PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

A GENERAL WATER CONSUMPTION PREDICTIVE METHODOLOGY FOR A MINING OPERATION IN CENTRAL CHILE: SEEPAGE, EVAPORATION AND MILL PLANT WATER DEMAND

FELIPE ANDRÉS PASTÉN ALMENDARES

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
ÁLVARO VIDELA LEIVA

Santiago de Chile, July 2015

PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

A GENERAL WATER CONSUMPTION PREDICTIVE METHODOLOGY FOR A MINING OPERATION IN CENTRAL CHILE: SEEPAGE, EVAPORATION AND MILL PLANT WATER DEMAND

FELIPE ANDRÉS PASTÉN ALMENDARES

Members of the Committee:
ÁLVARO VIDELA LEIVA
JOSÉ FRANCISCO MUÑOZ PARDO
SEBASTIÁN VIDELA HINTZE
CARLOS BONILLA MELÉNDEZ
Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Santiago de Chile, July 2015

Gratefully to my family

ACKNOWLEDGEMENTS

I've dreamed of this moment for so many nights. I thought I would be at home, in pijamas, with a cup of coffee writing and trying not to forget anyone in this section. Well, unexpected things happen, but that does not mean I am enjoying this moment any less. If it was possible, the whole world would be mentioned in between my words. So, if I forget someone, please forgive me. Also, I do not know how to write this section, so I am thinking of the words I would say face to face. It maybe atypical, but that is who I am.

First of all, I would like to thank my thesis committee. To Mr. Carlos Bonilla, who I would have loved to have met earlier: your advice was priceless and thanks for all the words of encouragement. To Mr. José Francisco Muñoz, who gave me the toughest and the best lessons of my thesis: I admire you and your career greatly. To Mr. Sebastián Videla, who taught me a lot in the professional area: I am glad that the person who was at the beginning of this journey could be present at the end of it. And to my advisor Mr. Álvaro Videla: you were there in the key moments of this period and thanks to your advice I am a better person and I will be an engineer you will be proud of.

I want to thank my family. Thank you for dealing with my cranky moods and my language. My sister, who is an admirable person, you always taught me that I have so much to learn and even when I screw things up, your forgiving smile is always there. My mom: your hugs and kisses were my fuel for continuing this path, and I want to keep having those for this new journey that I am starting. My dad: after the fights, the screams and all of the problems between us, one thing is clear to me. It can be said in these words: thanks for being my hero.

I want to thank my aunts Sandra and Marisol, who are guiding me towards a new and exciting world. I love working together with you. My aunt Susana, who has taught me how lifetime promises are fulfilled: with efforts and tears. My cousins Sandra, Diego, Constanza, Carlos: I love you guys as my brothers and sister and thanks for the moments we shared. I am a better man thanks to you. My grandparents Cristina and Manuel for opening the path for me, and I am glad you were the inspiration for all my people. And Pedro Ricardo, the man who gave his time to teach 5 young dumb kids to be adults. You are the real deal.

I want to thank Rocío. Thanks for giving me this healthy relationship and walking this new path with me. You had the courage to bring me back to earth when I was dreaming in the skies and thanks to that I am complete. You are a blessing.

I want to thank my friends. Alvaro, my first friend and after 25 years, I still admire your toughness and your wisdom. Alejandro, who has been in the good and the bad times, thanks for all of the drinks we shared. Mony: I would not be this reflexive and emotionally wise if it wasn't for you. I fixed my world and put my ghosts to rest thanks to you. Now, in your new journey, I will keep my promises and you will not be alone. Mati: you showed me how deep and simple life can be, and thanks for being there when I needed get rid of my demons. Felipe: the one who showed me how respect is earned: by giving your 100

I want to thank my friends from my master's years. Gabo: you were the source of success in my thesis. Thanks for the encouragement and the pressure you put on me for finishing my master's. From the TA hours to being friends, how unexpected and pleasant. Catalina: my sister and one hell of a girl. I know you'll be the great woman I envisioned a long time ago. Bruno, Nacho and Rolo from ”El Cuarto Estornudo”; you guys gave me back what I lost a few years ago which is my love for music and more awesome people close to my heart. Cristobal and Joaco: it was great to enjoy your company and learn from two excellent persons. Diego, Gonzalo, Joaquín and other alumni from the master program: thanks for finishing before me because you gave me motivation. Josefa: you showed me that even in the darkest hours, a radiant smile is enough to surprise me. I admire you and your guts. Please keep shining like you do.

I want to thank the people of my university. To María Paz: thanks for all of the times we laughed, and cried, and blamed the world. I miss those times. You were one of my pillars inside that department and I hope I was able to support you even a small amount of what you did. I am fortunate to have you in my path. To Juanita, Valeria, Karina, Miss Cecilia and whoever was in the mining department making my experience there a great moment.

Finally, I would like to thank Laura. You raised a good man and because of my words with you, I will keep being the great person I promised I would be. I still regret not having you here with us. Thanks for giving your life to me.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

As time goes by, water consumption is becoming more aggressive. Mining operations and mill plants are expecting to raise their water demands over the years. With that idea, a general water consumption predictive model is designed combining recovery and water loss factors from tailings' inventory changes. Mill plant requirements and recovery are modeled through Data Recollection and Validation. Water loss is composed mainly of evaporation and seepage. Infiltration is modeled using drainage columns. Evaporation inside and outside the pond zone is modeled using deBruin-Keijman equation and experimental columns. The model is validated by predicting important operational conditions.

RESUMEN

A medida que pasa el tiempo, el consumo de agua se ha vuelto más agresivo. Las operaciones mineras y las plantas de procesamiento esperan aumentar sus demandas de agua a lo largo de los años. Con esa idea, se diseñó un modelo general predictivo de consumo de agua combinando factores de recuperación y pérdidas del inventario de agua de los relaves. Los requerimentos y recuperaciones de la planta concentradora se modelan a través de la reconciliación de datos. Las pérdidas de agua se componen principalmente de evaporación e infiltración. La percolación se modela usando columnas de drenaje. La evaporación dentro y fuera de la zona del estanque se modela usando la ecuación de deBruin-Keijman y columnas experimentales. El modelo se valida prediciendo importantes condiciones operacionales.

1. ARTICLE BACKGROUND

1.1. Introduction

When this work started in 2013, water consumption has already been seen as scarce resource. In 2006, UNESCO declared water scarcity as a worldwide problem due to its impact as a life-giving resource, but also essential in socio-economic development (UNESCO, 2006).

Normally, mining operations are located in areas with dry climates where water is always scarce. Paradoxically, water is an essential resource for facilitating chemical reactions for ore processing. From hydro-metallurgical uses in leaching and solvent extraction to mineral concentration and solid transportation, water resources were always viewed as a complementary input for operating, and not as the core business of every processing plant.

Nowadays, mining operations and processing plants are expected to raise their water demands over the years (Betancour & Montes, 2013). Therefore, quantifying and optimizing consumption, recovery and losses are part of an effective water management strategy. This methodology has been widely applied within a vast number of industries and social environments such as neighborhoods and cities. However, the mentioned representations involve economic, political, social, hydrological, ecological, pollution and climatological variables. Thus, considering these conditions may occur in different contexts, there is no single and straight-forward water management (Koch & Grneward, 2009). Moreover, those platforms are designed to include complex water resources conditions such as river basin flows, hydro-geological models and water allocation problems that are sometimes far from the complications faced by mining companies.

The rest of this chapter is structured as follows: ”Main objectives” states the main objectives pursued in this work, ”Main conclusions” expose the main conclusions of this work and ”Future Research” trace possible paths for future research. Following this, after ”Article background” contains the main article of this thesis.

1.2. Main Objectives

The main goal of this thesis is to present a methodology for predicting water consumption in a mining operation. Its design is based on the water cycle surrounding the mining context. It has to help management decision with enough time in advance and support in the short and long run.

In order to demonstrate the contributions of this methodology, the article has one main objective which is predicting operational scenarios and comparing its results. Due to the availability of water data from the operation, the best way of comparing results is by modeling operational events occurred during the selected time period. The most relevant situation on this time horizon is a major emergency stop due to water shortage at the end of the selected year.

1.3. Methodology Construction

In this research, a general methodology refers to the wide application of the proposed construction method. Every water balance can be performed at macro and micro levels and the main equation can be written as follows:

$$\dot{Q}_{req} = \dot{Q}_{cons} - \dot{Q}_{trec}$$

The previous equation can be applied in any mining operation. However, estimating each term of the expression requires a detailed analysis of the operation and this research has done several studies on modeling each term in the particular mining context. $\dot{Q}_{trec}$ can be represented by the sum of two different factors: $\dot{Q}_{rec}$ and $\dot{Q}_{recycled}$. The first term is the amount of industrial water recovered inside the operation. In this particular industry, it is the result of the effectiveness on recovery from thickeners and filters. Meanwhile, $\dot{Q}_{recycled}$ shows recycled water. In other words, it is the amount of industrial water recovered outside the mill plant. While $\dot{Q}_{cons}$ and $\dot{Q}_{rec}$ are modeled by Data Validation and Reconciliation (DVR), finding an expression for $\dot{Q}_{recycled}$ by modeling the tailings impoundment arises as a fundamental task. It has to be done by representing changes in the tailing water body $W_{tailing}$. This way, the problem is reduced to:

$$(P)\begin{cases} \dot{Q}_{req} = \dot{Q}_{cons} - \dot{Q}_{rec} - \dot{Q}_{recycled} \\ \frac{\partial W_{tailing}}{\partial t} = \dot{Q}_{tailing} - \dot{Q}_{recycled} - \dot{Q}_{lost} \end{cases}$$

$\dot{Q}_{cons}$ and $\dot{Q}_{rec}$ are modeled by using 2013 operational data and the methodology is tested using 2014 values. For this task, values of mass, copper grade and solid percentage are obtained for each operational hour. Then, for each time interval, the optimization process is done. This allows to find each water stream from the mill plant and the data is consistent with balance equations and real variability. In terms of water recycling, the main source is located in the impoundment. Pumps were placed for sending the cumulated water back to the operation. Their task is modeled as a piecewise function where recycled water will be the maximum flux possible if the amount of water in storage is enough to feed the pumps.

Water losses are mainly in the tailings impoundment. The three processes involved in active deposition areas are seepage, evaporation and saturation; in the pond zone, the water body is just affected by radiation and infiltration (Wels & Robertson, 2003). When impoundment dimensions are large, as in our case study, pond zone behaviour can be considered to explain most of the tailings phenomena.

Evaporation is estimated in two different areas. In the pond zone, it is quantified by using deBruin-Keijman method (Rosenberry, Winter, Buso, & Likens, 2007). In unsaturated areas, it is estimated using Philip adjustment (Johnson, Yáñez, Ortiz, & Muñoz, 2010).

However, environmental data is needed for both models. Field data such as temperature, pressure, and water evaporated are collected in site from December 2014 to March 2015.

Seepage is modeled by using drainage columns. Adapted by Rivera and Paredes (2012), the columns were modified for studying tailings conditions by monitoring the humidity profile along the column. Special sensors able to track in acidic porous media were used. The equipment from Decagon monitored differences in the volumetric water content in one-minute intervals during 3 weeks. The seepage rate is calculated as the average of the volumetric water content from the first day.

1.4. Main Conclusions

For an integrated water management strategy and the construction of a predictive water methodology presented in this document, many factors have been included. Mill plant water requirements are modeled through data validation and reconciliation, allowing to extrapolate a consumption function and a recovery function for thickeners installed in the mining operation.

The results obtained allow the methodology to accurately extrapolate operational scenarios. During 2014, certain unaccounted conditions had developed, forcing a detention for several weeks. Under these circumstances, the methodology was capable of recreating these conditions, controlling make-up water consumption and modeling tailings water body to the point of critical water levels.

1.5. Further Research

The methodology presented can be improved by applying other advanced techniques and models. Consolidation models might predict not only water retained in the deposited tailings but also estimate water storage in a certain time horizon.

Seepage rate can be improved by applying literature models like Green-Ampt (Green & Ampt, 1911), Phillip's Two-Term (Philip, 1974) or Infiltration/Exfiltration models (Eagleson, 1978).

Also, monitoring station will improve estimations of environmental data like temperature, radiation and other in site variables needed for water loss predictions.

2. INTRODUCTION

Water is an essential part of mankind's progress. Not only it is a life-giving resource, but also essential in socio-economic development (UNESCO, 2006). However; as time goes by, water consumption is becoming more aggressive. Moreover, natural reserves are not being recovered quickly enough. Fresh water availability is being established as a global warning in any context.

Normally, mining operations are located in areas with dry climates where water is always scarce. Paradoxically, water is an essential resource for facilitating chemical reactions for ore processing. From hydro-metallurgical uses in leaching and solvent extraction to mineral concentration and solid transportation, water resources were always viewed as a complementary input for operating, and not as the core business of every processing plant. In the Chilean context, this was more notorious during the last copper super cycle, where prices sky-rocketed from 1.3 US$/lb by the end of 2008 to 4.58 US$/lb in 2011 (London Metal Exchange, 2014). Production needed to be increased fast; there was no room to be monitoring efficient uses of inputs.

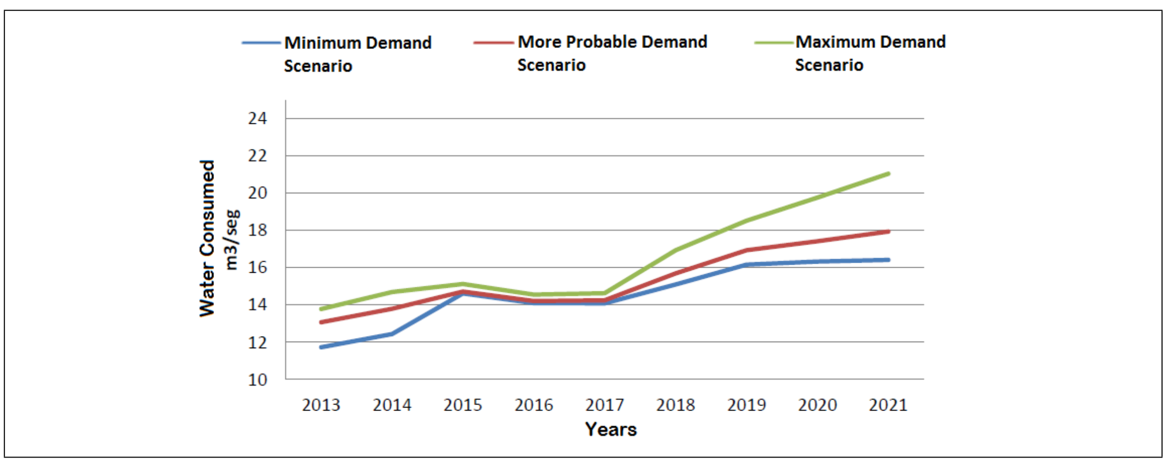

Figure 2.1. Projection of water demand. (Source: COCHILCO)

Nowadays, mining operations and processing plants are expected to raise their water demands over the years (see Figure 2.1) (Betancour & Montes, 2013). Therefore, quantifying and optimizing consumption, recovery and losses are part of an effective water management strategy. This methodology has been widely applied within a vast number of industries and social environments such as neighbourhoods and cities. Its applications can be identified from single industrial consumers to complex water right systems (Hu et al., 2014; Momblanch, Andreu, Paredes-Arquiola, Solera, & Pedro-Monzonís, 2014). Multiple models for simulation of water management have been developed, e.g., AQUATOOL (Andrew, Capilla, & Sanchs, 1996), MIKE HYDRO BASIN (Danish Hydraulic Institute, 2014), Aquadapt (Derceto, 2015), InfoMaster (Innovyze, 2015). However, the mentioned representations involve economic, political, social, hydrological, ecological, pollution and climatological variables. Thus, considering these conditions may occur in different contexts, there is no single and straight-forward water management (Koch & Grneward, 2009). Moreover, those platforms are designed to include complex water resources conditions such as river basin flows, hydro-geological models and water allocation problems that are sometimes far from the complications faced by mining companies.

On the other hand, water management in the industry is associated with waste-water managing and recovery. Applications on those directives are widely studied and documented in different journals and proceedings. Their objectives are focused on improving and/or optimizing water consumption through better recovery actions and/or improvements in processes (Alva-Argáez, Kokossis, & Smith, 1998; Rasekh & Brumbelow, 2015). Other researchers focused their investigation on water recycle-and-reuse strategies (Wang & Smith, 1994; Parthasarathy & Krishnagopalan, 2001). Also, applications like water allocation optimization are addressed (Condon & Maxwell, 2013; Roozbahani, Schreider, & Abbasi, 2015). Models are built, including more information as real-time control and context variables, e.g Energy and Water Quality Management Systems(Cherchi, Badruzzaman, Oppenheimer, Bros, & Jacangelo, 2015; Badruzzaman et al., 2014). However, mining applications regarding an integrated water management strategy are infrequent in literature.

This paper studies the application of a water management strategy in a mining operation. Section 2 establishes the objectives and methodology suggested, while in Section 3 data collection and experimentation are described. Section 4 discusses results obtained from the application of the equations and data validation. Evaporation rate curve is calculated. A consumption model derived from an optimization problem is deduced and the results from the methodology are reviewed. Data validation is done by predicting a major detention occurred on December of 2014 due to water scarcity. Finally, conclusions and improvements to this work are established.

3. OBJECTIVES AND METHODOLOGY

3.1. Objectives

Given the current water restriction affecting the mining industry, a water management methodology has become necessary. The main hypothesis is that a methodology for predicting freshwater requirements can be developed based on macro water balances, integrating mill plant requirements, seepage and evaporation control. Many models for simulation of water resource management have been developed in the last years (Koch & Grneward, 2009). However, some of the software tools on the market are focused on a river/reservoir system, which is far from the needs of the mining context. Operations in Chile obtain freshwater mainly by wells from old water-rights or by desalination processing plants.

With that idea in mind, the main goal is building a general water consumption predictive methodology. Its design is based on the water cycle surrounding the mining context. It has to help management decision with enough time in advance and support in the short and long run.

3.2. Methodology

The proposed methodology will be constructed considering a broad range of aspects and particularities for a typical Chilean Central Zone mill plant operation. But because it is widely known that water management strategies are different and complex, speaking of models designed for particular industries might counter its own general definition. Thus, clearing those doubts is necessary.

In this research, a general methodology refers to the wide application of the proposed construction method. Every water balance can be performed at macro and micro levels and the main equation can be written as follows:

$$\dot{Q}_{req} = \dot{Q}_{cons} - \dot{Q}_{trec} \tag{3.1}$$

In Equation 3.1, $\dot{Q}_{req}$ indicates the amount of make-up water needed and is measured in units of water volume in a fixed time horizon. $\dot{Q}_{cons}$ is water consumed by the operation. $\dot{Q}_{trec}$ is the amount of water recovered.

Equation 3.1 can be applied in any mining operation. However, estimating each term of the expression requires a detailed analysis of the operation and this research has done several studies on modeling each term in the particular mining context, thus adding value for developing a work methodology and a model for an industry where water is becoming one of the main drivers of the business.

3.2.1. Mining Operation's Description

The division is located in central Chile, near Santiago. It is composed of two mill plants with process rates of nearly 148,000 metric tonnes of mineral per day in total. The ore body is composed of copper sulphide with grades around 1% and molybdenum.

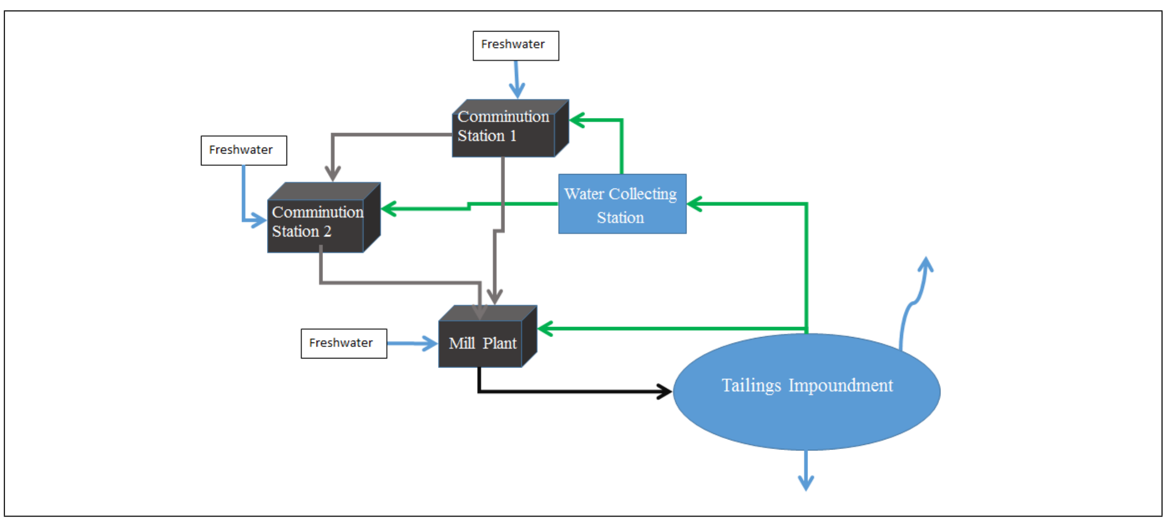

Figure 3.1. Simplified water cycle of the operation.

The water cycle in the operation can be represented by Figure 3.1. Mineral is extracted from the mine and sent to comminution stations one and two. Ore material is crushed and prepared to be processed. Water is needed to form the slurry and to send the material to Mill plant for processing. The mineral is transported by mining pipelines. Before processing, the slurry is combined with water to prepare less viscous fluxes. At the mill plant, copper and molybdenum concentrate production is performed and tailings are produced. During the processing, mineral fluxes Waste materials are sent to the tailing impoundment. There, part of the water will be lost due to evaporation, infiltration and retention in the material deposited. However, some of the water is recovered and sent back to the operation to be used at mill plants and comminution stations.

3.2.2. Mathematical Modeling

From the water cycle shown in Figure 3.1, some adjustments need to be done to Equation 3.1. $\dot{Q}_{trec}$ can be represented by the sum of two different factors: $\dot{Q}_{rec}$ and $\dot{Q}_{recycled}$. The first term is the amount of industrial water recovered inside the operation. In this particular industry, it is the result of the effectiveness on recovery from thickeners and filters. Meanwhile, $\dot{Q}_{recycled}$ shows recycled water. In other words, it is the amount of industrial water recovered outside the mill plant. This way, Equation 3.1 is written as follows:

$$\dot{Q}_{req} = \dot{Q}_{cons} - \dot{Q}_{rec} - \dot{Q}_{recycled} \tag{3.2}$$

$\dot{Q}_{cons}$ and $\dot{Q}_{rec}$ are modeled by Data Validation and Reconciliation (DVR). However, to find an expression for $\dot{Q}_{recycled}$, modeling the tailings impoundment arises as a fundamental task. It has to be done by representing changes in the tailing water body $W_{tailing}$ represented by:

$$\frac{\partial W_{tailing}}{\partial t} = \dot{Q}_{tailing} - \dot{Q}_{recycled} - \dot{Q}_{lost} \tag{3.3}$$

In Equation 3.3, $\dot{Q}_{tailing}$ accounts the amount of water sent to the tailings impoundment after the mill plant processing, and $\dot{Q}_{lost}$ quantifies all the water losses.

In the end, the proposed water management problem is reduced to Equation 3.2 and 3.3. Now every term needs to be modeled.

$$(P)\begin{cases} \dot{Q}_{req} = \dot{Q}_{cons} - \dot{Q}_{rec} - \dot{Q}_{recycled} \\ \frac{\partial W_{tailing}}{\partial t} = \dot{Q}_{tailing} - \dot{Q}_{recycled} - \dot{Q}_{lost} \end{cases}$$

3.2.3. Water Consumption Modeling

Full understanding of the operation processes is required to get a good estimation of water consumption $\dot{Q}_{cons}$. A detailed flowsheet is provided in Figure 3.2. Given the processing plant structure, Data Validation and Reconciliation (DVR) is applied to describe every stream of the process. As nonmodel-based balances, these are used extensively to evaluate and analyze data taken for the purpose of developing process models to be used in model-based balances (Richardson & Morrison, 2003). Deeper discussion about data availability is provided in Section 4.

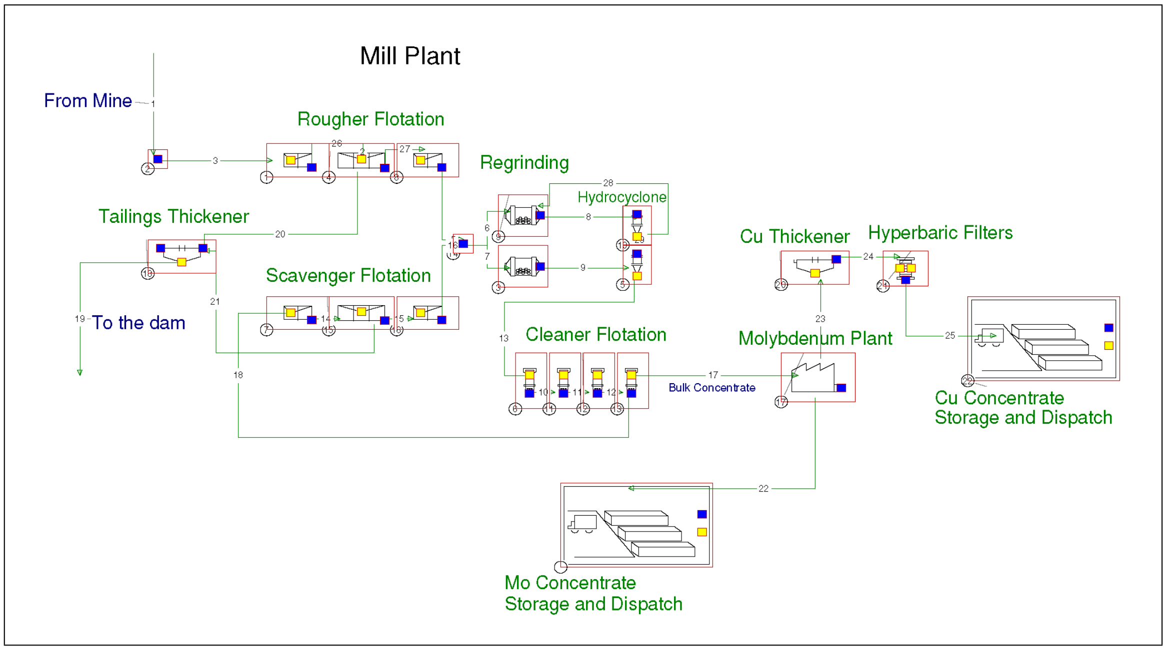

Figure 3.2. Operational flowsheet.

The main expressions are written as mass, copper and water balance equations in each node of the system. $X_{i,j}^t$ and $\bar{X_{i,j}}^t$ denote mass flux and measured mass flux of dry solid material from arc (i, j) in a time t respectively. Copper grade of flux from arc (i, j) and measured copper grade are denoted by $g_{i,j}^t$ and $\bar{g_{i,j}}^t$, while $s_{i,j}^t$ and $\bar{s_{i,j}}^t$ are the solid percentage estimated and measured of fluxes from arc (i, j) in a time t. Error terms $e_{i,j}^t$ are declared variables included for calibration purposes. All of them are in set V and T.

The balance problem for a time t is well represented by:

$$\text{Min} \sum_{(i,j)\in L} \frac{(X_{i,j}^t - \bar{X_{i,j}}^t)^2}{(\sigma_{X_{i,j}})^2} + \sum_{(i,j)\in M} \frac{(g_{i,j}^t - \bar{g_{i,j}}^t)^2}{(\sigma_{g_{i,j}})^2} + \sum_{(i,j)\in N} \frac{(s_{i,j}^t - \bar{s_{i,j}}^t)^2}{(\sigma_{s_{i,j}})^2} \tag{3.4}$$

subject to

$$\sum_{(i,j)\in V} X^t_{i,j} = \sum_{(j,k)\in V} X^t_{j,k} \qquad \forall (i,j),(j,k)\in V, \forall t\in T \quad (3.5)$$

$$\sum_{(i,j)\in V} X^t_{i,j}\cdot g^t_{i,j} = \sum_{(j,k)\in V} X^t_{j,k}\cdot g^t_{j,k} \qquad \forall (i,j),(j,k)\in V, \forall t\in T \quad (3.6)$$

$$\sum_{(i,j)\in V} X^t_{i,j}\frac{1-e^t_{i,j}\cdot s^t_{i,j}}{e^t_{i,j}\cdot s^t_{i,j}} = \sum_{(j,k)\in V} X^t_{j,k}\frac{1-e^t_{j,k}\cdot s^t_{j,k}}{e^t_{j,k}\cdot s_{j,k}} \quad \forall (i,j),(j,k)\in V, \forall t\in T \quad (3.7)$$

$$0\le g^t_{i,j}, s^t_{i,j}\le 1 \qquad \forall (i,j)\in V, \forall t\in T \quad (3.8)$$

$$\frac{X^t_{i,j}\cdot g^t_{i,j}}{X^t_{i,k}\cdot g^t_{i,k}}\le 1 \qquad \forall (i,j),(i,k)\in V', \forall t\in T \quad (3.9)$$

Sets L, M, N represents the collection of arcs with available data for mass flux, grade and solid percentage respectively. V' represents the arcs needed for determining the recovery of process nodes. L, M, N and V' are proper subsets of V. Due to its large scale and Non-Linear conditions, KNITRO solver method has been selected (Byrd, Nocedal, & Waltz, 2006).

The balance problem determines all of the streams circulating in the Mill plant. With this information, it is defined $\bar{w}_{in}$ and $\bar{X}$ as the average income water stream and material respectively as follows:

$$\bar{w}_{in} = \sum_{\forall t\in T}\sum_{\forall (i,j)\in I} X^t_{i,j}\cdot\frac{1-s^t_{i,j}}{s^t_{i,j}} \quad (3.10)$$

$$\bar{X} = \sum_{\forall t\in T}\sum_{\forall (i,j)\in P} X^t_{i,j} \quad (3.11)$$

Where sets I and O as the collection of arcs representing fluxes where water is added and leaves the system respectively. Also, sets P and R represent the mineral arcs entering and leaving the system. This way, water consumed $\dot{Q}_{cons}$ is written as a function of the mineral input per day x_{tpd} as follows: 3.12:

$$\dot{Q}_{cons}(x_{tpd}) = \frac{\sum\limits_{\forall t \in T}(\sum\limits_{(i,j) \in I} X_{i,j}^t \cdot \frac{1-s_{i,j}^t}{s_{i,j}^t} - \bar{w}_{in})(\sum\limits_{(i,j) \in P} X_{i,j}^t - \bar{X})}{\sum\limits_{\forall t \in T}(\sum\limits_{(i,j) \in P} X_{i,j}^t - \bar{X})^2} \cdot (x_{tpd} - \bar{x}) + \bar{w}_{in} \tag{3.12}$$

3.2.4. Water Recovery and Recycling Modeling

From the analysis done in the previous section, water streams from the mill plant were determined. By considering these data, an expression similar to Equation 3.12 can be constructed. Let us define $\bar{w}_{out}$ as the average outcome water stream such that:

$$\bar{w}_{out} = \sum_{\forall t \in T} \sum_{\forall (i,j) \in O} X_{i,j}^t \cdot \frac{1 - s_{i,j}^t}{s_{i,j}^t} \tag{3.13}$$

If R is the mean water recovery percentage, the function is written as follows:

$$\dot{Q}_{rec}(x_{tpd}) = R \cdot (\frac{\sum\limits_{\forall t \in T}(\sum\limits_{\forall (i,j) \in O} X_{i,j}^t \cdot \frac{1-s_{i,j}^t}{s_{i,j}^t} - \bar{w}_{out})(\sum\limits_{\forall (i,j) \in P} X_{i,j}^t - \bar{X})}{\sum\limits_{\forall t \in T}(\sum\limits_{\forall (i,j) \in P} X_{i,j}^t - \bar{X})^2} \cdot (x_{tpd} - \bar{X}) + \bar{w}_{out}) \tag{3.14}$$

For water recycling, the main source is located in the impoundment. Pumps were placed for sending the cumulated water back to the operation. Assuming that the pump system is always working to its full capacity, their task is modeled as a piecewise function where recycled water will be the maximum flux possible if the amount of water in storage is enough to feed the pumps:

$$\dot{Q}_{recycled} = \begin{cases} \dot{Q}_{maxpumps} & : \dot{Q}_{maxpumps} \leq \dot{Q}_{storage} \\ \dot{Q}_{storage} & : \dot{Q}_{maxpumps} > \dot{Q}_{storage} \end{cases} \tag{3.15}$$

3.2.5. Water Loss Modeling

In terms of water loss (see Figure 3.3), the three processes involved in active deposition areas are seepage, evaporation and saturation; in the pond zone, the water body is just affected by radiation and infiltration (Wels & Robertson, 2003). When impoundment dimensions are large, as in our case study, pond zone behaviour can be considered to explain most of the tailings phenomena.

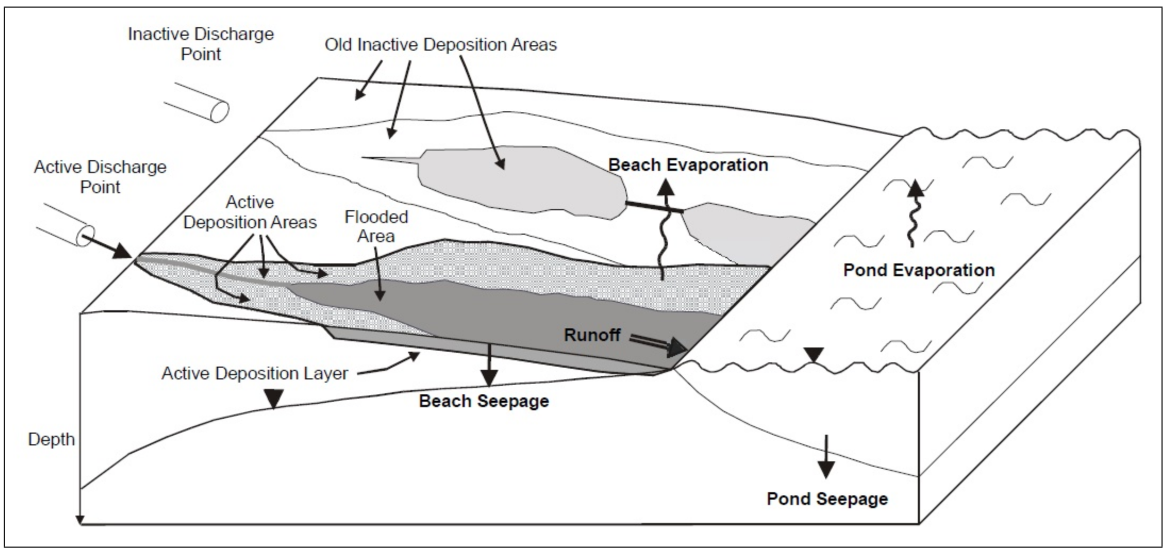

Figure 3.3. Schematic diagram of tailings deposition. (Source:Wels and Robertson (2003))

3.2.5.1. Evaporation Modeling

For estimating water loss, an energy balance is needed. Impoundments can be treated as an immense water reservoir where radiation is the main source of heat. Losses are due to convective air and water transport, and latent heat of vaporization. After some algebra, the Bowen-ratio energy-budget method is deduced, which is considered the most robust and the most accurate method for determining evaporation (Harbeck, Kohler, & Koberg, 1958; Gunaji, 1968; Sturrock, Winter, & Rosenberry, 1992; Lenters, Kratz, & Bowser, 2005; Rosenberry et al., 2007). However, data needed for the model is collected by special equipment (Bowen station) and its installation in operation was practically impossible during the research development. To estimate losses, another model is selected.

A significant number of studies have been conducted in numerous lakes for quantification of fluxes and many evaporation methods had been developed. Some of them are widely used for evapotranspiration like Penmann-Monteith (Allen, Pereira, Raes, & Smith, 1998) or Priestley-Taylor (Priestley & Taylor, 1972). Rosenberry et al. (2007) tested deBruin-Keijman expression (Equation 3.16), providing accurate values compared with the BREB method and will be used in this study.

$$E_{pond} = \frac{s}{s+\gamma}\frac{Q_n - Q_x}{l_w \cdot \rho_w} \cdot 86.4 \tag{3.16}$$

Where net radiation is Q_n, Q_x is the changes in heat stored in the water body. Psychrometric constant γ for Formula 3.16 is calculated as shown in Equation 3.17 where c_p is the specific heat of air at constant pressure $[MJ/(kg * C)]$, P is the atmospheric pressure $[kPa]$.

$$\gamma = \frac{c_p P}{\epsilon \cdot L} \tag{3.17}$$

On the other hand, s is the slope of the saturated vapor pressure-temperature curve at mean air temperature which is given by (Murray, 1967).

$$s = \frac{4098 \cdot (0.6108 \cdot e^{\frac{17.27T}{T+237.3}})}{(T+237.3)^2} \tag{3.18}$$

Allen et al.(1998) provided a way to estimate net radiation as the difference between two terms. One of them is Net Solar Radiation R_{ns}. It is corrected by the albedo.

$$R_{ns} = (1 - \text{albedo})R_s \tag{3.19}$$

Net Radiation has to be corrected by subtracting emissions from Earth itself. This is known as Net Longwave Radiation R_{nl} and it is estimated using Stefan-Boltzmann law of a black body radiation, corrected by air moisture and clearness index. In Equation 3.20, σ is the Stefan-Boltzmann constant, $T_{min,max}$ represent minimum and maximum temperature respectively, e_a is the real water vapor pressure and CI is the clearness index.

$$R_{nl} = \sigma \frac{(T_{max}^4 + T_{min}^4)}{2} (0.34 - 0.14\sqrt{e_a})(1.35CI - 0.35) \tag{3.20}$$

When evaporation is estimated outside the pond zone, it cannot be modeled directly. In figure 3.3, it is denoted by Beach Evaporation. Rates are affected by atmospheric demand, porous-medium pore space and transport properties (Brutsaert, 2005). There are many research activities focused on studying the effect of the properties of upper soil layers in the evaporation process (Assouline, Narkis, Gherabli, Lefort, & Prat, 2014) and measurements of evaporation in different regions (Assouline et al., 2008). In this case study, the evaporation phenomenon is quantified as a function of the difference between the phreatic level and the surface. Given that the material around the pond zone is also exposed to radiation, the water contained here is assumed to evaporate at lower rates.

Philip (1957) and Johnson et al. (2010) proposed exponential decrement evaporation models based on a fitting constant α determined by experimentation. While the models are written as a function of the water depth, it is possible to adjust the expressions due to geometrical hypothesis. Considering the pond zone as its equivalent circular surface, evaporation rate is then described by Equation 3.21. Here, r_l is the equivalent radius of the exposed pond zone and ω is the beach slope angle.

$$E(r) = \begin{cases} E_{pond} & : r \in [0, r_l[\\ E_{pond} e^{-\alpha \frac{r - r_l}{\tan \omega}} & : r \in [r_l, \infty[\end{cases} \tag{3.21}$$

Mathematically, water loss due to evaporation can be estimated as follows next:

$$\partial Q_{ev} = E(r) \cdot \partial A \tag{3.22}$$

$$\partial Q_{ev} = E(r) \cdot r \partial r \partial \theta \tag{3.23}$$

$$Q_{ev} = \int_0^{2\pi} \int_0^{\infty} (E(r) \cdot r) \partial r \partial \theta \tag{3.24}$$

$$Q_{ev} = \int_0^{2\pi} \int_0^{r_l} (E(r) \cdot r) \partial r \partial \theta + \int_0^{2\pi} \int_{r_l}^{\infty} (E(r) \cdot r) \partial r \partial \theta \tag{3.25}$$

$$Q_{ev} = \pi {r_l}^2 \cdot E_{pond} + 2\pi \int_{r_l}^{\infty} (E_{pond} e^{-\alpha \frac{r - r_l}{\tan \omega}} \cdot r) \partial r \tag{3.26}$$

$$Q_{ev} = \pi {r_l}^2 \cdot E_{pond} + 2\pi \cdot E_{pond} \frac{\alpha \tan(\omega) r_l + \tan(\omega)^2}{\alpha^2} \tag{3.27}$$

3.2.5.2. Seepage Modeling

Seepage problems are an important topic in engineering and have particular applications to groundwater simulations or geotechnical modeling (Pedroso, 2015). In the mining context, these are fundamental for interdisciplinary tasks like slope stability for tailings walls or water management.

Junqueira et al.(2011) have studied water loss from oil sands using drying column tests. Outflow volumes were periodically monitored. The rate of under-drainage was progressively reduced with time . Rivera & Paredes (2012) modified the drainage columns to replicate tailings deposition. Sensors and data tracking equipment controlled Volumetric Humidity in a certain time length.

Seepage rate S_r is considered to be constant on the contact surface between tailing material deposition conditions. Water loss due to infiltration is calculated as follows:

$$\partial Q_{sp} = S_r \cdot \partial A \tag{3.28}$$

$$\partial Q_{sp} = S_r \cdot r\partial\theta \frac{\partial z}{cos(\omega)} \tag{3.29}$$

$$\partial Q_{sp} = S_r \cdot r\partial\theta \frac{\partial r}{\tan\omega \cdot \sin(\omega)} \tag{3.30}$$

$$Q_{sp} = \int_0^{r_l} \int_0^{2\pi} \frac{S_r \cdot r \cdot \tan\omega}{\sin(\omega)} \partial\theta\partial r \tag{3.31}$$

$$Q_{sp} = \frac{S_r \cdot r_l^2 \pi}{\cos(\omega)} \tag{3.32}$$

3.2.5.3. Entrainment Modeling

When tailings is deposited, water is entrained in the pore spaces of the material, avoiding its recovery after consolidation. Entrainment losses depend mainly on the particle size of the tailings with fine clay tailings entraining much more water than freely draining coarse sand tailings. Water losses due to entrainment are expected to be relatively constant for tailings with a defined particle size distribution (Wels & Robertson, 2003). For predicting water entrained, the water retention curve is needed. Qiu and Sego (2001) studied ore tailings and determined water retention curves shown in Figure 3.4, which will provide information about tailings water storage.

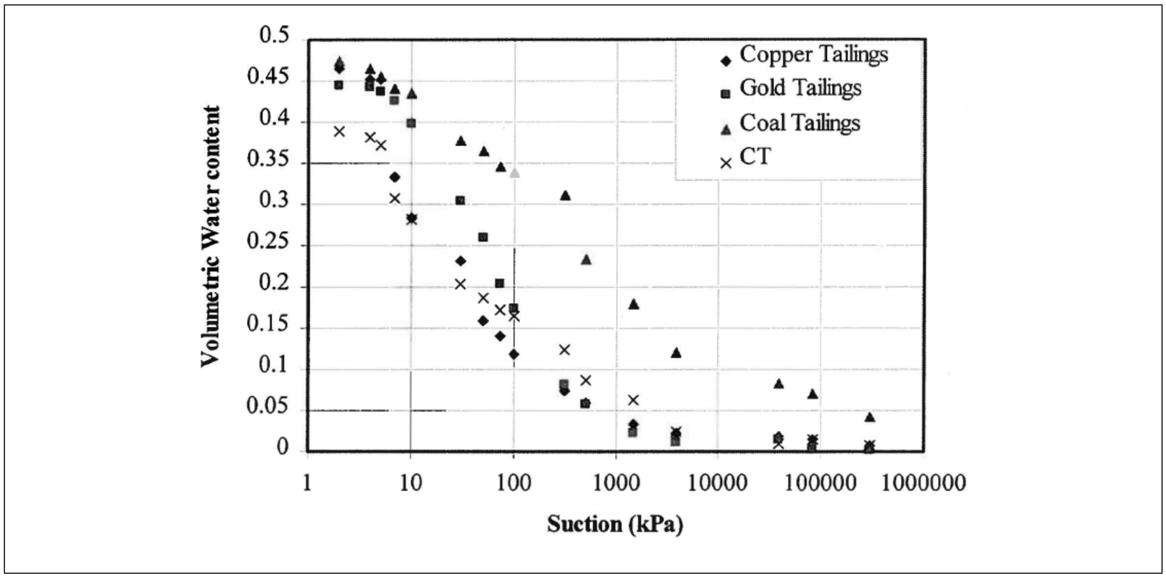

Figure 3.4. Water Retention Curve for Ore Tailings. (Source: Qiu and Sego(2001))

4. DATA COLLECTION AND EXPERIMENTATION

Experimental data is a key element for the proposed general methodology. In fact, most of the equations required for this project need environmental or experimental values for their applications.

4.1. Water Data from Mill Plant

Data for estimating water consumption was obtained through the PI system. Figure 4.1 simplifies the Mill plant fluxes. Streams 3,4,5 and 10 are tailing fluxes sent to the tailing impoundment or thickener. Arc 1 represents the input stream to the operation.

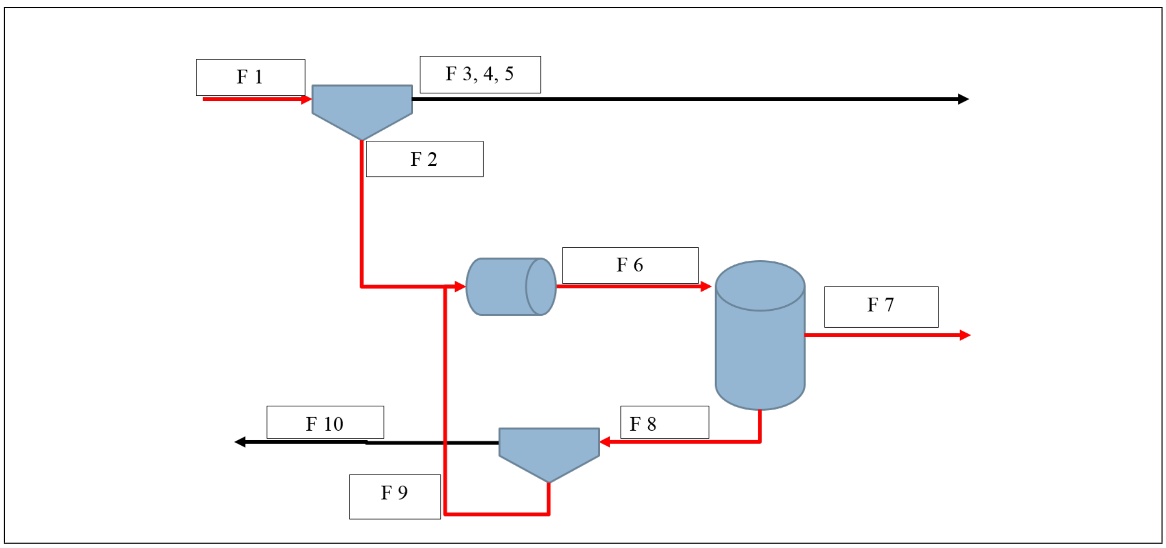

Figure 4.1. Mill plant streams flowsheet.

As it was established in Section 3, mineral, grade and solid percentage values were recovered. Data availability is shown in Table 4.1.

Table 4.1. Data availability.

Flux	Mass Flux Data	Grade Data	Solid Percentage Data
1	Yes	Yes	Yes
2	No	Yes	No
3	No	Yes	Yes
4	No	Yes	Yes
5	No	Yes	Yes
6	No	No	No
7	No	Yes	Yes
8	No	No	No
9	No	No	No
10	No	Yes	Yes

4.2. Evaporation Data

Equations 3.19 and 3.20 require environmental data. Monthly Average Radiation values were provided by NASA LaRC project. Temperature, clearness index and pressure data were provided by weather stations near the operation and in Santiago.

4.3. Evaporation Experiments

The methods and equations presented in Section 3 were developed for lakes, rivers or natural reservoirs (Rosenberry et al., 2007). However, industrial water rates might present differences compared to freshwater rates. In order to improve the predictability of the model, the effective industrial water evaporation rate in the area is measured. If numerical differences were present, correction factors would be applied.

Regarding evaporation outside the pond zone, rates in unsaturated porous areas near the surface are required for accurate water loss estimation. In literature, the drying process on unsaturated materials has been studied extensively, relating dry fronts with capillary and receding regimes, and studying characteristic properties (Coussot, 2000; Lehmann, Assouline, & Or, 2008). However, those approaches do not include factors from the mining industry, like the impact of solid additives present in the liquid (Keita, Faure, Rodts, & Coussot, 2013). It is because of those reasons that experimental tests were needed.

Evaporation Columns were designed for measurement of water loss. The design is shown in 4.2. It is composed by two columns connected by a hose with a filter for preventing material flux. One side is filled with tailings and water. The other side possesses just water and a cover designed for avoiding water evaporation. Because atmospheric pressure and kinetic energy are kept constant, water height has to be the same in both columns.

Figure 4.2. Evaporation column design.

4.4. Seepage Experiments

For the case study, tailings deposition occurs on tailings layers. Material arrives to the impoundment with solid percentages high enough for allowing water fluxes into the ground. Due to these conditions, quantifying water infiltration becomes a fundamental task. For accomplishing this, constructing a humidity profile by applying the methodology proposed by Rivera and Paredes was opted (2012).

The experimental design is shown is figure 4.3. Humidity is measured using soil sensors and dataloggers in different points of the tailings column. Seepage rate needed for Equation 3.21 is calculated as changes in humidity over a time length.

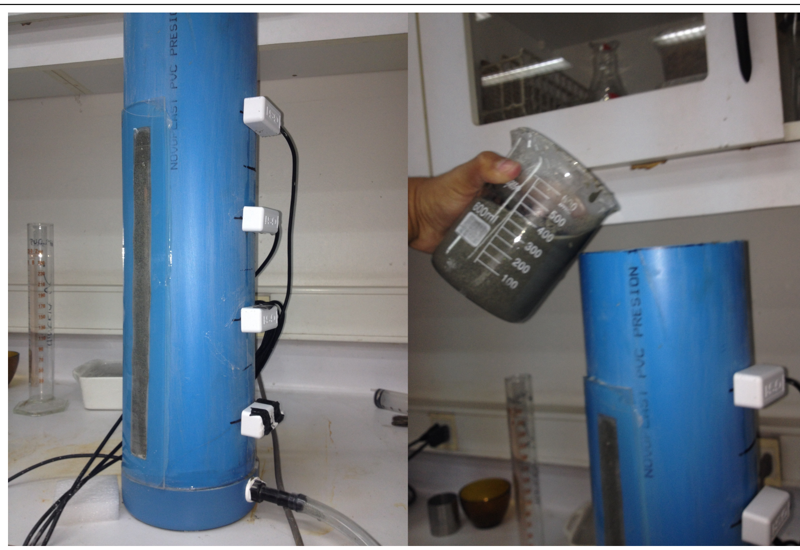

Figure 4.3. Seepage column design.

5. RESULTS AND ANALYSIS

5.1. Model Factors Analysis

Figure 5.1 shows the relation between industrial water and freshwater evaporation rates. As the slope of the line reveals that the evaporation rates for freshwater and industrial water are different, the unexpected behavior is attributed to the concentration of remaining surfactant in the slurry. For representing this phenomenon in the model, the evaporation rate calculated from Equation 3.16 is corrected by an effective evaporation factor obtained from the slope.

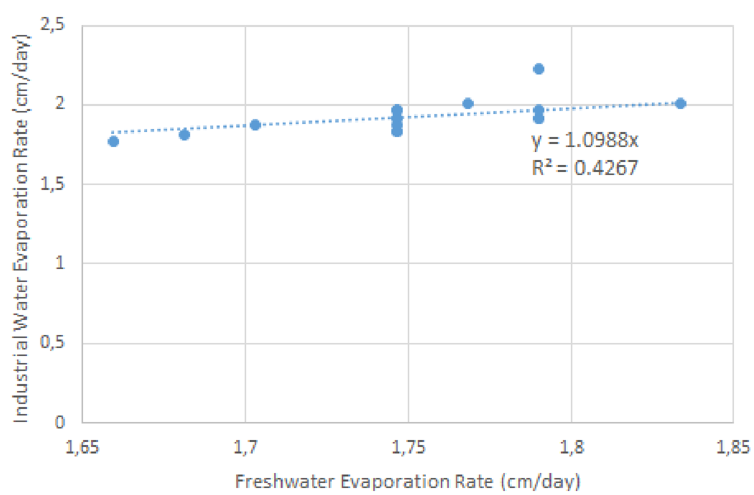

Figure 5.1. Evaporation rates from industrial and freshwater.

With respect to the comparison mentioned in Section 3, Figure 5.2 presents deBruin-Keijman model results compared to real evaporation data. From the graph on the left, it is possible to perceive that the model presents a good R^2 value and controlled data spread. In the right-hand graph, real data is contrasted with deBruin-Keijman values where radiation variability was considered, and the results were improved significantly. This corroborates the accuracy of the method for estimating evaporation under tailings conditions.

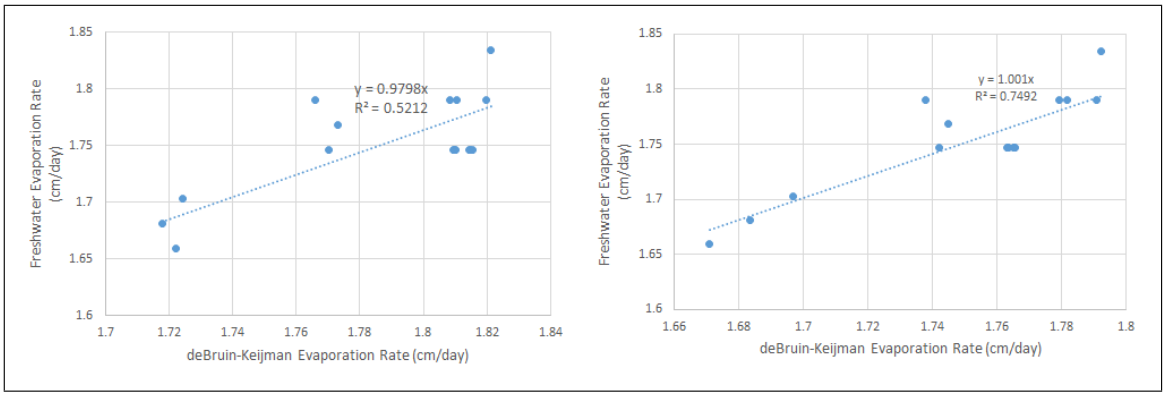

Figure 5.2. Evaporation rates comparison between deBruin-Keijman method and real data.

For evaporation rate outside the pond zone, it can be represented as a decreasing exponential function (see Figure 5.3). R^2 value is relatively high and the trend is mostly captured. Part of the variability of the data could be attributed to other factor such as soil compaction or clogged filters. From the figure, α is obtained. With this, water evaporated from outside the pond zone is shown to be relatively inferior, corresponding to an average of 1.51% of the total water loss by evaporation. However, this amount is at least 1/4 of the water recovered by filtration or 1/10 of the total water used for floculant preparation.

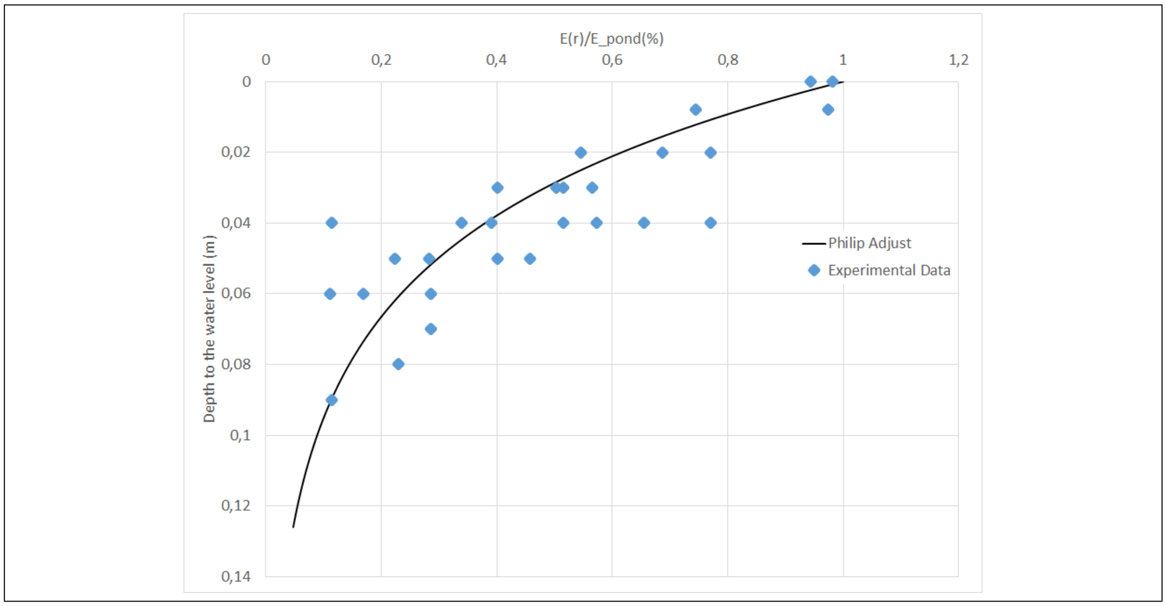

Figure 5.3. Evaporation rates curve for unsaturated areas.

Regarding the seepage analysis, the humidity profile needed is shown in Figure 5.4. Water is percolated rapidly during the first couple of minutes, and then the process reaches stable rates significantly inferior in magnitude. Thanks to this phenomenon, around 90% of the water is percolated on the first day since deposition. For quantifying seepage for daily processes, the analysis is performed using data from the first day. A seepage rate is obtained by calculating the average water lost per interval of time.

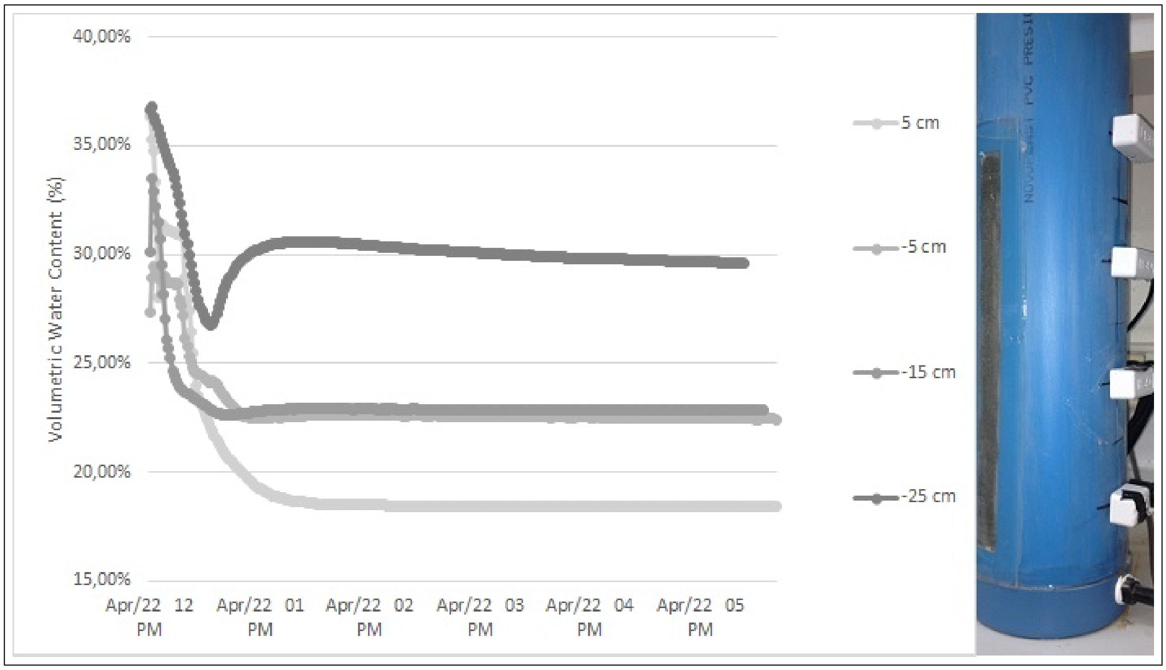

Figure 5.4. Humidity profile from seepage columns

In terms of water consumption, Figure 5.5 shows the relation between total tonnage sent to mill and water required by the operation. For daily production, most of the data is cumulated around 80,000 - 100,000 tonnes per day, which is the normal mill plant throughput. Days with less processing rates are modeled too. These data represent working days with detention times, but it is possible to quantify consumption from the mill plant's valid operational hours. As the slope of the figure shows, the mill plant needs around 3.08 m^3 of water per each tonne of mineral input, which is a standard water requirement in the mining industry. For simplicity and due to data availability, water needed for start-up is not considered, which might be an underestimation of total consumption.

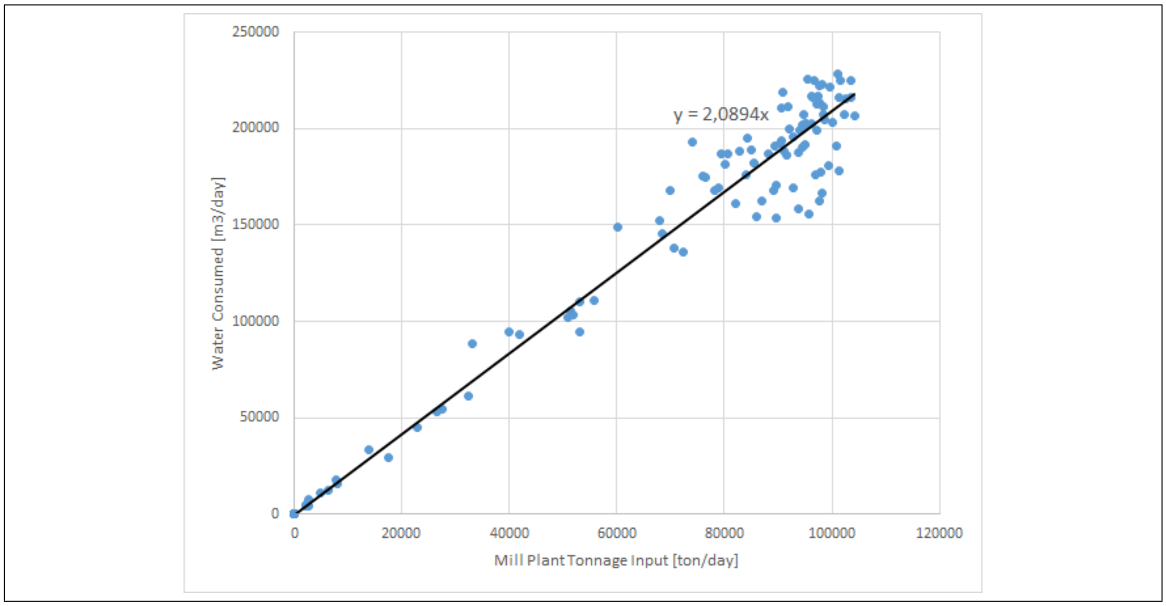

Figure 5.5. Water consumption results.

Figure 5.6 presents data trend behavior. As mentioned in Section 3, modeling water streams from thickeners is derived directly from the optimization results. With this, 58.3% of the water sent to the tailings impoundment is recovered by Mill plant 2. Further discussion of the impact of this term in the water management strategy is provided in Section 5.3.

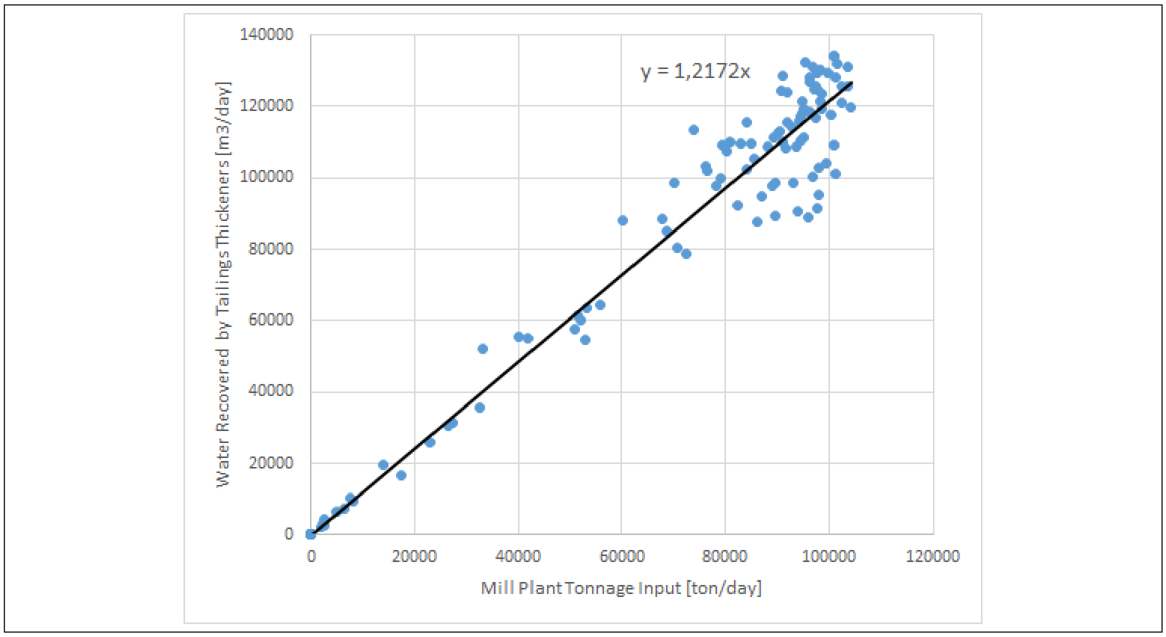

Figure 5.6. Water recovery results.

5.2. Model Results Analysis

As discussed in Section 3, the effectiveness of the proposed methodology is validated by contrasting its results with operational data. With this goal in mind, two main water variables need to be monitored: make-up water consumption and tailings water storage. To evaluate consumption, the daily amount of water obtained from wells is needed. However, real-time values are not monitored directly as it was done with parameters like grade or throughput. In this case, make-up water is contrasted with the wells' capacity and information about wells water extraction from the company. In terms of water storage, although water level in the dam is not monitored, it is known that an important mill plant detention was executed at the end of 2014 due to water scarcity. According to operational rules of the mill plant and the tailings system, if the levels are lower than 20% of the tailing level, the pump system cannot work under its full capacity and water shortage will be detected immediately.

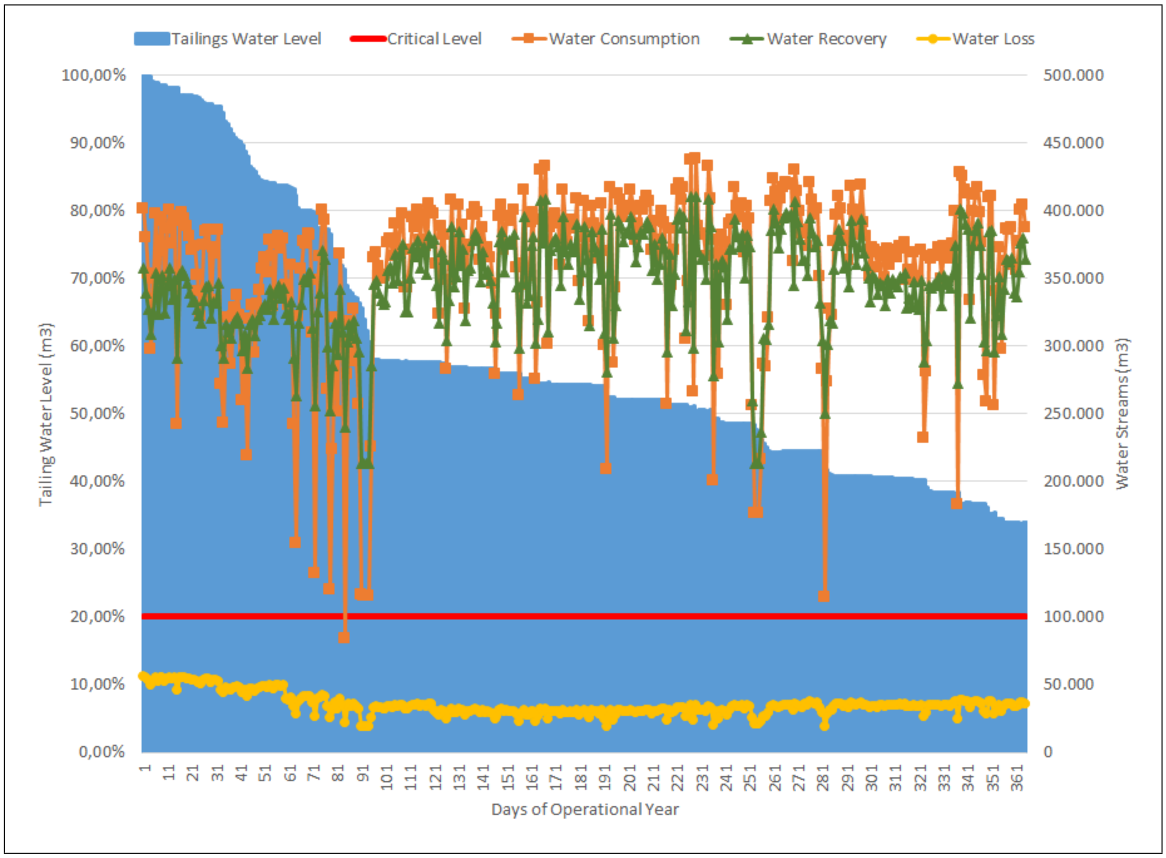

Figure 5.7. Water management methodology data prediction - Normal Case.
Bar graph represents tailings water levels from 100% with is the beginning of the operational year. Critical level represents tailings levels where pumps will not operate to its required capacity and water shortage will occur. Line graphs represents water consumption from the operation, water total recovery recirculated to the mill plants and water losses

Figure 5.7 presents the methodology results in terms of water consumption, recovery, tailings levels and water losses. In this case, losses consider only evaporation without correction factors and entrainment, water recovery quantifies fluxes recovered in thickener and the tailing pump system, and water consumption accounts requirements from both mill plants. As the figure 5.7 shows, critical storage levels are not reached and the average make-up water demand is between 90%-96% of the wells capacity. Under these circumstances, no detention should have been executed during the 2014 operational year and mill plant consumption should be guaranteed until 2015.

Now, if the methodology is completed including seepage, corrected and residual evaporation and entrainment, new results are obtained. Figure 5.8 illustrates the updated prediction of water requirements. As the figure shows, water loss increased significantly compared to the previous case. Among 23.9%-50.3% of extra water is lost because of seepage inclusion. Also, the most notorious changes are identified during summer months, where evaporation has a more significant impact too. From the figure, make-up water demand did not change because operational conditions were kept constant for both analyses. However, critical tailing levels are reached by the beginning of the final month of the period analyzed. In conclusion, this methodology structure accurately predicts the 2014 operational scenario including the critical detention due to water scarcity.

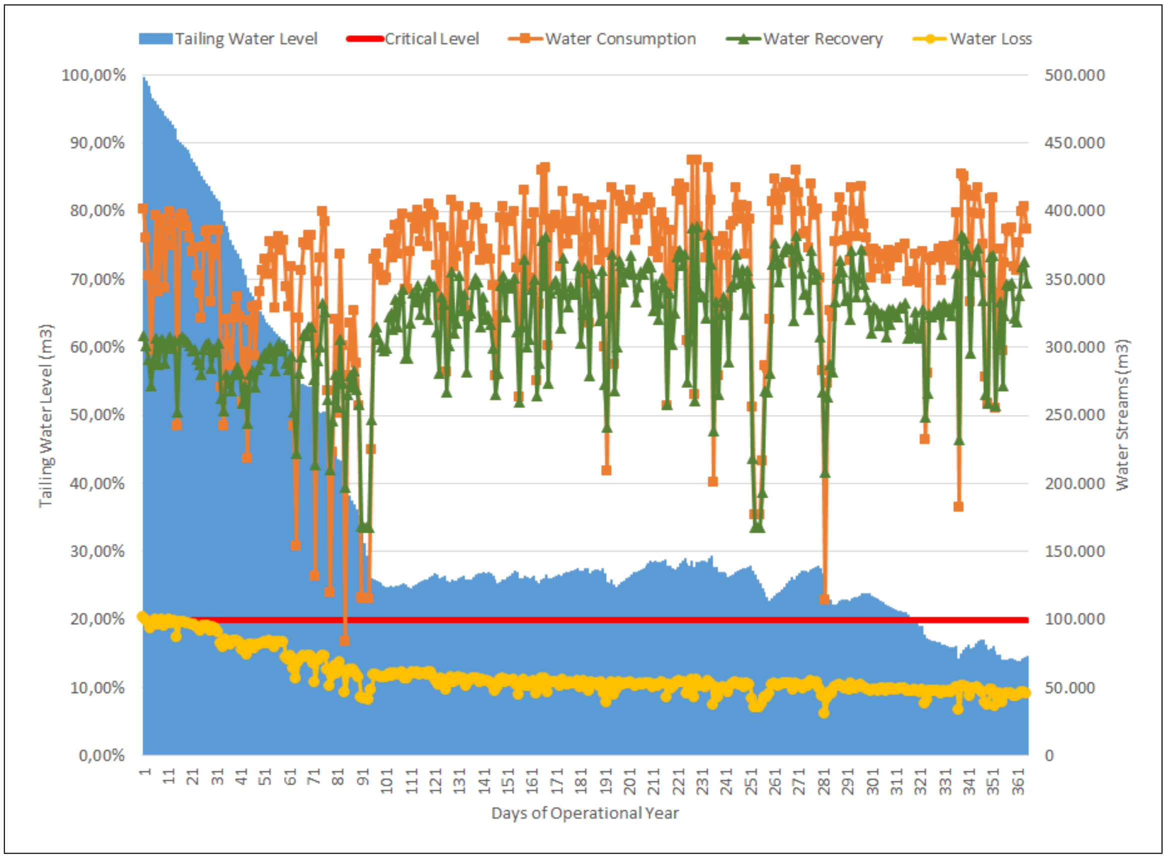

Figure 5.8. Water management methodology data prediction - Critical case.
Bar graph represents tailings water levels from 100% with is the beginning of the operational year. Critical level represents tailings levels where pumps will not operate to its required capacity and water shortage will occur. Line graphs represents water consumption from the operation, water total recovery recirculated to the mill plants and water losses

5.3. Water Management Decisions

Given the methodology structure, it is possible to identify areas for improvement. Among 25% - 34% of the water sent to the tailing impoundment will be lost due to evaporation and seepage. Meaning that up to 19% of the total water required by the mill plant is lost this way. Also, tailings levels will be low at some point, affecting water recycled from the dam and thus having an impact on water supply for mill plant consumption.

Regarding water management strategy in the short run, the main goal is avoiding water loss due to evaporation and seepage. To target radiation loss, numerous attempts have been made by altering storage design from increasing reservoir depth, to installing windbreaks or reducing exposed surface (Craig, 2005; Assouline, Narkis, & Or, 2010). Covers appear as a possible policy. A deeper analysis needs to be performed but roughly if the exposed surface can be reduced in an equivalent radius of 50 m, losses are decreased among 16% - 35%.

In the long run, better improvements can be performed. As it was noticed in Section 3, water recovery is extremely limited to the thickener in Mill plant 2. Neglecting spatial availability, if another thickener of the same characteristics can be installed for Mill plant 1, an average of 46% of the water losses can be recovered directly. Not only water are losses decreased, but also water supply increases.

Also, changes in the thickening process might come into the analysis. Thickened tailings technology has been implemented successfully in other mining operations, obtaining its benefits: increasing water fluxes for mill plant consumption, eliminating the losses associated with the transport and storage of water either at the tailings facility or in holding ponds (Fourie, 2003), beach slopes increase compared to conventional lower solid percentage concentration tailings disposal, allowing greater volumes of tailings to be stored in the same surface footprint (Engels, 2015), etc.

Along with these policies, changes in the impoundment structure, covering tailings contact area for avoiding seepage and even changing tailings dam dimensions for allowing higher water storage capacity might be considered too. However, a detailed economic analysis has to be performed for verifying availability of these actions.

Finally, it is necessary to consider investments in water desalination technology. In Chile, many greenfield and brownfield mining projects have considered and/or invested in desalination plants, including greater amounts of freshwater for consumption.

6. CONCLUSIONS AND FUTURE RESEARCH

For an integrated water management strategy and the construction of a predictive water methodology presented in this document, many factors have been included. Mill plant water requirements are modeled through data validation and reconciliation, allowing to extrapolate a consumption function and a recovery function for thickeners installed in the mining operation. To represent all the water recycled, an analysis of the tailings dam was performed, including all the water losses associated with the water body. These losses include evaporation of industrial water by radiation, infiltration of water through porous material and water entrainment. The proposed methodology fuses methodologies from different areas, normally not applied in the mining industry.

The results obtained allow the methodology to accurately extrapolate operational scenarios. During 2014, certain unaccounted conditions had developed, forcing a detention for several weeks. Under these circumstances, the methodology was capable of recreating these conditions, controlling make-up water consumption and modeling tailings water body to the point of critical water levels.

Water management decisions are supported by the methodology results. Reduction of water loss arises as one of the main short run policies. In particular, targeting evaporation losses can be achieved by covering exposed surface. For long run policies, installing an extra thickener for mill plant 1, changing thickening technology, modifying the tailings impoundment dimensions and including desalination plants are options to keep in mind.

The present methodology might be improved by relaxing some conditions and hypotheses applied. Seepage modeling and entrainment will be explained in a better way considering literature models like Green-Ampt (Green & Ampt, 1911), Phillip's Two-Term (Philip, 1974) or Infiltration/Exfiltration models (Eagleson, 1978). Also, a consolidation analysis will improve the water available for pump extraction.

REFERENCES

Allen, R., Pereira, L., Raes, D., & Smith, M. (1998). *Crop evapotranspiration - guidelines for computing crop water requirements - fao irrigation and drainage paper 56*. FAO.

Alva-Argáez, A., Kokossis, A., & Smith, R. (1998). Wastewater minimisation of industrial systems using an integrated approach. *Computers & Chemical Engineering*, *22, Supplement 1*(0), S741 - S744. (European Symposium on Computer Aided Process Engineering-8) doi: http://dx.doi.org/10.1016/S0098-1354(98)00138-0

Andrew, J., Capilla, J., & Sanchs, E. (1996). Aquatool, a generalized decision-support system for water-resources planning and operational management. *Journal of Hydrology*, *177*(3-4), 269-291.

Assouline, S., Narkis, K., Gherabli, R., Lefort, P., & Prat, M. (2014). Analysis of the impact of surface layer properties on evaporation from porous systems using column experiments and modified definition of characteristic length. *Water Resources Research*, *50*, 39333955.

Assouline, S., Narkis, K., & Or, D. (2010). Evaporation from partially covered water surfaces. *Water Resources Research*, *46*(10), n/a–n/a. (W10539) doi: 10.1029/2010WR009121

Assouline, S., Tyler, S., Tanny, J., Cohen, S., Bou-Zeid, E., Parlange, M., & Katul, G. (2008). Evaporation from three water bodies of different sizes and climates: Measurements and scaling analysis. *Advances in Water Resources*, *31*, 160-172. doi: 10.1016/j.advwatres.2007.07.003

Badruzzaman, M., Cherchi, C., Oppenheimer, J., Gordon, M., Bunn, S., & Jacangelo, J. (2014). Implementation of energy and water quality management systems modified with a ghg module. In *Proceedings of the annual conference & exposition '15, awwa conference.*

Betancour, M., & Montes, C. (2013). *Proyección de demanda de agua fresca en la minería* *del cobre, 2013-2021* (Tech. Rep.). COCHILCO.

Brutsaert, W. (2005). *Hydrology: An introduction*. Cambridge University Press.

Byrd, R. H., Nocedal, J., & Waltz, R. A. (2006, February). *Knitro: An integrated package for nonlinear optimization.* Web Article. Retrieved from http://www.ziena.com/papers/integratedpackage.pdf

Cherchi, C., Badruzzaman, M., Oppenheimer, J., Bros, C. M., & Jacangelo, J. G. (2015). Energy and water quality management systems for water utility's operations: A review. *Journal of Environmental Management*, *153*(0), 108 - 120. doi: http://dx.doi.org/10.1016/j.jenvman.2015.01.051

Condon, L. E., & Maxwell, R. M. (2013). Implementation of a linear optimization water allocation algorithm into a fully integrated physical hydrology model. *Advances in Water Resources*, *60*(0), 135 - 147. doi: http://dx.doi.org/10.1016/j.advwatres.2013.07.012

Coussot, P. (2000). Scaling approach of the convective drying of a porous medium. *The European Physical Journal B - Condensed Matter and Complex Systems*, *15*(3), 557-566. doi: 10.1007/s100510051160

Craig, I. P. (2005). *Loss of storage water due to evaporation - a literature review.* (Tech. Rep.). Toowoomba, Australia.: University of Southern Queensland, National Centre for Engineering in Agriculture. doi: 1000580/0

Danish Hydraulic Institute. (2014). *Mike hydro basin - mike by dhi product flyer.* Web Article. Retrieved from http://www.mikebydhi.com/-/media/shared%20content/mike%20by%20dhi/flyers%20and%20pdf/software%20flyers/water%20resources/mbd_catextract_mikehydrobasin_uk.pdf

Derceto. (2015). *Introducing derceto aquadapt.* Web Article. Retrieved from http://www.derceto.com/Products-Services/Derceto-Aquadapt

Eagleson, P. S. (1978). Climate, soil, and vegetation: 3. a simplified model of soil moisture movement in the liquid phase. *Water Resources Research*, *14*(5), 722–730. doi: 10.1029/WR014i005p00722

Engels, J. (2015). *High density thickened tailings (hdtt) storage.* Web Article. Retrieved from http://www.tailings.info/disposal/thickened.htm

Fourie, A. B. (2003). *In search of the sustainable tailings dam: Do high-density thickened tailings provide the solution.* South Africa.

Green, W. H., & Ampt, G. A. (1911). Studies on soil phyics. *The Journal of Agricultural Science*, *4*, 1-24. doi: 10.1017/S0021859600001441.

Gunaji, N. (1968). Evaporation investigations at elephant butte reservoir in new mexico. *International Association of Scientific Hydrology*, *78*, 308-325.

Harbeck, G., Kohler, M., & Koberg, G. (1958). *Water-loss investigations: Lake mead studies. professional paper 298.* (Tech. Rep.). US Geological Survey.

Hu, X.-J., Xiong, Y.-C., Li, Y.-J., Wang, J.-X., Li, F.-M., Wang, H.-Y., & Li, L.-L. (2014). Integrated water resources management and water users' associations in the arid region of northwest china: A case study of farmers' perceptions. *Journal of Environmental Management*, *145*(0), 162 - 169. doi: http://dx.doi.org/10.1016/j.jenvman.2014.06.018

Innovyze. (2015). *Advanced arcgis-based analytical asset management and capital planning.* Web Article. Retrieved from http://www.innovyze.com/products/infomaster/

Johnson, E., Yáñez, J., Ortiz, C., & Muñoz, J. (2010). Evaporation from shallow groundwater in closed basins in the chilean altiplano. *Hydrological Sciences Journal*, *55*(4), 624-635. doi: 10.1080/02626661003780458

Junqueira, F., Sanin, M., Sedgwick, A., & Blum, J. (2011). Assessment of water removal from oil sands tailings by evaporation and under-drainage, and the impact on tailings consolidation. In *Proceedings tailings and mine waste.*

Keita, E., Faure, P., Rodts, S., & Coussot, P. (2013, Jun). Mri evidence for a receding-front effect in drying porous media. *Phys. Rev. E*, *87*, 062303. doi: 10.1103/PhysRevE.87.062303

Koch, H., & Grneward, U. (2009). A comparison of modelling systems for the development and revision of water resources management plans. *Water Resources Management*, *23*, 1403-1422.

Lehmann, P., Assouline, S., & Or, D. (2008, May). Characteristic lengths affecting evaporative drying of porous media. *Phys. Rev. E*, *77*, 056309. doi: 10.1103/PhysRevE.77.056309

Lenters, J., Kratz, T., & Bowser, C. (2005). Effects of climate variability on lake evaporation: results from a long-term energy budget study of sparkling lake, northern wisconsin. *Journal of Hydrology*, *308*, 168-195.

London Metal Exchange. (2014). *London metal exchange: Copper.* Web Article. Retrieved from http://www.lme.com/en-gb/metals/non-ferrous/copper/

Momblanch, A., Andreu, J., Paredes-Arquiola, J., Solera, A., & Pedro-Monzonís, M. (2014). Adapting water accounting for integrated water resource management. the júcar water resource system (spain). *Journal of Hydrology*, *519, Part D*(0), 3369 - 3385. doi: http://dx.doi.org/10.1016/j.jhydrol.2014.10.002

Murray, F. W. (1967). On the computation of saturation vapor pressure. *Journal of Applied Meteorology and Clomatology*, *6*(1), 203-204. doi: 10.1175/1520-0450(1967)006<0203:OTCOSV>2.0.CO;2

Parthasarathy, G., & Krishnagopalan, G. (2001). Systematic reallocation of aqueous resources using mass integration in a typical pulp mill. *Advances in Environmental Research*, *5*(1), 61 - 79. doi: http://dx.doi.org/10.1016/S1093-0191(00)00043-5

Pedroso, D. M. (2015). A solution to transient seepage in unsaturated porous media. *Computer Methods in Applied Mechanics and Engineering*, *285*(0), 791 - 816. doi: http://dx.doi.org/10.1016/j.cma.2014.12.009

Philip, J. R. (1957). Evaporation, and moisture and heat fields in the soil. *Journal of Atmospheric Sciences*, *14*(4), 354-366. doi: 10.1175/1520-0469(1957)014<0354:EAMAHF>2.0.CO;2

Philip, J. R. (1974). Recent progress in the solution of nonlinear diffusion equations. *Soil Science*, *04*. doi: 10.1097/00010694-197405000-00004

Priestley, C. H. B., & Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review*.

Qiu, Y., & Sego, D. (2001). Laboratory properties of mine tailings. *Canadian Geotechnical Journal*, *38*(1), 183–190.

Rasekh, A., & Brumbelow, K. (2015). A dynamic simulation-optimization model for adaptive management of urban water distribution system contamination threats. *Applied Soft Computing*, *32*(0), 59 - 71. doi: http://dx.doi.org/10.1016/j.asoc.2015.03.021

Richardson, J., & Morrison, R. D. (2003). Principles of mineral processing. In M. C. Fuerstenau (Ed.), (p. 363-389). SME.

Rivera, D., & Paredes, L. (2012). *Estudio experimental del potencial de infiltración de relaves espesados ttd depositados directamente sobre suelos naturales.*

Roozbahani, R., Schreider, S., & Abbasi, B. (2015). Optimal water allocation through a multi-objective compromise between environmental, social, and economic preferences. *Environmental Modelling & Software*, *64*(0), 18 - 30. doi: http://dx.doi.org/10.1016/j.envsoft.2014.11.001

Rosenberry, D., Winter, T., Buso, D., & Likens, G. (2007). Comparison of 15 evaporation methods applied to a small mountain lake in the northeastern usa. *Journal of Hydrology*, *340*, 149-166.

Sturrock, A., Winter, T., & Rosenberry, D. (1992). Energy budget evaporation from williams lake: a closed lake in north central minnesota. *Water Resources Research*, *28*(6), 1605-1617.

UNESCO. (2006). *The 2nd un world water development report: "water, a shared resposibility"* (Tech. Rep.). Author.

Wang, Y., & Smith, R. (1994). Wastewater minimisation. *Chemical Engineering Science*, *49*(7), 981 - 1006. doi: http://dx.doi.org/10.1016/0009-2509(94)80006-5

Wels, C., & Robertson, A. M. (2003). Conceptual model for estimating water recovery in tailings impoundments. In *Tailings and mine waste: Proceedings of the tenth international conference, vail, co. colorado state university, october 12* (Vol. 15, p. 87-94).

APPENDIX

A. DATA RECONCILIATION FORMULATION

In mineral processing data control is fundamental for optimizing processes, improving recovery and ore grades. Processing characterization is done by developing the detailed material balances of the operation. However, sampling streams from those balances might present errors.

Here is an example consisting on one processing unit:

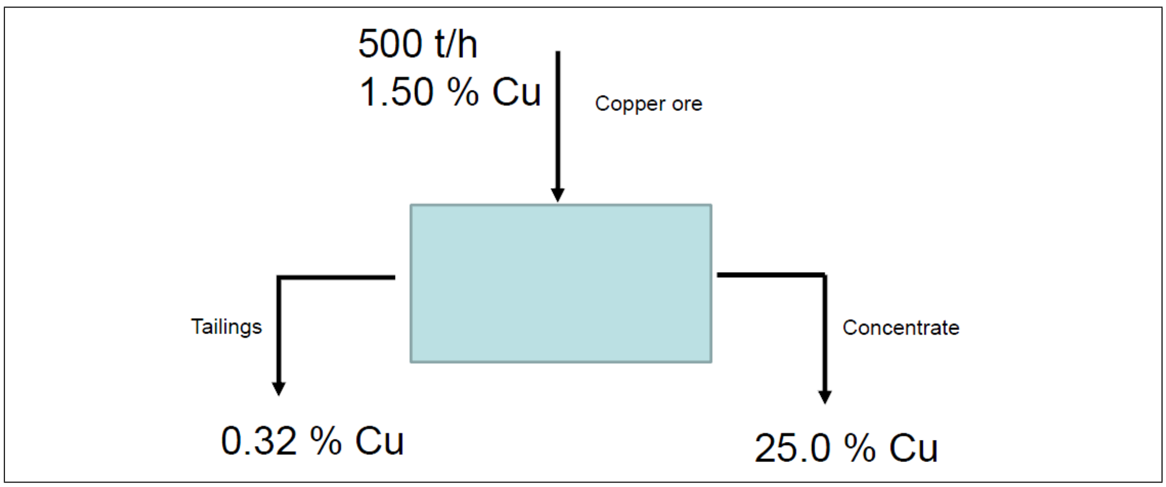

Figure A.1. Example of Data Reconciliation - Initial case

By using recovery formula:

$$R = \frac{C \cdot c}{F \cdot f} = \frac{c - t}{f - t} \rightarrow C = 24 \text{ t/h} \quad \& \quad T = 476 \text{ t/h} \tag{A.1}$$

However, sampling process contains errors associated. It is frequent to detect inconsistencies in mill plants sampling. In this case, the sampled process is detailed in Figure A.2.

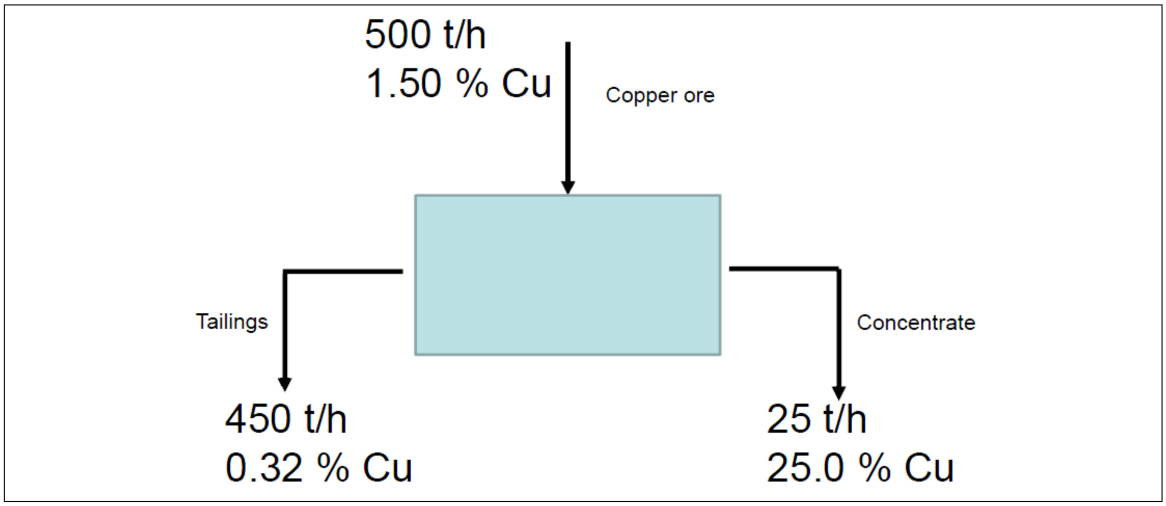

Figure A.2. Example of Data Reconciliation - Sampled case

As it is shown, calculated concentrate and tailings streams are not the same as the sampled ones and for obtaining correct balances, one of the measured fluxes might be ignored. However, before discarding or ignoring data, it is recommended to adjust data available considering the sampling error and thus obtaining the balances.

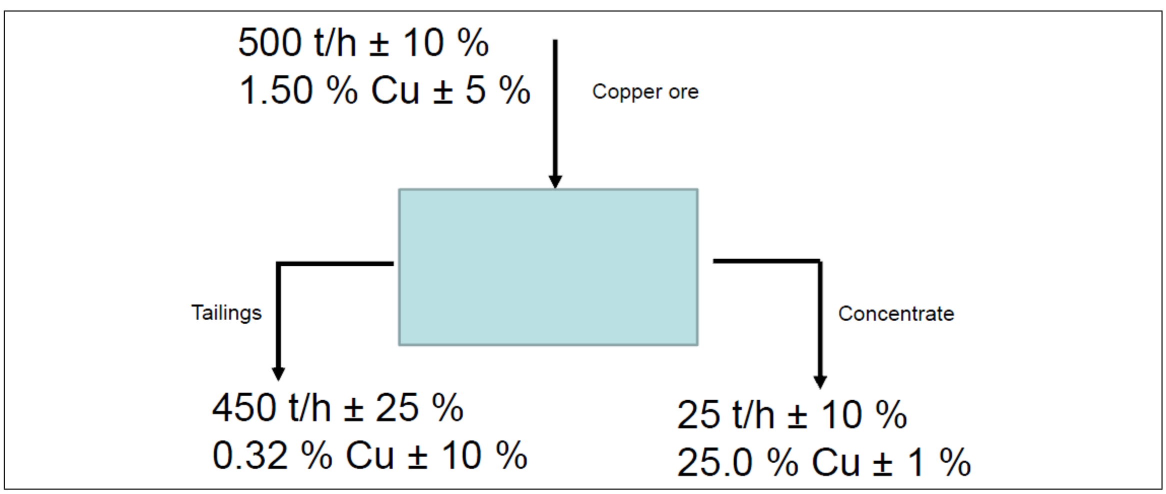

Figure A.3. Sampled Data with Deviation Errors

Figure A.3 shows the data with the corresponding errors and Figure A.4 shows the conciliated values for the proposed example. None of the initial sampled streams were correct and almost every value needed to be adjusted.

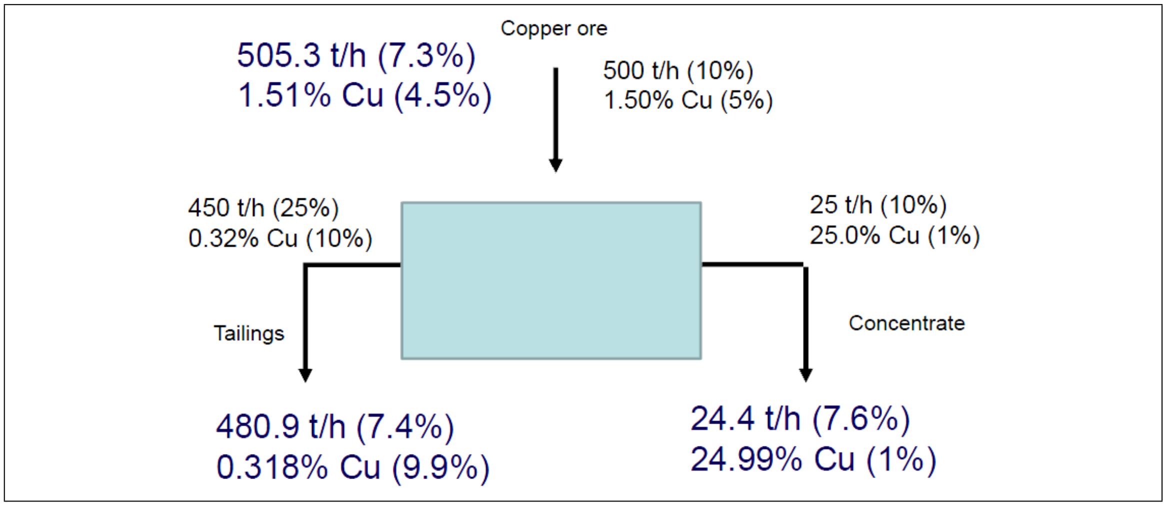

Figure A.4. Conciliated values for example case

In the same way, the data reconciliation problem is established. It is necessary to find estimations of values X_1, X_2, X_3, Q_1, Q_2, Q_3 as close as the original values $\bar{X}_1$, $\bar{X}_2$, $\bar{X}_3$, $\bar{Q}_1$, $\bar{Q}_2$, $\bar{Q}_3$. Also, the problem has to consider the sampling error $\sigma_{\bar{X}_1}$, $\sigma_{\bar{X}_2}$, $\sigma_{\bar{X}_3}$, $\sigma_{\bar{Q}_1}$, $\sigma_{\bar{Q}_2}$, $\sigma_{\bar{Q}_3}$ verifying the mass and grade balances.

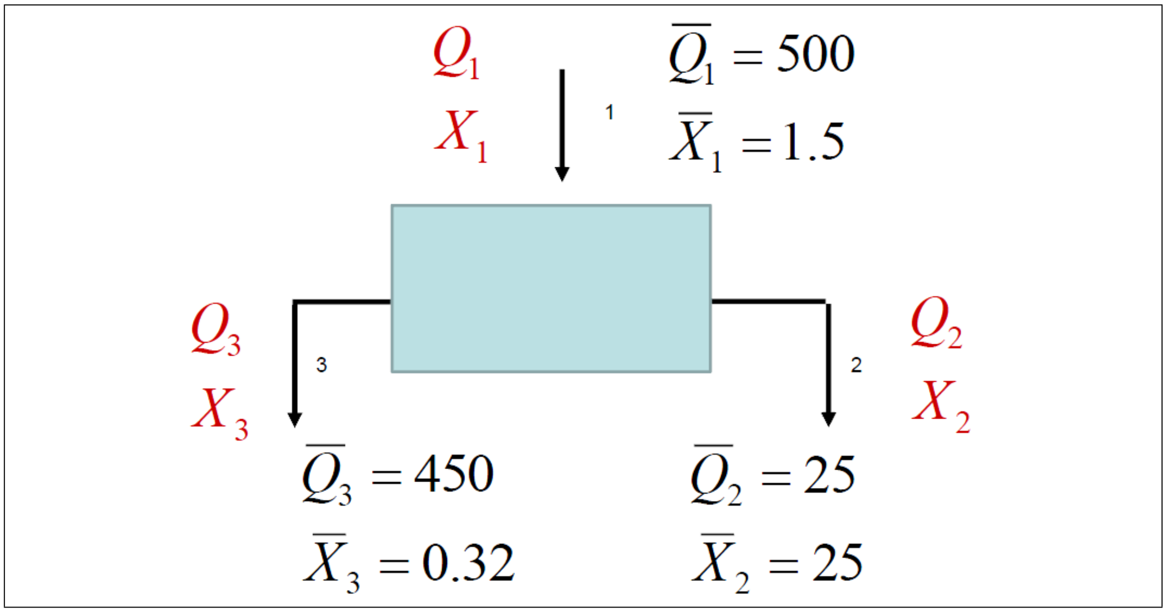

Figure A.5. Data Reconciliation Problem

The optimization problem is given in A.2.

$$\text{Min} \sum_{i=1}^{3} \frac{(Q_i - \bar{Q}_i)^2}{(\sigma_{\bar{Q}_i})^2} + \sum_{i=1}^{3} \frac{(X_i - \bar{X}_i)^2}{(\sigma_{\bar{X}_i})^2} \tag{A.2}$$

Subject to

$$Q_1 - Q_2 - Q_3 = 0 \tag{A.3}$$

$$Q_1 \cdot X_1 - Q_2 \cdot X_2 - Q_3 \cdot X_3 = 0 \tag{A.4}$$