000	1352.3
	Silice G3-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	15000	526.5
Particle Size G4	Silice G4-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	0	601.8
	Silice G4-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	2500	1012.9
	Silice G4-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	5000	987.8
	Silice G4-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	10000	900
	Silice G4-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	15000	865.3
	Silice G4-0ppm-CP10/Slag(50/50)	CP10 - Slag	7.47	25	0	1001.2
	Silice G4-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	2500	1684
	Silice G4-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	5000	2737
	Silice G4-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	10000	1383.7
	Silice G4-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	15000	916.1

Table 10: UCS for 180 Days, 4.5% binder and 75,65% solid

	Recipe	Binder type	E/C	% Fine	sulfates (ppm)	UCS (kPa)
Particle Size G1	Silice G1-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	0	3457
	Silice G1-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	2500	3583
	Silice G1-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	5000	3618.6
	Silice G1-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	10000	4122.8
	Silice G1-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	72	15000	3708.9
	Silice G1-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	72	0	3251.5
	Silice G1-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	2500	2370
	Silice G1-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	5000	2521
	Silice G1-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	10000	188.25
	Silice G1-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	72	15000	406.34
Particle Size G2	Silice G2-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	0	1339
	Silice G2-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	2500	2519.6
	Silice G2-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	5000	2352
	Silice G2-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	10000	2390
	Silice G2-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	45	15000	2596
	Silice G2-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	45	0	1943
	Silice G2-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	2500	2192.3
	Silice G2-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	5000	3206.4
	Silice G2-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	10000	2100
	Silice G2-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	45	15000	1021.3
Particle Size G3	Silice G3-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	0	1255
	Silice G3-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	2500	1737
	Silice G3-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	5000	2067.3
	Silice G3-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	10000	2237
	Silice G3-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	32.5	15000	2139
	Silice G3-0ppm-CP10/Slag (50/50)	CP10 - Slag	7.47	32.5	0	1206
	Silice G3-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	2500	2210
	Silice G3-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	5000	2819.6
	Silice G3-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	10000	1627.4
	Silice G3-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	32.5	15000	906.5
Particle Size G4	Silice G4-0ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	0	778
	Silice G4-2500ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	2500	1378
	Silice G4-5000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	5000	1325
	Silice G4-10000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	10000	1334
	Silice G4-15000ppm-CP10/CP50 (50/50)	CP10 -CP50	7.47	25	15000	1494.3
	Silice G4-0ppm-CP10/Slag(50/50)	CP10 - Slag	7.47	25	0	1071
	Silice G4-2500ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	2500	1859.6
	Silice G4-5000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	5000	3042
	Silice G4-10000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	10000	1537.5
	Silice G4-15000ppm-CP10/Slag (20/80)	CP10 - Slag	7.47	25	15000	1000

3.5.2. Time dependant backfill performance

In this study, attention is paid to the strength as only output parameter. In general, the mechanical resistance of cemented backfill increases with the curing time; this is what commonly called the hardening process. It is proven that the UCS after 100 days of curing period may have the maximum strength and must fit with the mining design targeted values.

Figure 12 to Figure 15 present the obtained UCS according to curing days for samples prepared with CP10-CP50 binder and with different particle sizes. One can observe that for the G1 samples (containing 72% of fine particles) the sample with 10,000ppm sulphate has the best performance. That means, this particle size distribution corresponds to an optimal gradation for this recipe and that this specific sulphate concentration contributed to the paste backfill hardening. Coarser particle size distribution affects negatively the strength acquisition of the tested backfills. One can also deduce that sulphate concentration has not a significant effect on the hardening processes and that a plateau in terms of strength was reached for the sample made with the finer tailings G1 but not for the other tailings studied (G2, 3 and 4).

For samples prepared with CP10-Slag, the obtained results for UCS according to the curing days are presented in Figure 16 to Figure 19. The results show that UCS increases with curing time. Sulphate concentration of the mixing water seems to have more effect on CP10-Slag than its effect on the other binders (except for the finer tailings (G1)). However, 15,000ppm sulphates is high concentration and leads to strength loose. The best strength obtained corresponds to the coarser tailings, differently than for Portland cement-based recipe, and free sulphate mixing water.

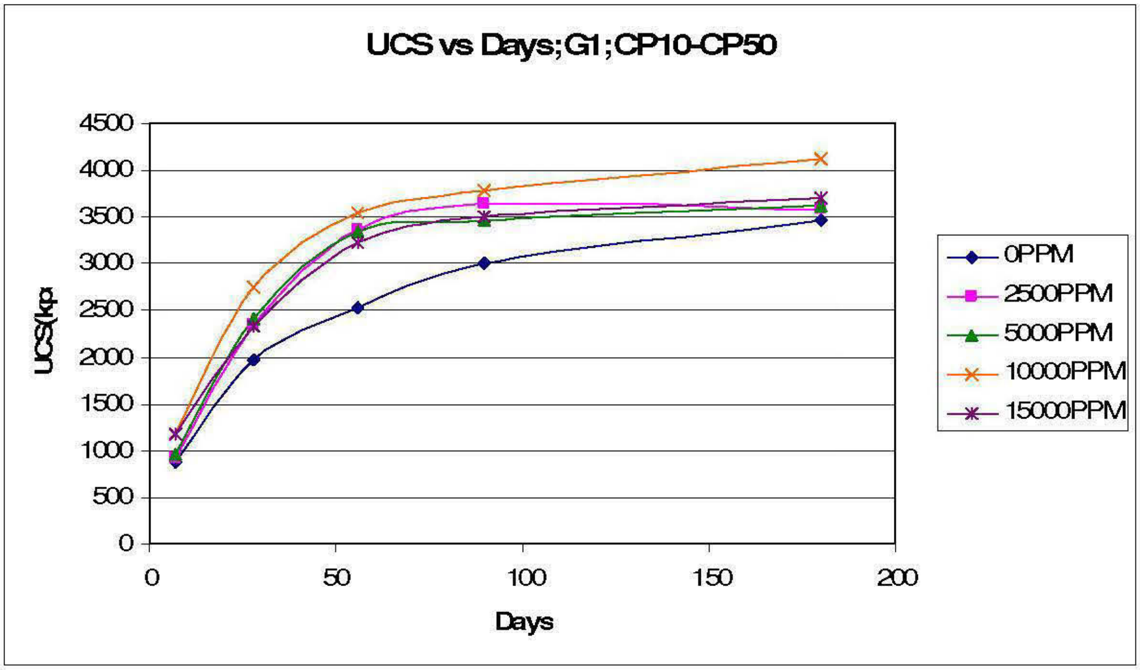

Figure 12: UCS vs Days for 72% fine particles; CP10:CP50

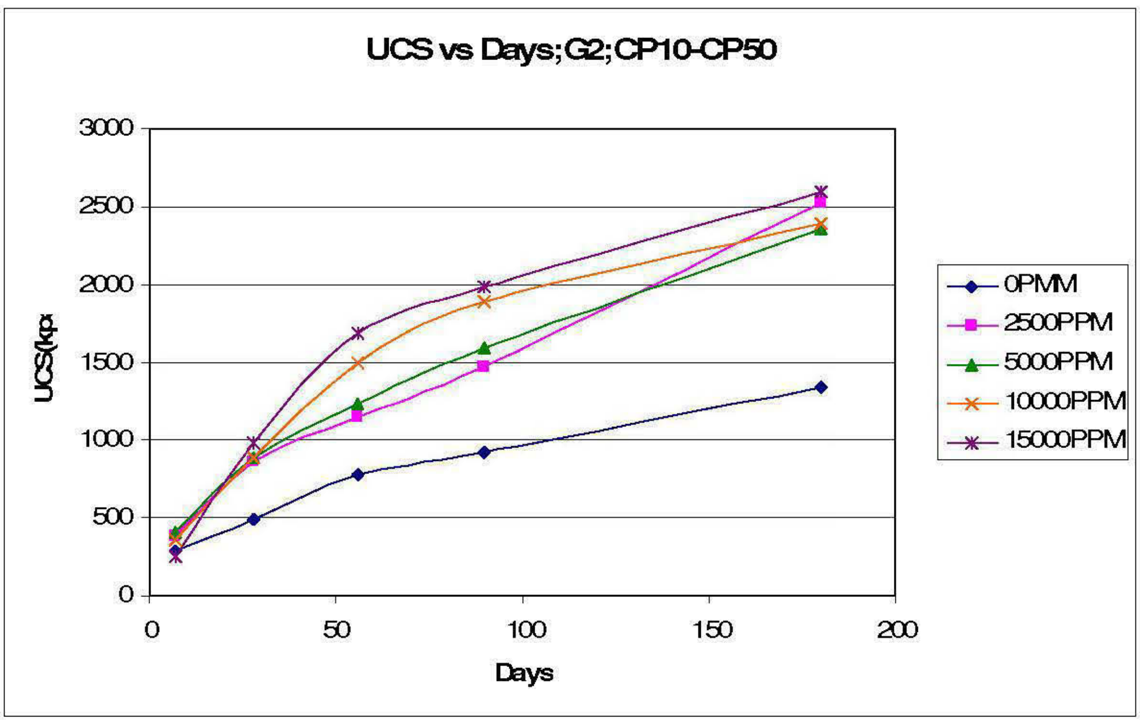

Figure 13: UCS vs Days for 45% fine particles; CP10:CP50

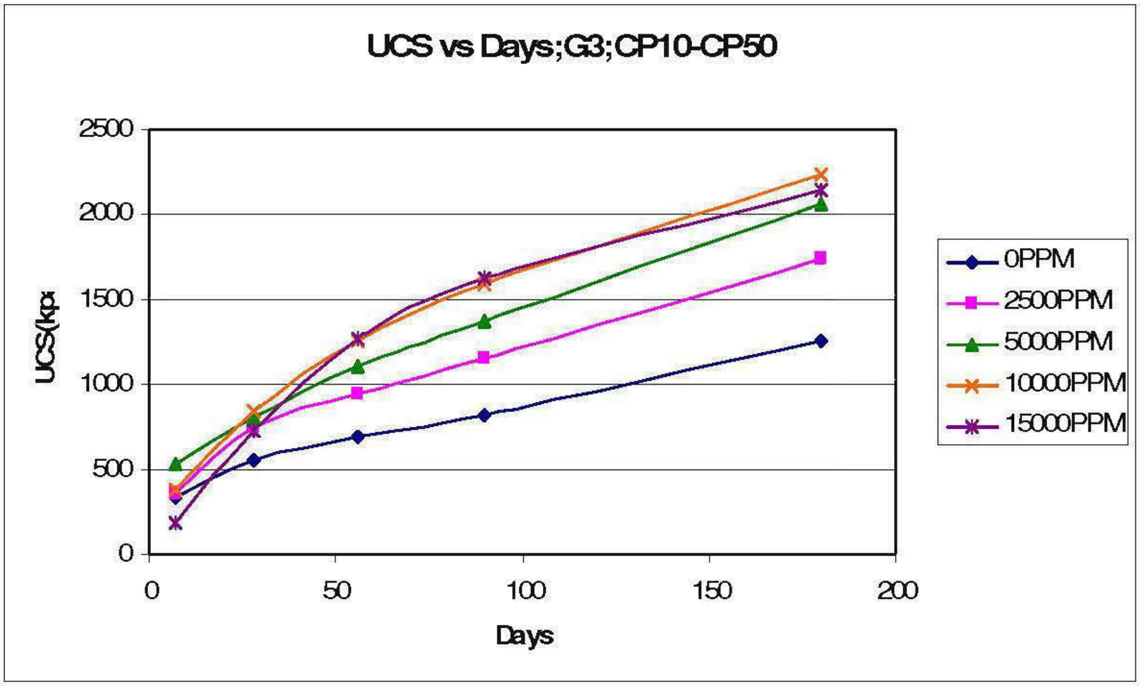

Figure 14: UCS vs Days for 32% fine particles; CP10:CP50

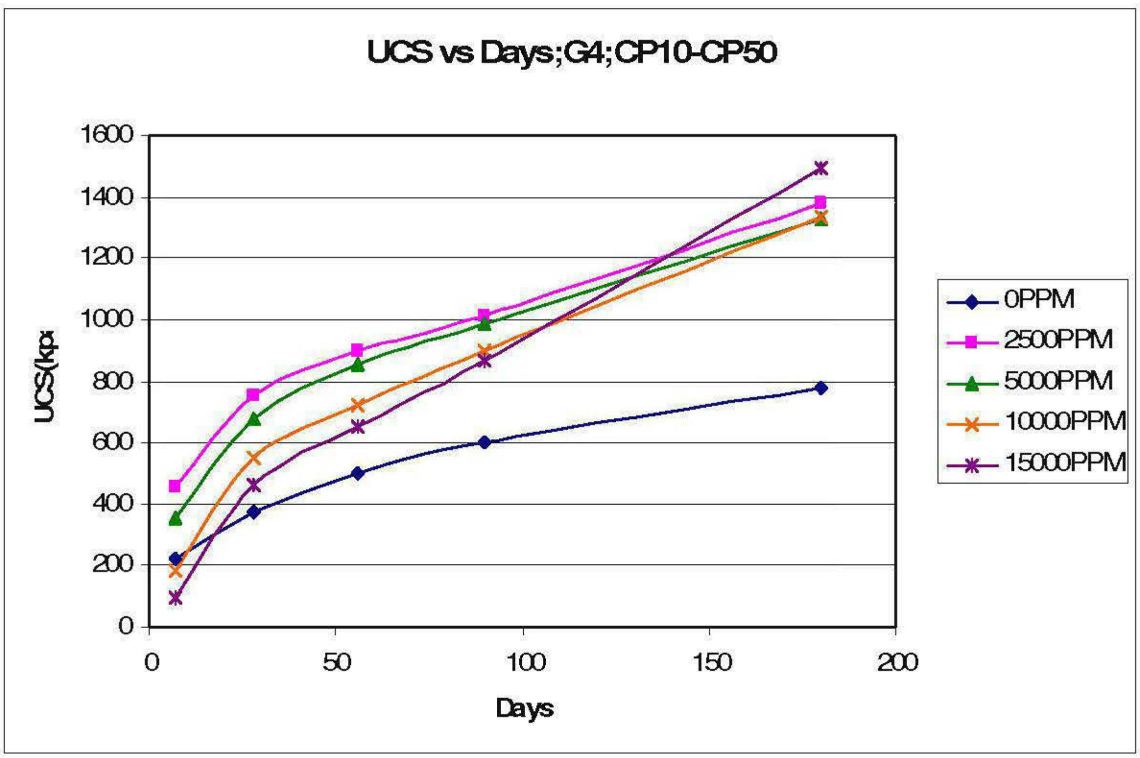

Figure 15: UCS vs Days for 25% fine particles; CP10:CP50

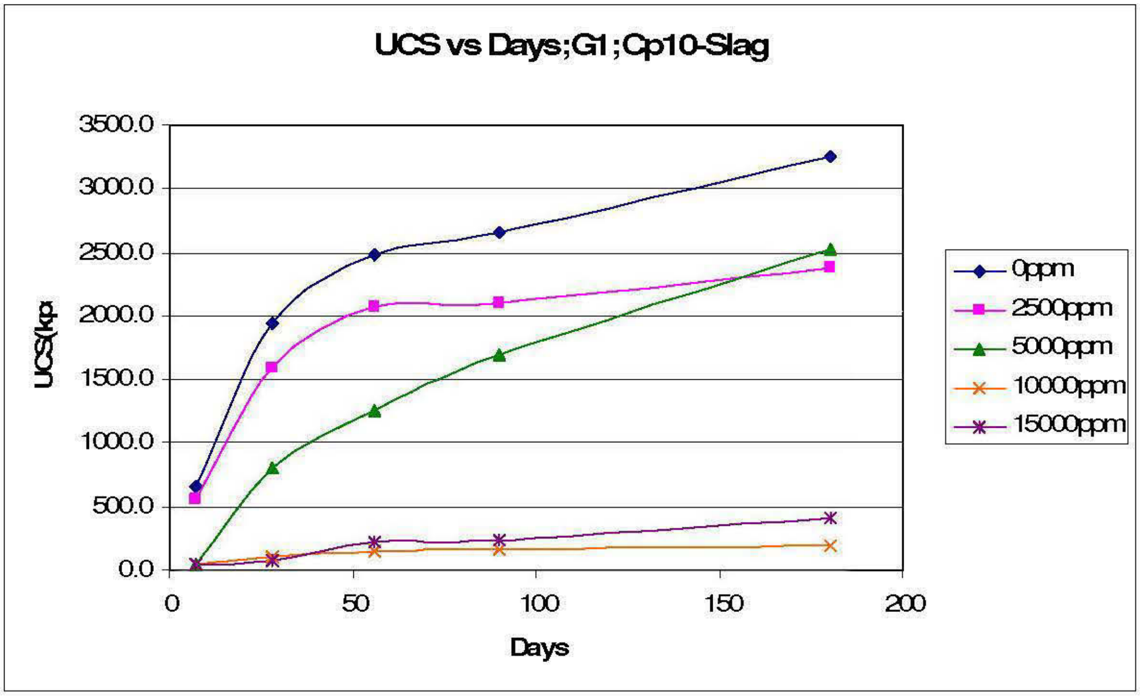

Figure 16: UCS vs Days for 72% fine particles; CP10: Slag

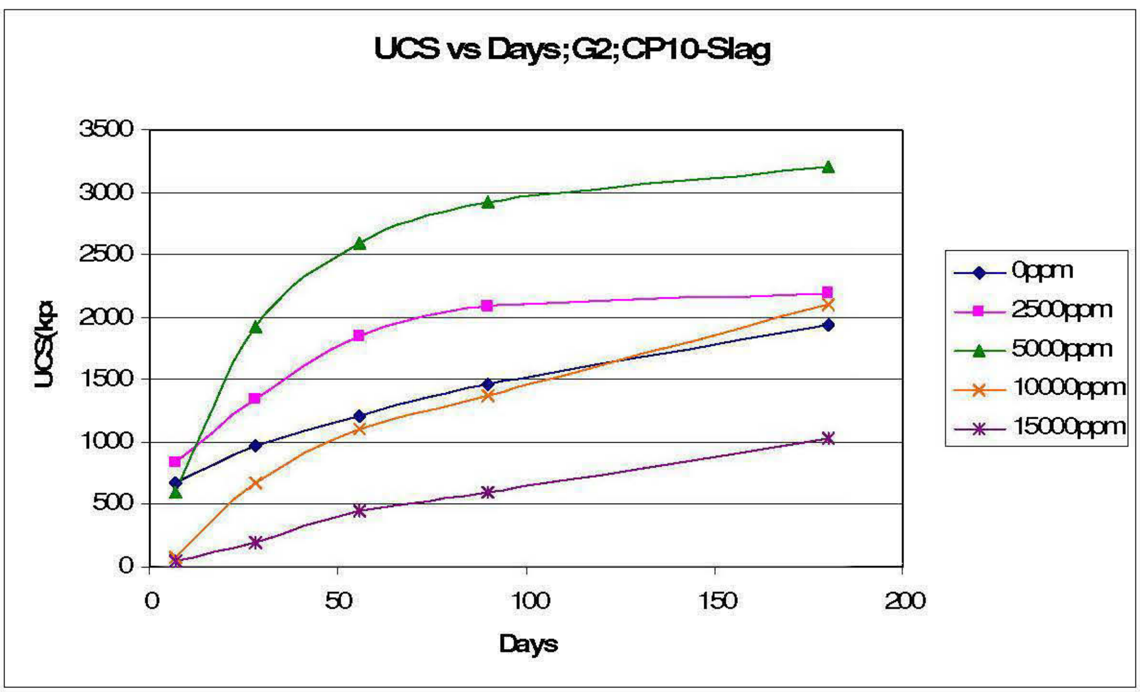

Figure 17: UCS vs Days for 45% fine particles; CP10: Slag

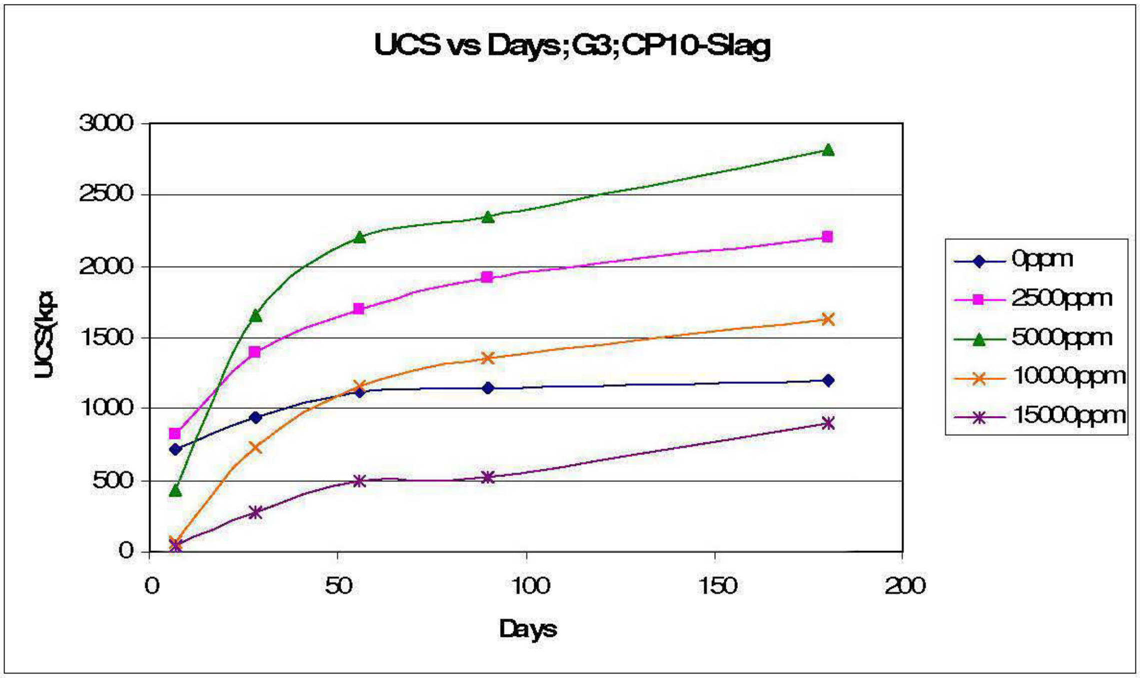

Figure 18: UCS vs Days for 32% fine particles; CP10: Slag

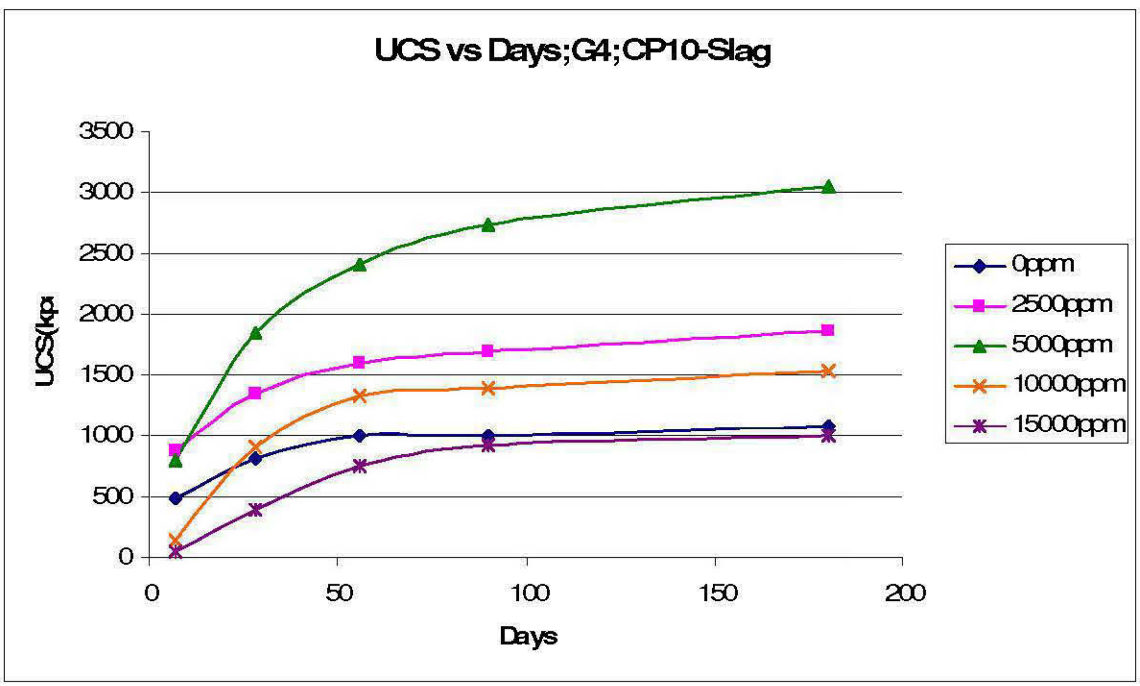

Figure 19: UCS vs Days for 25% fine particles: CP10: Slag

3.5.3. Influence of binder on backfill

Surprisingly the recipe with 75% of fines and CP10-CP50 gives the best UCS. Normally, the UCS is higher for CP10-Slag binder than CP10-CP50 when the sulfates content are lower than 2500 PPM, as shown in Figure 20 to Figure 24. It is important to remember that UCS decreases for CP10-Slag when sulfate content increases. In other words, CP10-CP50 has better UCS performance for rich sulfates tailings.

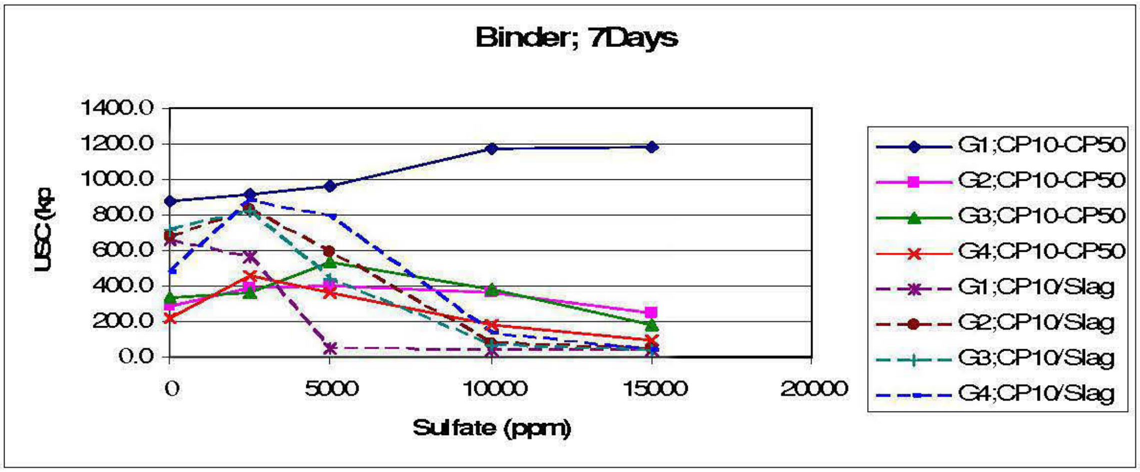

Figure 20: UCS according to the content sulfates for the CP10-CP50 and CP10-Slag (7 days of cure)

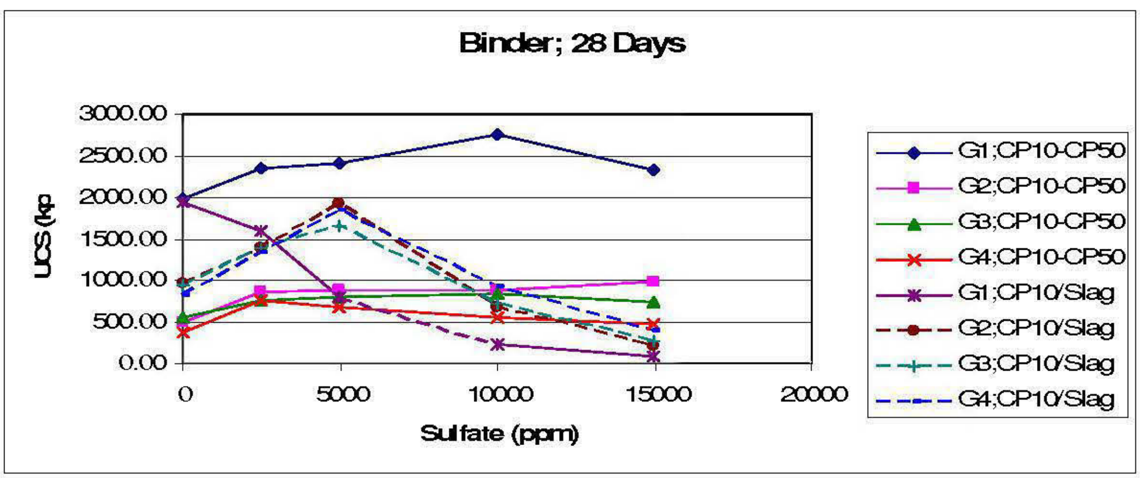

Figure 21: UCS according to the content sulfates for the CP10-CP50 and CP10-Slag (28 days of cure)

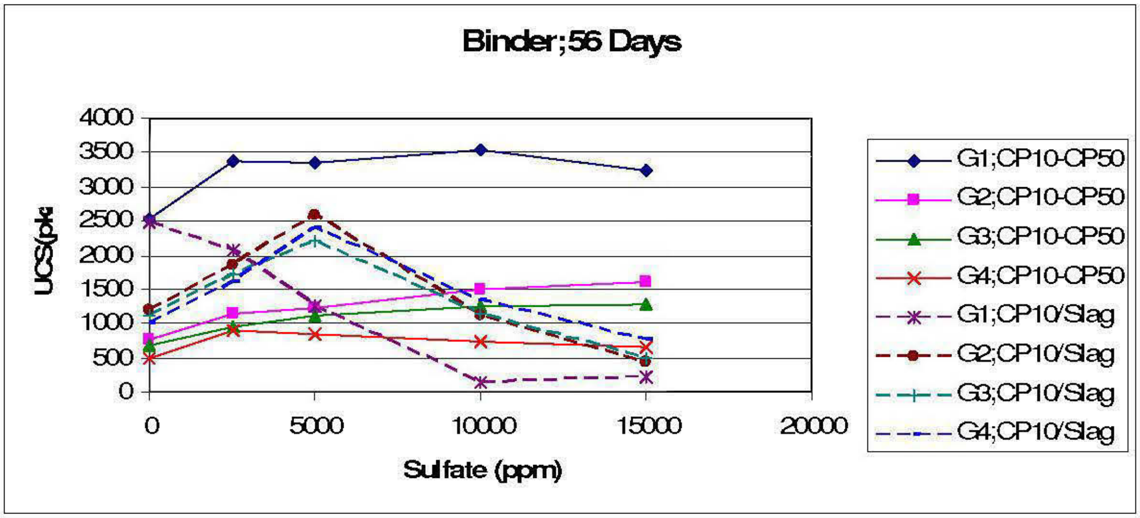

Figure 22: UCS according to the content sulfates for the CP10-CP50 and CP10-Slag (56 days of cure)

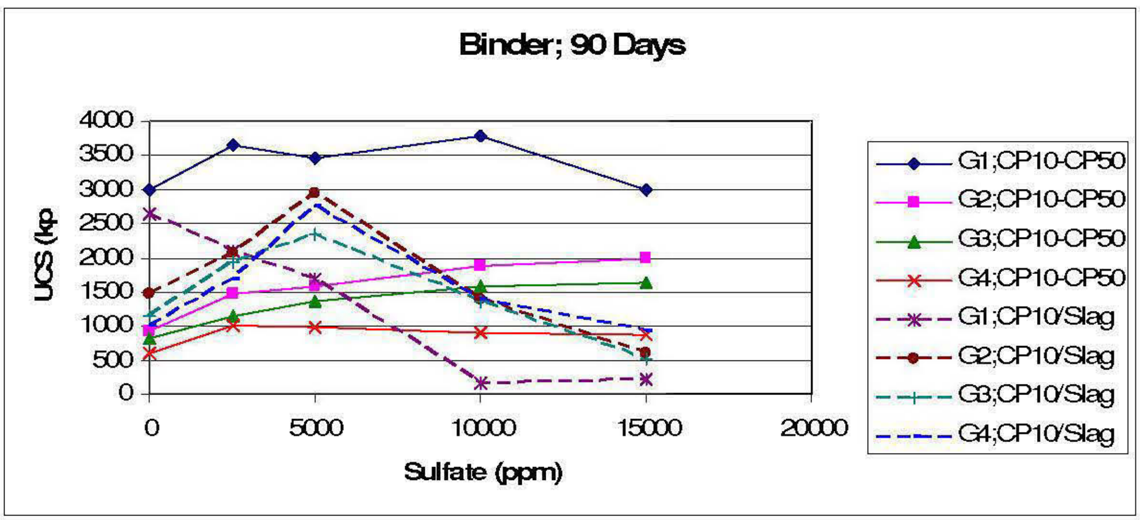

Figure 23: UCS according to the content sulfates for the CP10-CP50 and CP10-Slag (56 days of cure)

This phenomenon is explained as the effect of sulfates on the hydration of binders. Generally, the hydration of CP10-Slag is slower than the hydration of CP10-CP50 in the same presence of sulfates. Indeed, slag starts its hydration just after the hydration of CP10. This is the main reason why CP10-Slag has lower UCS than CP10-CP50 within sulfates rich tailings. Note that the sample with 75% fines and CP10-CP50 gives the best UCS value.

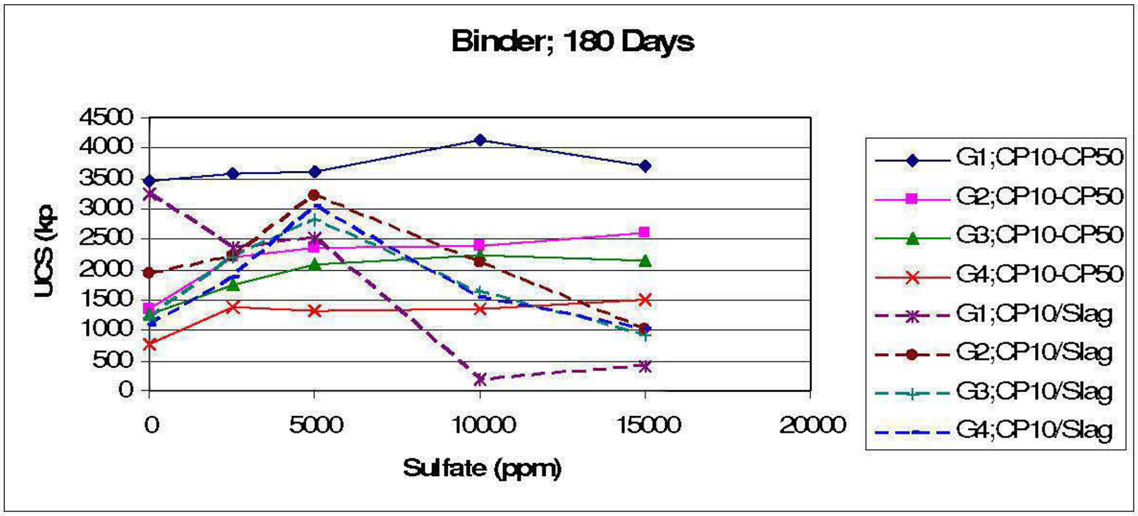

Figure 24: UCS according to the content sulfates for the CP10-CP50 and CP10-Slag (180 days of cure)

3.5.4. Effect of fine particles content on strength properties

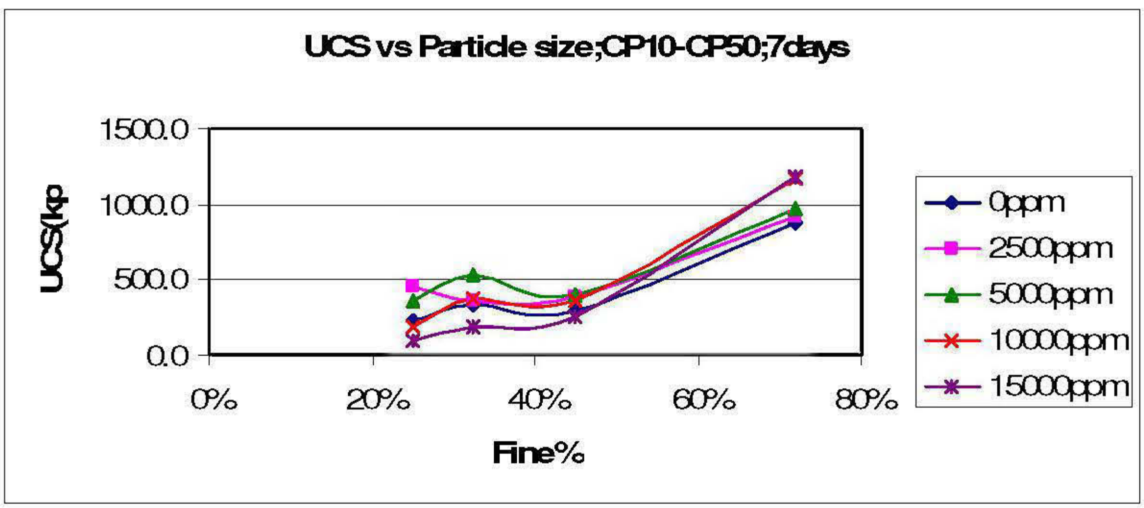

Figure 25: UCS vs Particle size; CP10:CP50; 7days

The analysis of the particle size distribution effects on the mechanical resistance is obtained by using four different particle sizes in the mixtures.

Figure 25 to Figure 29 show the obtained UCS according to the particle size distributions. The obtained results show that the mechanical resistance is very high for fine particles and sulfate rich tailings.

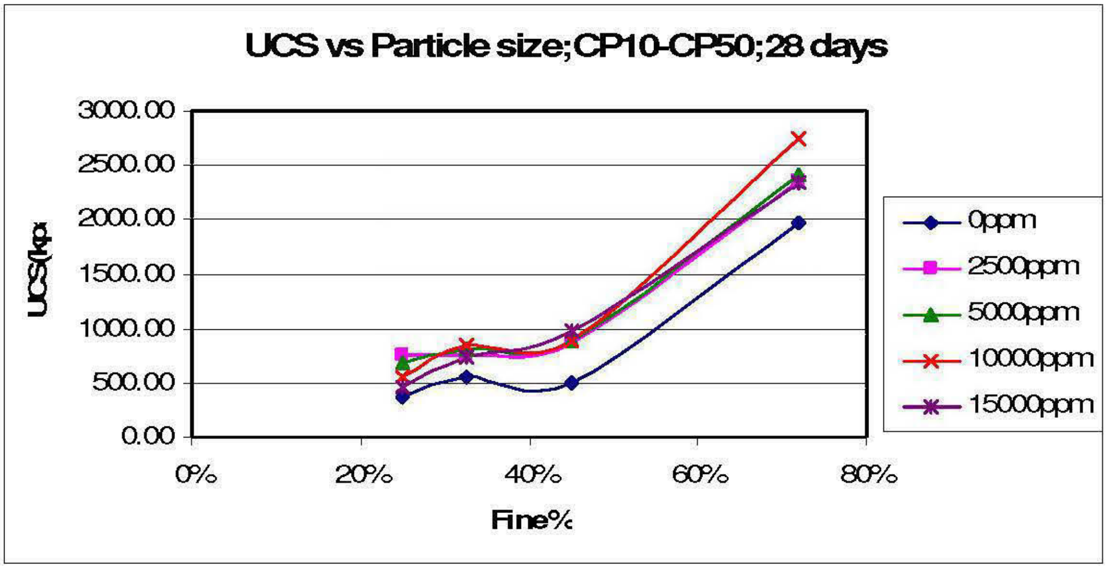

Figure 26: UCS vs Particle size; CP10:CP50; 28 days

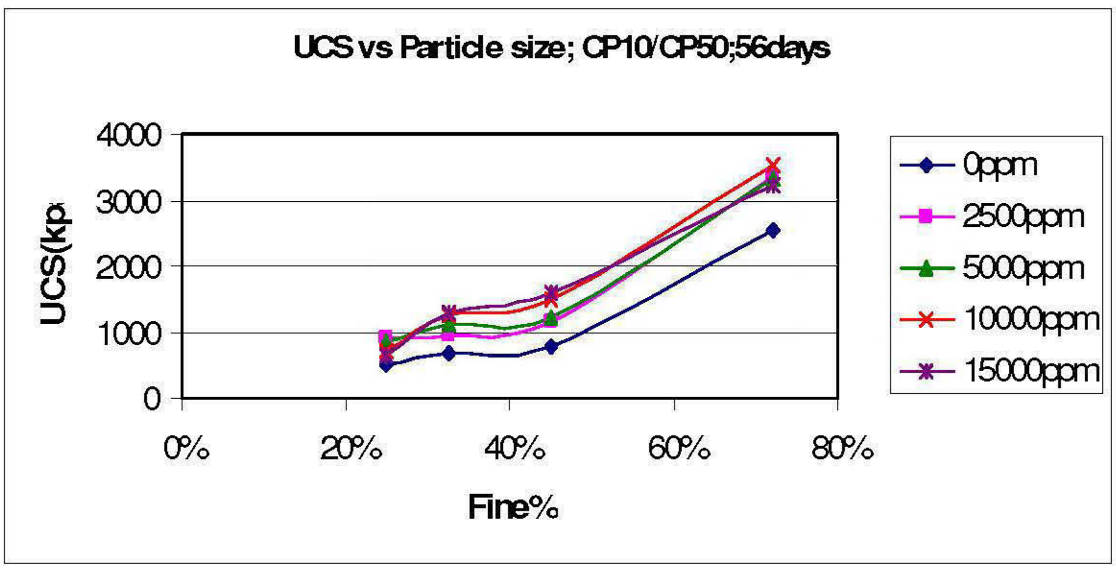

Figure 27: UCS vs Particle size; CP10:CP50; 90 days

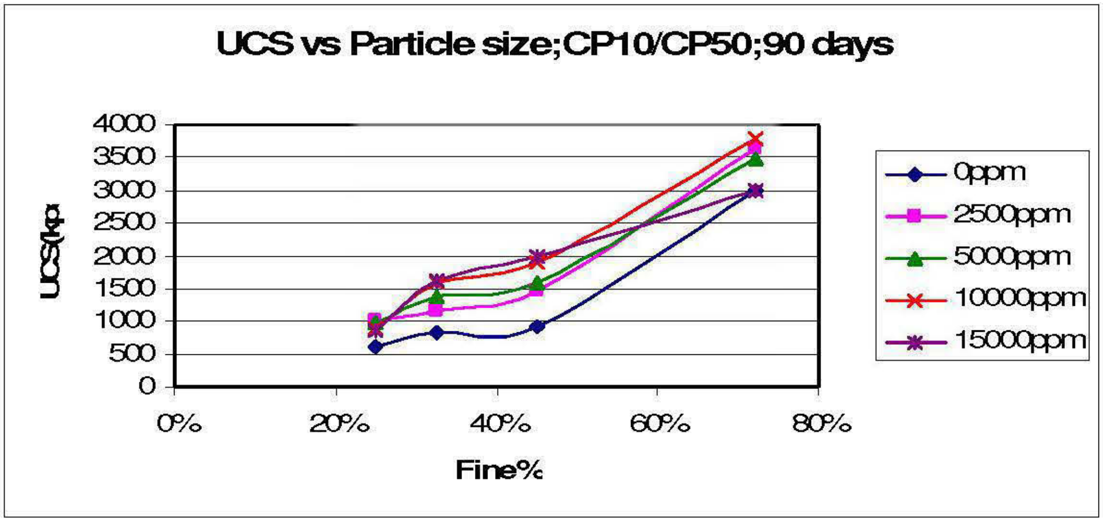

Figure 28: UCS vs Particle size; CP10:CP50; 90 days

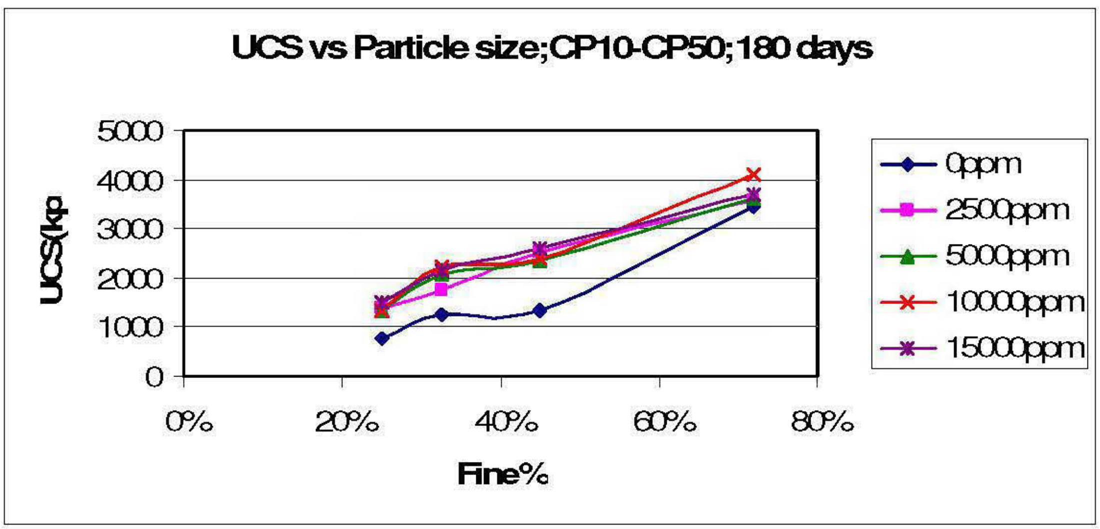

Figure 29: UCS vs Particle size; CP10:CP50; 180 days

The mechanical resistance curve shows a peak for the particle size distribution with particle sizes from 32.5% to 45% of fine particles. However, as mentioned before, UCS starts to decrease when particles become very fine. Note that fine tailings need more water than coarse tailings to reach the same consistency. In other words, with a constant water content, UCS of fine tailings is higher that the coarse one. This is confirmed by the rheology test done on the two batches, G_1 and G_3.

For Cp10-Slag binder, the effect of particle size distribution on the mechanical resistance is different at 7 days of curing period. The mechanical resistance is higher for coarse particles than for fine particles. Figure 30 shows that at 7 days of curing period, resistance tends to decrease with the fine tailings. Normally, the inhabitation of CP10 prevents the development of mechanical resistance in all particle size distributions. It becomes more visible for sulfates concentration of 5000 PPM, with particle sizes between 45% and 72% of fine particles, where the reduction in resistance is remarkable. At 28, 56 and 90 days of curing time, resistance increases with the smoothness of tailings for sulfates concentration between 0 PPM to 2500 PPM, and decreases with sulfates range of 5000 PPM to 15000 PPM, (Figure 31 to Figure 33). At sulfate concentration around 1000-15000 PPM, the hydration of slag is already started, as well as the phenomena of sulfate attack.

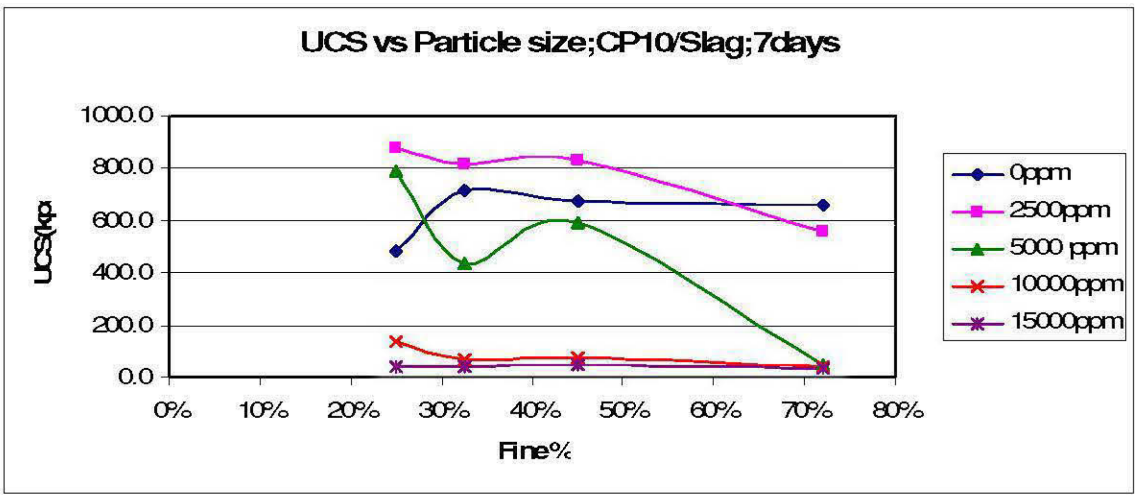

Figure 30: UCS vs Particle size; CP10: Slag; 7 days

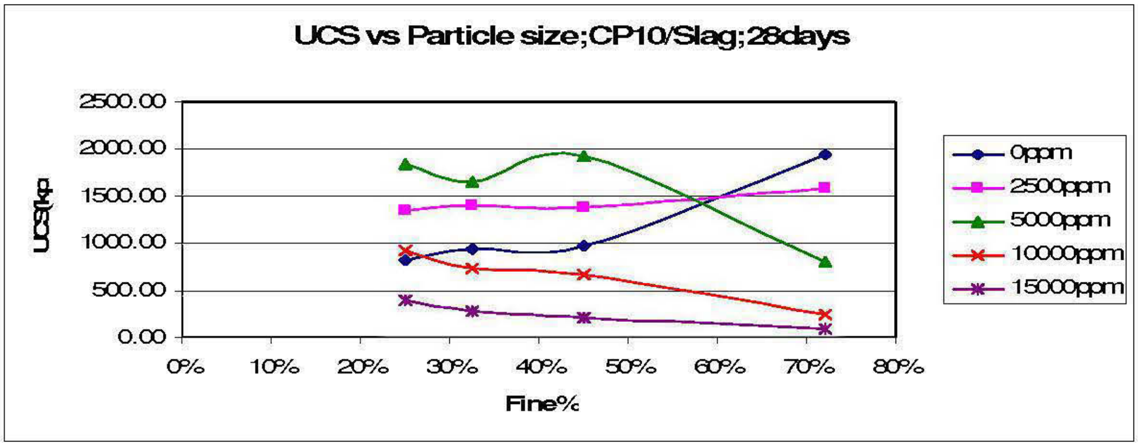

Figure 31: UCS vs Particle size; CP10: Slag; 28 days

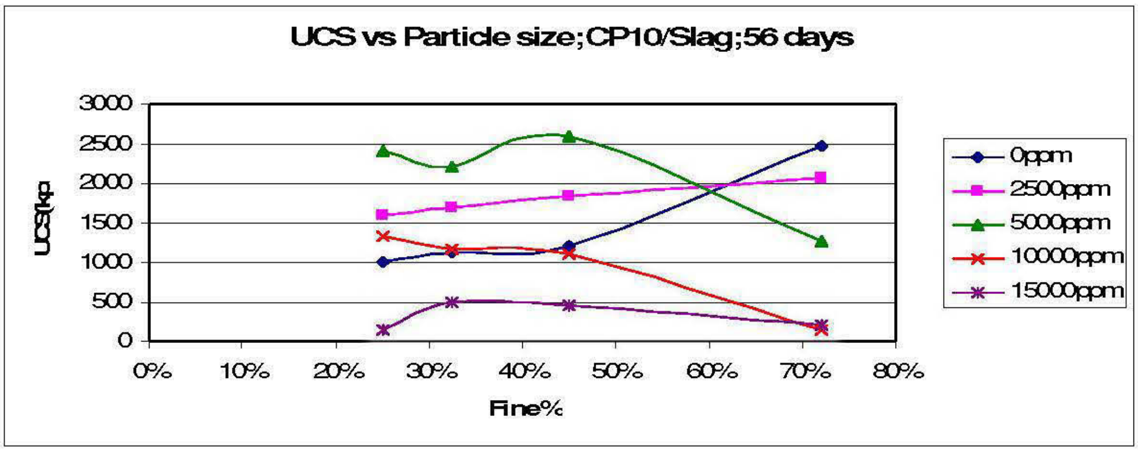

Figure 32: UCS vs Particle size; CP10: Slag; 56 days

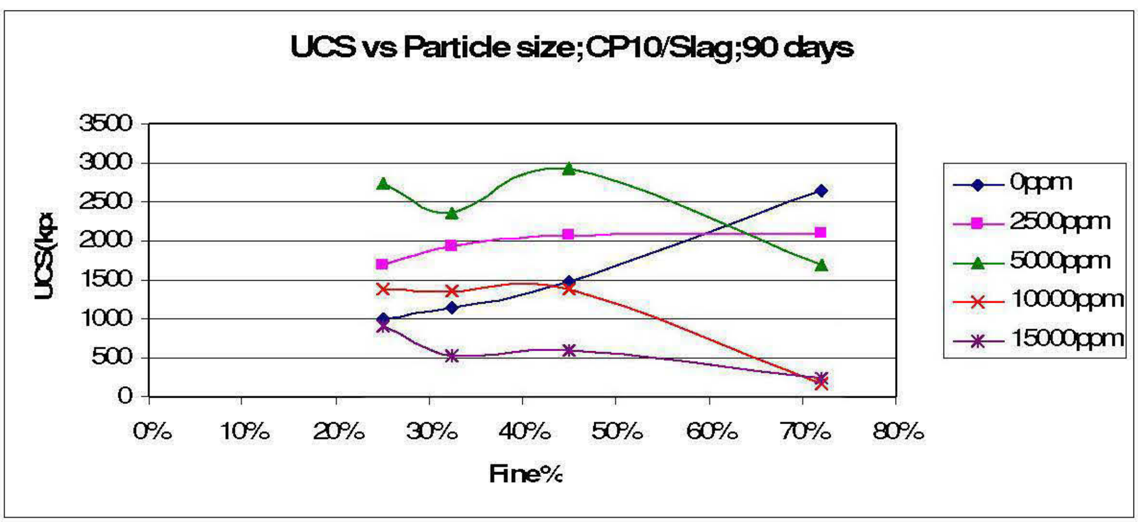

Figure 33: UCS vs Particle size; CP10: Slag; 90 days

Figure 34 presents the obtained UCS versus the particle size distribution of CP10-Slag at 180days of curing period. Results show that just for 0PPM sulfate content UCS increases by smoothness of particles. It also demonstrates that the samples, made by coarse particles give better UCS for rich sulfate tailings.

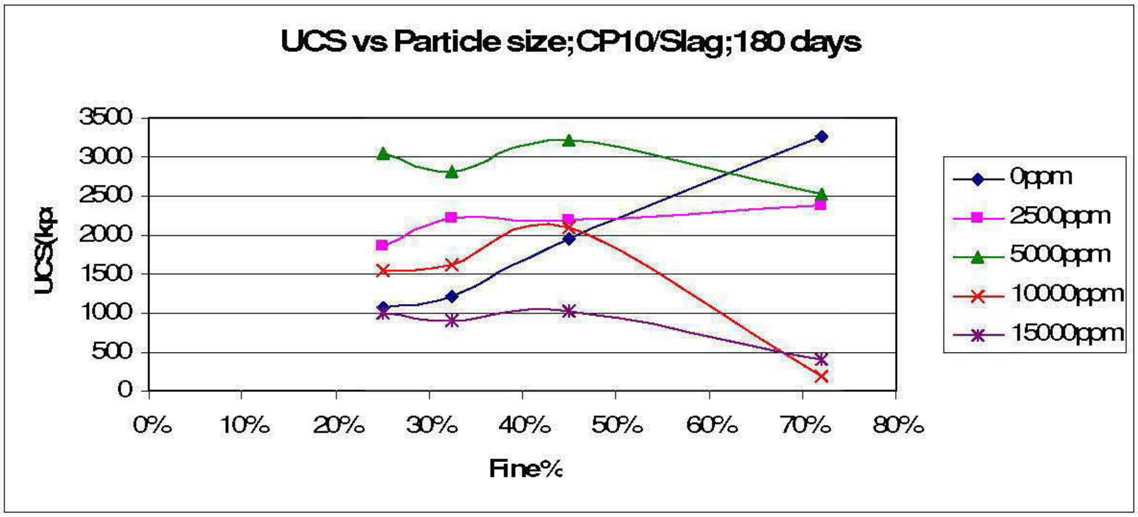

Figure 34: UCS vs Particle size; CP10: Slag; 180 days

3.5.5. Effect of sulphate concentration on strength properties

The sulfates effect is different depending on the particle size distribution and the curing time. For all the particle sizes, there is an increase in the mechanical resistance with the sulfate concentration increasing up to the given maximum value, for seven days. After this peak, mechanical resistance gradually decreases as the sulfates content increases.

The optimum sulfates content is between 2500 PPM and 5000PPM for coarse particles, (G_3 and G_4) and more than 10000 PPM for the fine particles, as presented in Figure 35.

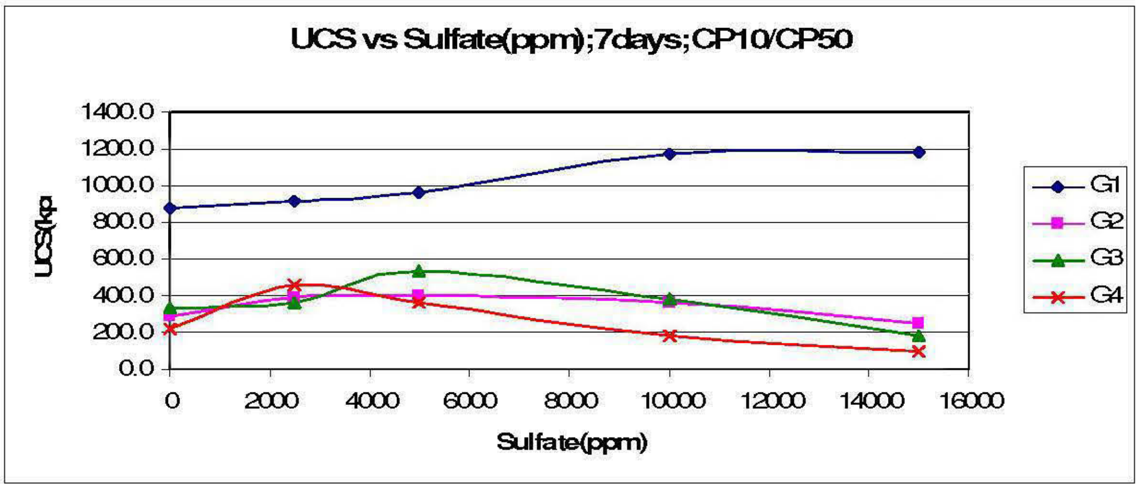

Figure 35: UCS vs Sulfate content; CP10:CP50; 7days

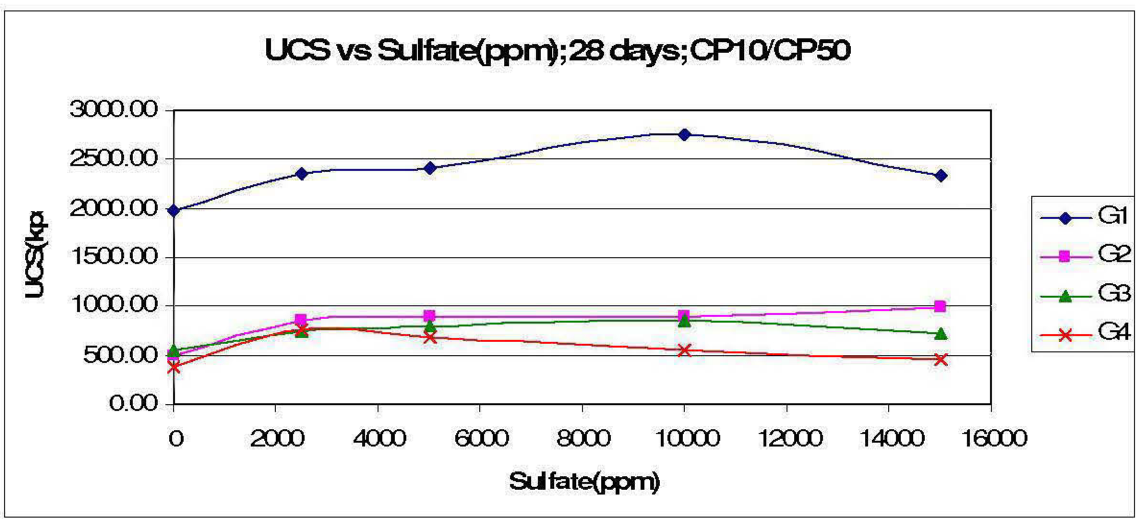

Figure 36: UCS vs Sulfate content; CP10:CP50; 28 days

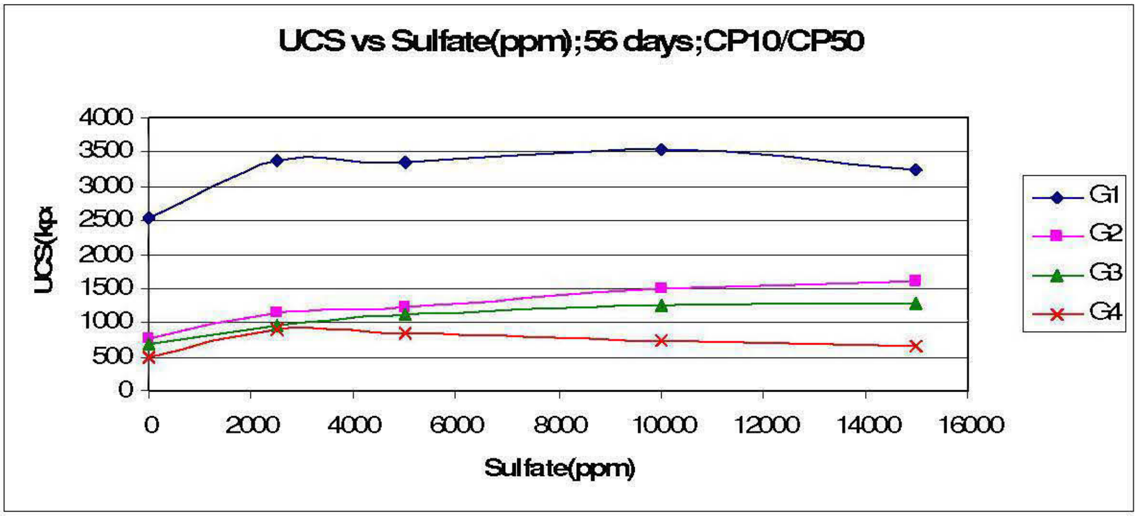

Figure 37: UCS vs Sulfate content; CP10:CP50; 56 days

At 28 days of curing, as shown in Figure 36, the differences in the paste backfill behavior are noticeable. For fine particles size distribution G_1, mechanical resistance decreases starting from 10000 PPM of sulfates content. It is the opposite as it was for 7 days.

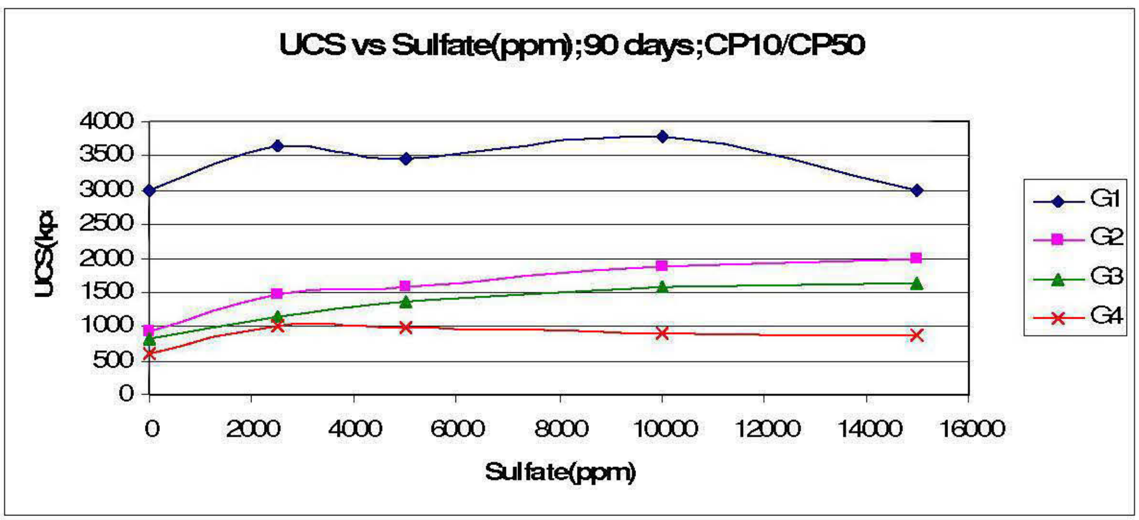

Figure 38: UCS vs Sulfate content; CP10:CP50; 90 days

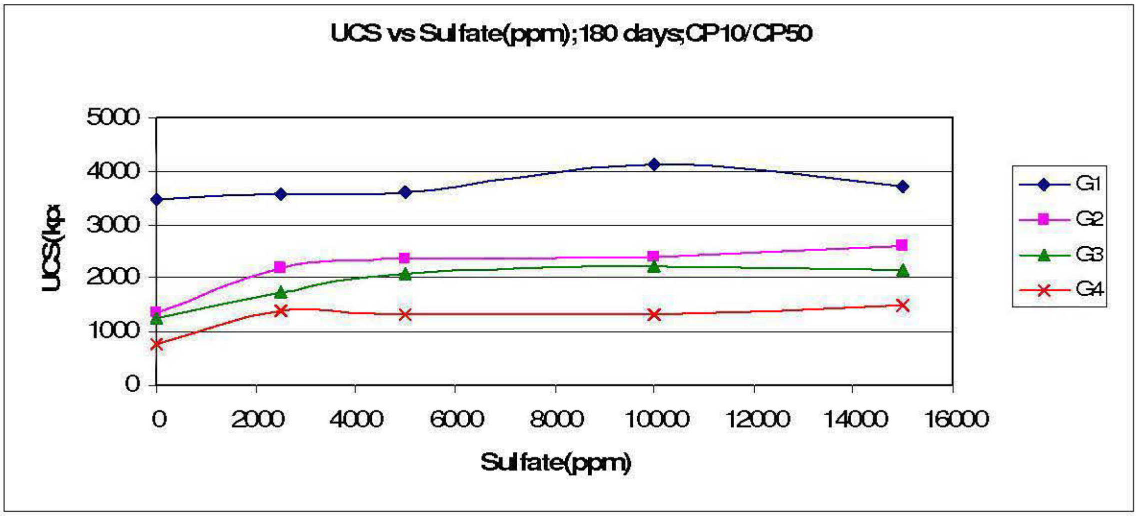

Figure 39: UCS vs Sulfate content; CP10:CP50; 180 days

At 56, 90 and 180 days of curing time (Figure 37 to Figure 39) for fine tailings mechanical resistance decreases at 10000 PPM of sulfate content, for G_2 and G_3 the UCS increases by the rate of sulfate content. It is important to highlight that for G_4 UCS decreasing start at 2500 PPM.

The results obtained for CP10-Slag binder are different from the results in case of CP10-CP50, Figure 40 to Figure 44. The mechanical resistance increases with the sulfates content and decreases after reaching the optimum sulfates content point $\left(1000 < SO_4^{2-} < 10000\right)$ except for G_1. The precipitation of sulfate can occur, to help the hardening process in parallel with the appearance of hydrated phases such as $C - S - H$, which increases the cohesion.

The next stage happens in already hardened material. Sulfate continues its precipitation until saturation and expansion occurs respectively.

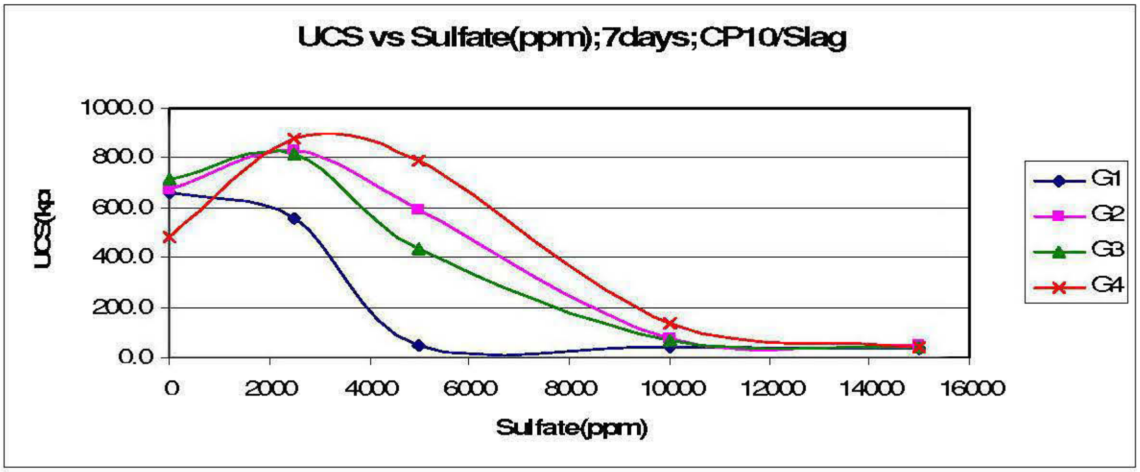

Figure 40: UCS vs Sulfate content; CP10: Slag; 7 days

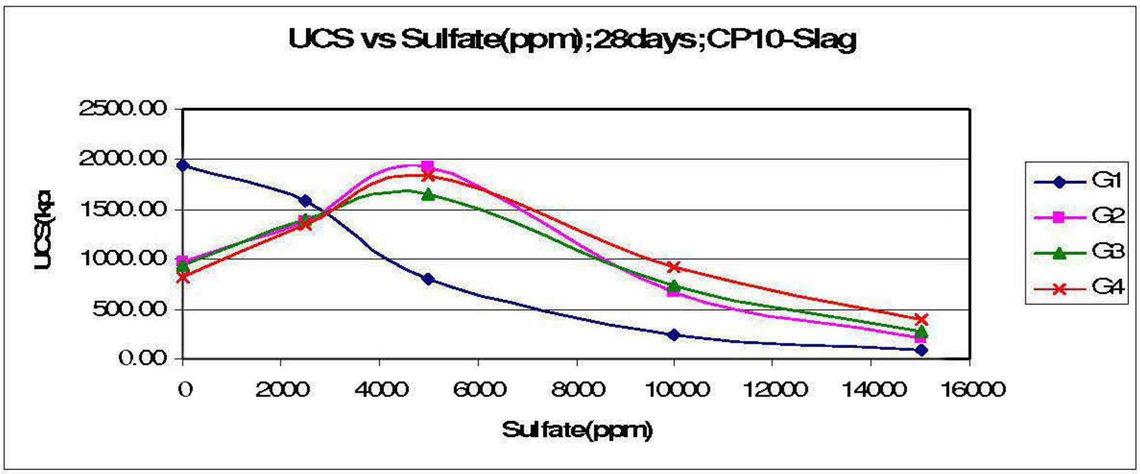

Figure 41: UCS vs Sulfate content; CP10: Slag; 28 days

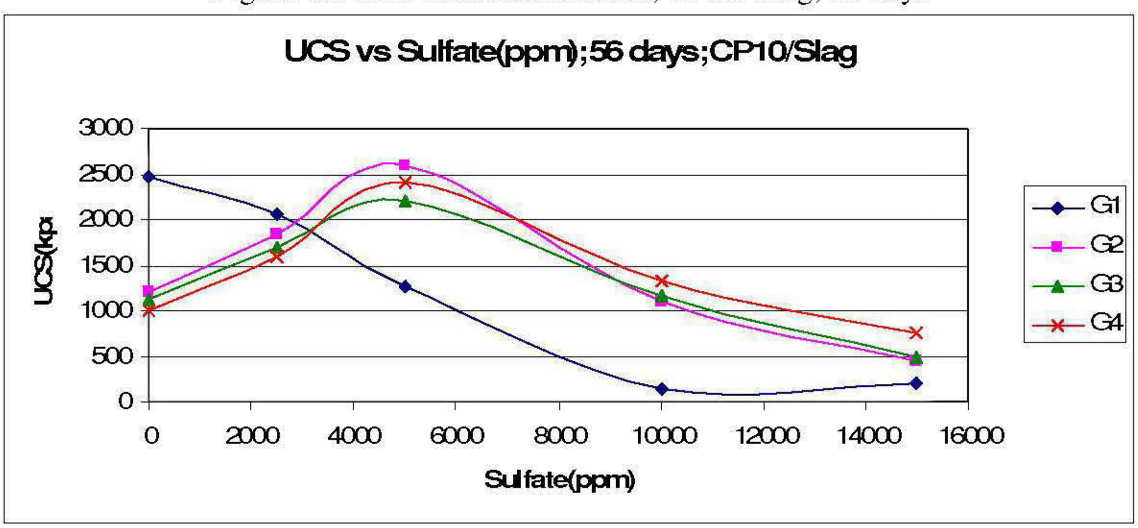

Figure 42: UCS vs Sulfate content; CP10: Slag; 56 days

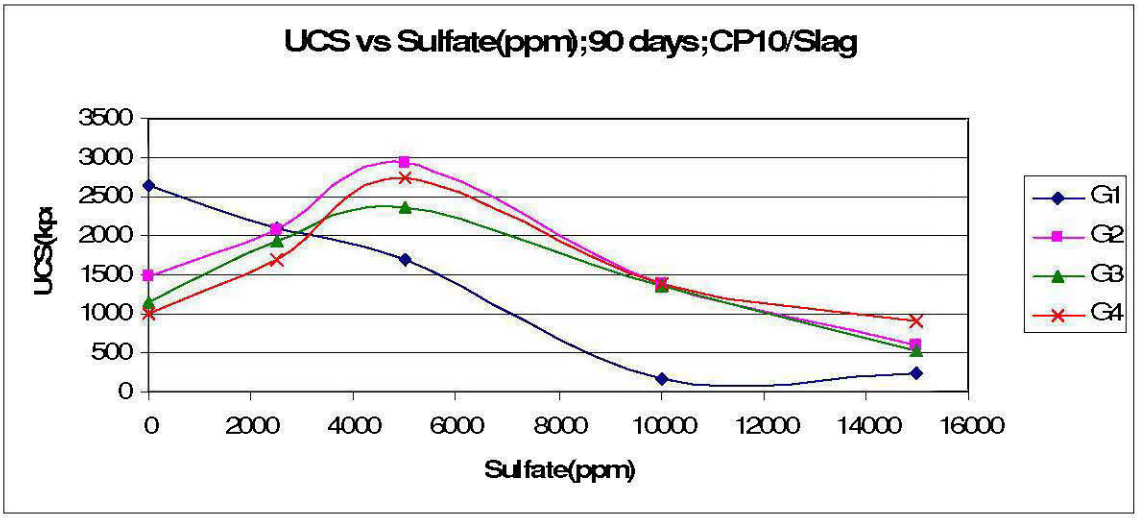

Figure 43: UCS vs Sulfate content; CP10: Slag; 90 days

The difference between the CP10-CP50 and CP10-Slag at curing time intervals happened because of the sulfates resistance properties of CP50, and also because of precipitation role, which boosts the hydration.

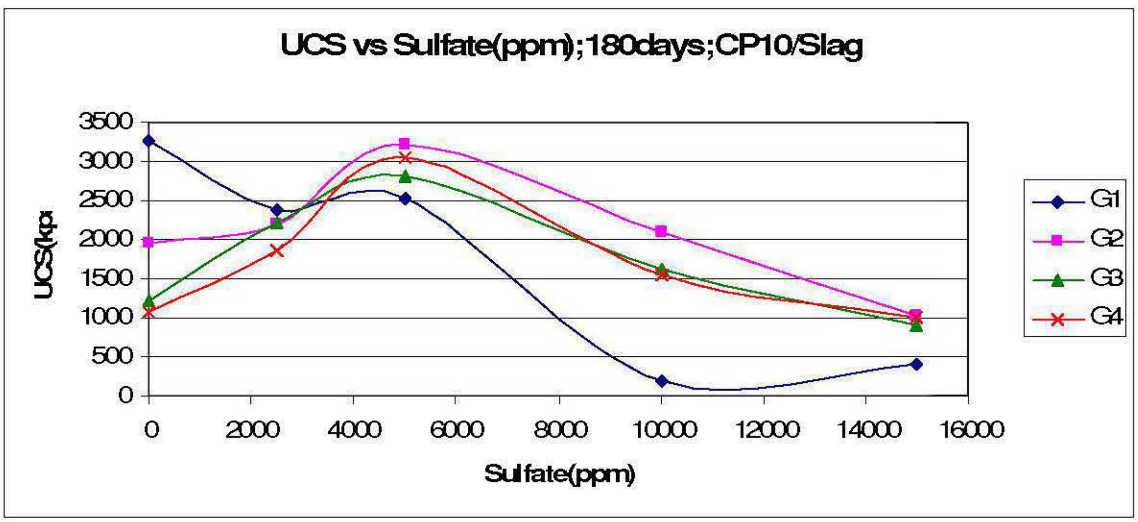

Figure 44: UCS vs Sulfate content; CP10: Slag; 180 days

3.6. Development ANN model implementing results

During the laboratory study, for each recipe three samples were prepared then, totally 600 paste backfill samples were carried out. Each UCS is the mean value of three results obtained for each recipe. The most important work in implementing an ANN model is the selection of input variables which greatly depend on engineering judgment and experience. However, in this work, we divided the input into two sets. A set of 188 nodes is used for training and another set is used for testing the ANN.

Applied procedure for the ANN model is:

1. Input data: Input data used to implement this model is particle size, sulphate content, binder type and curing time and output is UCS, Figure 45. However, used data sets for each of the ANN models have been subdivided into two groups-"modeling" data and "validation" data. Validation data is used to assess the predictive ability of the network on "unseen" data.
2. Data Pre-processing: recorded data and observation error are inevitable. Hence, bad and abnormal data is identified, discarded, or adjusted using a statistical method to avoid contamination of the model.
3. Scaling: regarding the fact that input and output data have very different ranges, the direct use of network data may cause convergence problems. However, all the input and output variables have been scaled to be in the [0, 1] range.
4. Training: each layer's weight and biases are initialized when the neural network is setup. The network adjusts the connection strength among the internal network nodes until the proper transformation that links past inputs and outputs cases is learned.
5. Simulation: using the trained neural network to predict the outputs of validation data
6. De-scaling: the neural network output need de-scaling to present the desired UCS values.

In this study, Matlab 7.0 software is used in neural network analyses having three layers feed forward network that consists of an input layer (6 neurons), one hidden layer (23 nerouns) and one output layer.

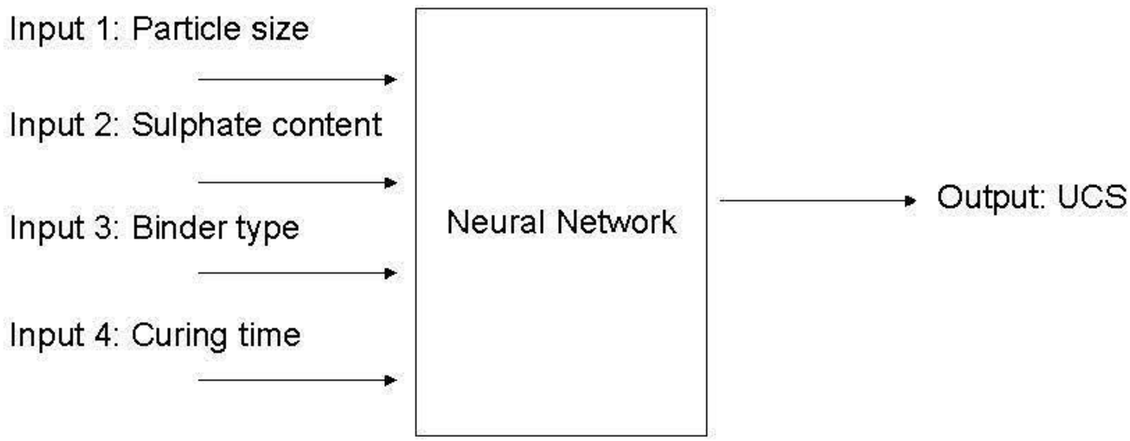

Figure 45: Neural network inputs and output

Figure 46 shows the ANN output where it is compared to the actual UCS. For more accurate evaluation of the prediction performance of the model, the root mean square error is used here.

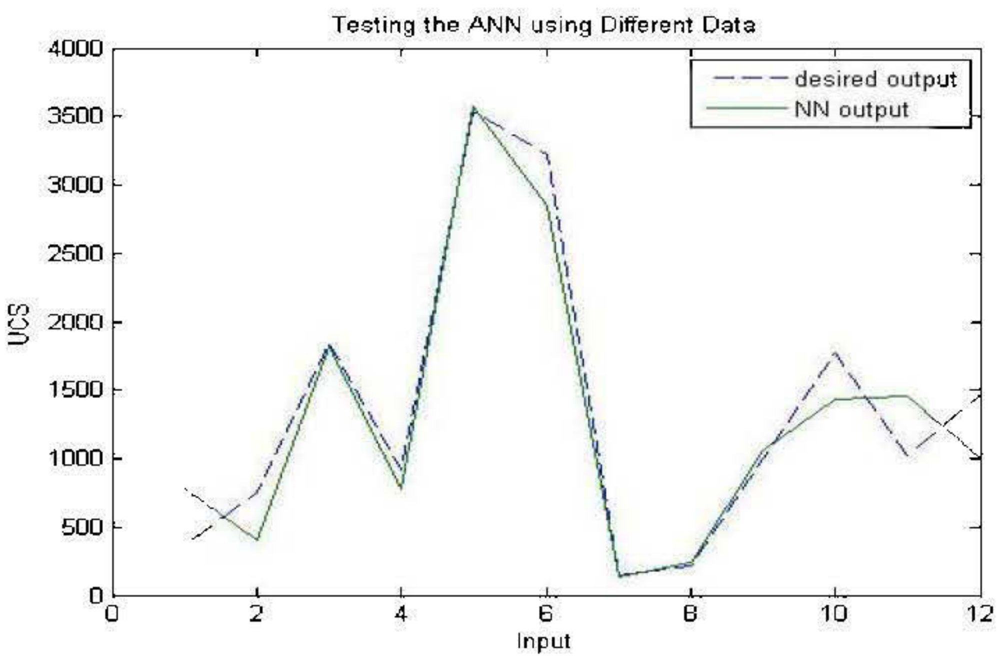

Figure 46: Evaluation of the ANN performance

The network goal is obtained after 85 iterations. The correlation between predicted and measured data (Figure 47) indicates a very strong coefficient of determinations $R^2 = 0.947$.

As values of UCS vary, error observations are important for the UCS forecasting process. Then root mean square error (RMSE) is used here for error analysis:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_M - X_P\right)^2} \tag{22}$$

Where X_M is the measured UCS and X_P is predicted UCS, obtained RMSE is: $\sigma = 0.25$.

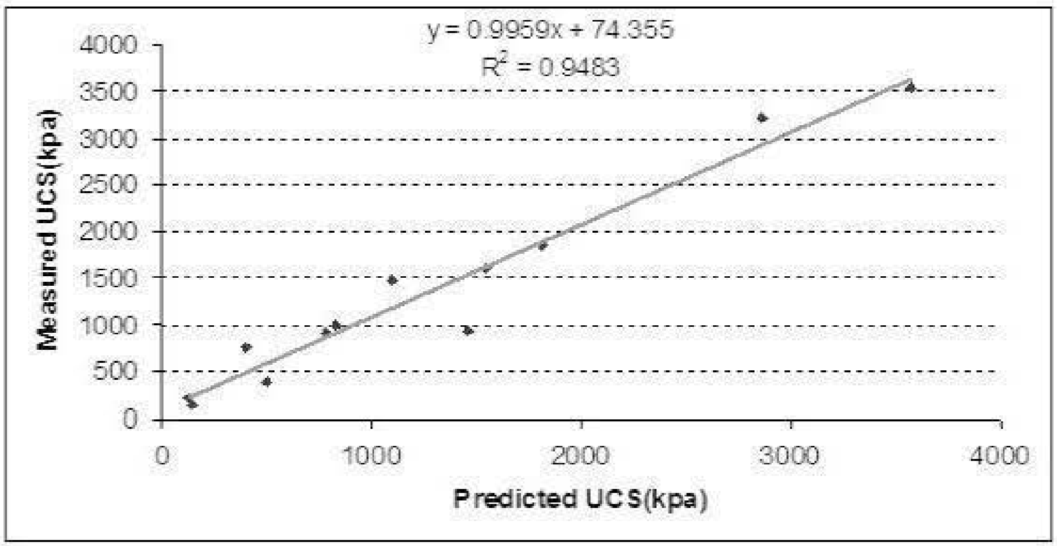

Figure 47: Predicted UCS (kPa) versus measured UCS (kPa)

Finally, the use of cemented paste backfill (CPB) is an increasingly important component for underground mining operations. It is proven that different parameters within the backfill can significantly affect the mechanical resistance; the main performance criterion when using cemented paste backfill technology. This is why, in the mine backfilling operations, a slight change in the binder content leads to substantial UCS and cost variation. Binder is the most important backfill related cost.

In this work, more than 600 cemented paste backfill moulds were prepared, targeting various recipes by using silica as tailings. The work allowed investigating the effects of four different particle sizes, two types of binder and five types of mixing water and sulphate content at five different curing times. Also an ANNs is applied tentatively to predict the UCS value. A simple multi-layered feed forward ANN has been used here and results show that the ANN is able to interpolate among the input variables data of training sets to provide the forecasted UCS. This can represent the first stage of implemental, a more unique neural network model that could be used in the mining industry.

Conclusion

Tailings can be stored below ground in previous worked out voids. The tailings are mixed with a binder, usually cement, and then transferred into the underground voids to fill them and to help support underground mines. The supporting effect of backfill materials is essential for safe and selective extraction of ore deposits and for stability of underground opening.

Selecting the most suitable backfill material for an underground mine is a challenging task. The final decision depends upon a series of investigation, namely: laboratory testing, in-situ testing, numerical modeling, and in-situ monitoring.

Laboratory and in situ testing are important in characterizing the backfill material and also in providing input data for numerical analyses and in understanding the mechanism of failure. In some mine design cases, the mine operators do not have either the facility or the finance to carry out all the site investigations and tests in order to obtain the input data required to run the computer programs developed. Regarding the fact that tailings are different from area to area, mining companies have to launch a new set of laboratory test for each new area.

For this reason, one of the objectives of this work is to develop an Artificial Neural Network (ANN) model as a global computer tool to predict the performance of cemented paste back fill, and Unconfined Compressive Strength (UCS), by using silica for the first time. By using silica as tailings, we were able to control and minimize the effects of other mineral compounds presented in the real tailings. It is proven that tailing grains are not reactive in the condition of paste backfilling. Then, choosing silica as tailings is appropriate decision.

In our model, more than 600 samples were prepared and four types variable were used as inputs to neural network: particle size distribution, sulfate content, curing time and binder type.

Many studies have reported that ANNs perform well when faced with problems that fall within the domain of input that were used for training. This can be seen as a problem of interpolation. However, it also proven that the performance of an ANN deteriorates rapidly when the input vectors are far from the space of inputs used for training. To overcome this problem, we tried to ensure that the applied ANN did not extrapolate by using the widest limits of examples during training.

The network goal was obtained after 85 iterations. The correlation between predicted and measured data showed a very strong coefficient of determinations. Also, we investigated the effects of considered parameters on the backfill performance.

Recommendations for future research:

- Cemented backfill testing programs could be extended to study the effect of geothermal changes on strength of backfills under high confining pressures in conventional triaxial testing. This would be relevant to deep mining applications with in Canada.
- Better results can be obtained by using more input data.
- Using Fuzzy Neural Network; neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks.

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