Enhanced Geometallurgical Characterization - Mini Pilot Plant Leveraged by Digital Twin Development

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ABSTRACT
Flotation is the most used separation process worldwide. Flotation characterization is usually carried out in batch conditions at laboratory scale. A phenomenological description of the flotation process is challenging, however, the evaluation of flotation performance in a contextual manner by means of a pilot plant is beneficial to reduce uncertainty on metallurgical results. In addition, leveraging pilot plant results by digitalize them helps describe the process dynamically. Consequently, flotation pilot plant testing allows a Digital Twin (DT) to be generated by combining ore characteristics, process information and a digital architectural platform. Therefore, the generation of a Digital Twin of the flotation pilot plant provides a tool to explore and evaluate new operating scenarios. This allows an optimum scenario to be identified and scaled up (i.e., industrial operation). In other words, the pilot plant with its digital twin may become the physical twin of the industrial plant as long as a robust scale-up methodology is available. This contribution proposes an innovative and enhanced geometallurgical characterization to evaluate ore variability and its metallurgical performance holistically. It is believed that this new proposed approach will help plant operators improve their technical and economic performance.

Keywords: Pilot Plant, Digital Twin, Geometallurgy, Flotation, Dynamic Modelling/Simulation, Scale-up.

1. Introduction

The mining industry is facing a challenging environment. Complex geological resources and decreasing ore grades make the characterization process intense and expensive. High-quality mineralogical information is needed to design, construct, commission and operate mineral processing plants (Nad et al., 2022).

The availability of innovative instrumentation generates significant amount of data (information) that can help monitor and control processes better. The digitalization of this information help leverages process description. Digital mineral processing developments allow data in real-time to be managed efficiently. In addition, instrumentation and sensor-based systems allow flowsheets to be monitored and controlled. Analysis of process data using machine learning and artificial intelligence is becoming more and more common to process control and automation (Jooshaki et al., 2021). Data may now be collected from many sources throughout a mineral processing plant, i.e., at a much higher degree of resolution (Koistinen et al., 2020).

Digitalization is the ability to turn existing products or services into digital variants, and thus offer advantages over tangible products (Nad et al., 2022).

Digitalization in the mineral processing and beneficiation industry is commonly interpreted as strategies of process control. Flotation is becoming better instrumented, and therefore, there is now information available that was not considered in the past.

Artificial Intelligence (AI) studies of ore processing, and the flotation process are increasing as time is going by. Similarly, Machine Learning (ML) applications in mineral processing have been focused on flotation and ore sorting (Jooshaki et al., 2021). Digital Twin applications have been used to map out different processing scenarios. These scenarios consider alternative operating conditions and varying ore characteristics to define ore boundary conditions. The integration of geometallurgical data, feed ore characteristics, and plant online sensor data with a detailed dynamic mineral particle-based processing model of the plant is today urgently required (Ross, 2019).

Digital Twin of a mineral processing plant, in particular, flotation separation process will allow different processing scenarios to be explored, i.e., to generate answers to “what-if” questions. In addition, advanced process control of different plant areas may be implemented, so that the best approaches to different production events and scenarios can be explored in context (i.e., flowsheet configuration) (Kortelainen, 2019).

This paper describes the use of a flotation mini pilot plant in combination with a digital twin of it to explore processing scenarios and their metallurgical performance. It is also explored in this contribution that the mini pilot plant configuration is considered a physical twin of an industrial plant by having a robust scale-up methodology associated with the pilot plant. This article proposes an advanced way of conducting a flotation geometallurgical characterization of a given ore.

2. SGS Mini Pilot Plant (MPP)

2.1. Description

The Mini Pilot Plant (MPP) designed, constructed, commissioned, and operated by SGS is an autonomous mobile installation, well-instrumented with the capability of processing ores with real circuits configurations, i.e., to emulate commercial industrial plants (see Figure **1**).

The MPP can be used to explore processing scenarios considering grinding, classification, flotation and solid-liquid separation. In particular, the flotation section of the MPP consist of 12 mechanical cells with air injection measured through mass flow meters. The flexibility of the MPP allows a variety of circuit configurations to be explored. It is believed that the MPP flexibility may help accommodate the industrial context of each client (SGS, 2021).

Figure 1: SGS Mini Pilot Plant (MPP), flotation units.

In addition, it is worthwhile mentioning that the MPP has got re-grinding capabilities, and column flotation cleaning unit.

MPP can be operated through a centralized control interface with remote accessibility.

The testwork using MPP allows results to be produced in order to evaluate metallurgical performance in context (i.e., flowsheet configuration). Metallurgical performance is determined by capturing data and characterizing metallurgical samples with a XRF handheld analyzer. This makes characterization data fast availability.

Note that the MPP uses Denver mechanical flotation cells design. Figure **2** shows a diagram that provides specific details of the flotation cell system used in the MPP. Note that air injection occurs through the agitator shaft, tailings discharges by means of a weir, and concentrate froth is removed by an automatic scraper. MPP mechanical flotation cells are 1.7 (L) each, the cross-sectional area of every cell is 140.22 (cm^2). The standard impeller speed used in the MPP flotation system is 1000 RPM, and the superficial gas velocity range used is of 0.25 – 0.60 (cm/s). The average feed flow rate is 167 (g/min).

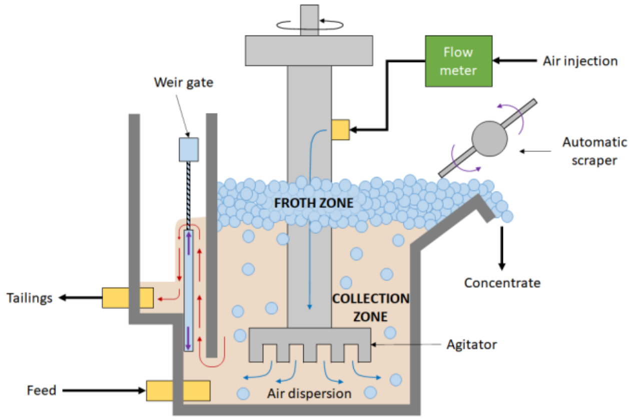

Figure 2: MPP Flotation cell system.

It is important to highlight that the MPP is a mobile processing equipment (Rig) which allows ore metallurgical processing to be carried out in-situ (i.e., industrial plants locations). It is worthwhile noting that this MPP feature helps characterizing different industrial process streams which facilitates the advanced geometallurgical characterization (i.e., capturing of ore variability).

Having described the MPP hardware, it is now possible to provide a dynamic mass balance description of the flotation configuration to be used in the development of the Digital Twin. Note that the MPP has got the flexibility to accommodate different configurations. However, the Digital Twin will be considered using a simple flowsheet to illustrate the development approach.

2.2. Digital representation of the MPP

The modelling and simulation of the main flotation components of the MPP are presented in this section. A dynamic model was considered to represent the flotation operation of the MPP. Data generated in the MPP were used to establish the dynamic description of the process.

Figure **3** shows the digital representation of the flotation flowsheet configured in the MPP. Note that the flowsheet configuration used has a Rougher flotation stage, which consisted of six mechanical cells in series, and a Cleaner stage which also considered six mechanical cells in series. This configuration was studied in open and closed circuit, i.e., the former is a three-product configuration, and the latter is a two-product configuration. The closed circuit considered the recirculation of the Cleaner tail to a node that also fed the fresh feed and made up the Rougher flotation feed. The main purpose of considering these two configurations was to illustrate the development the Digital Twin associated to the MPP. Note that open flowsheet run operating results are presented in the appendix section of this paper.

Figure **3** also shows the digital system equations which are precursor of the dynamic modelling/simulation of the MPP configuration. Note that this description is based on a steady-state process operation (i.e., no accumulation) which in other words, means no time dependency. On the other hand, a dynamic description of the process is time dependent (Quintanilla et al., 2021), which require a set of differential equations to be solved. It is also important to indicate that the steady-state models help determine the interaction among process variables, on the contrary, dynamic models help quantify process changes under changing conditions, and determine how and when new steady-state is reached.

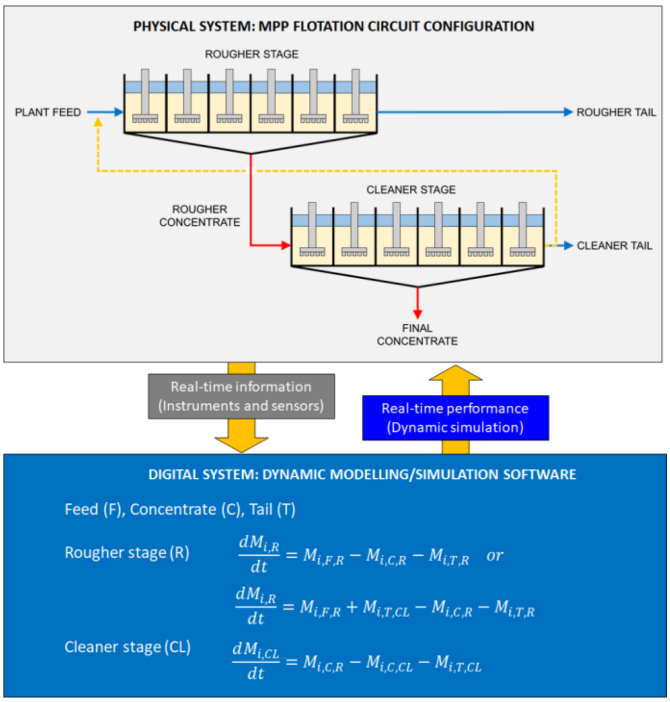

Figure 3: Flotation flowsheet configured in MPP. Digital representation based on real-time information and dynamic modelling/simulation description.

In the physical system, the model development is based on key compartments which describe the physical system phenomenologically. At the same time, these compartments have key process parameters associated which are measured through smart instrumentation and sensors. The integration of key compartments, key parameters measurement, and a robust phenomenological models allow digital modelling/simulation to be generated in the MPP context.

Figure 4 illustrates a representation of a digital modelling structure for the MPP flotation cell system. Note that the input considers the volumetric flow rate and feed grade. For the cell digital representation, the models are defined taking into account the number of the cell (along the Rougher or Cleaner stage), mineral species, froth and pulp zones, and product streams (i.e., tailings and concentrates). Furthermore, the parameters related to these compartments are mineral mass, rate constant, feed mass flow, volumetric flow, and froth and/or pulp level. Finally, the main objective of this digital representation (i.e., modelling/simulation) is to obtain valuable and gangue content on froth and pulp phases, which are a function of each parameter defined previously.

By integrating the results of each cell by a mass balance and reconciliation process, it is possible to establish the overall metallurgical performance of the MPP.

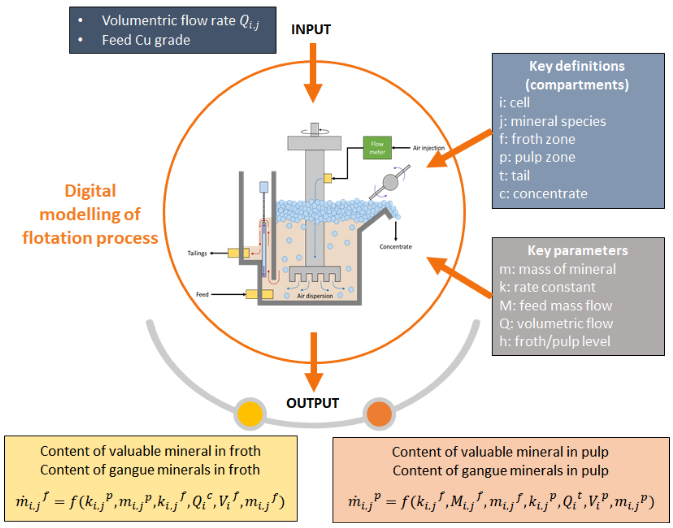

Figure 4: Digital modelling general structure for the flotation process in the MPP flotation cell system.

In order to capture process information and describe correctly the process configuration, key instruments and sensor-based systems are required. In addition, three main aspects need to be considered: robust simulation environment, high fidelity models and real-time two-way communication with the physical process. The latter is essential to have a Digital Twin (Kortelainen, 2019).

Figure **5** depicts the level definition that establishes the requirement to have a Digital Twin. It is seen in this figure that three instances are considered to reach the two-way communication with the physical process. These are Digital Model, Digital Shadow, and Digital Twin. In other words, the Digital Twin has fully integrated automatic data flow in both directions (Kritzinger et al., 2018).

Having obtained a Digital Twin, this can be used to mimic a real process. In practical terms, this provides a safety net for an industrial operation because DT can explore in a safe way, new operating conditions without negative impacts on industrial performance. In addition, a Digital Twin allows deep process understanding to be obtained, i.e., integration between process variables, knowledge of dynamic phenomena (delays, time constants, bottlenecks), and planning, process development.

It is also important to indicate that a Digital Twin helps establish advanced process monitoring/measurement. It also helps link other measurement to key process variables, e.g., image-based froth measurement, and soft sensors development.

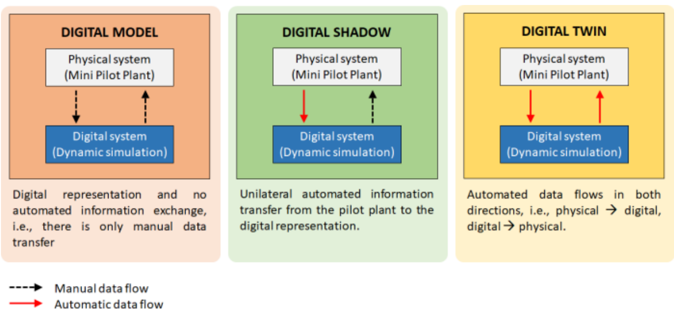

Figure 5: Level definition of the integrated data flow between MPP and Dynamic modelling/simulation description.

3. MPP and Digital Twin

3.1. Digital environment in mineral processing

A powerful method for analyzing a vast amount of data is Machine Learning (ML). This approach is ideal for mineral processing data mining since the availability of new and innovative instrumentation and sensors. In other words, there is available more information generated that can now be ML'ed (Jooshaki et al., 2021).

ML algorithms may diagnose the metallurgical performance embedded in collected processing data. That is to say, ML can be used to develop data-driven models for mineral processing equipment (e.g., mills, flotation cells) (McCoy, 2019).

The combined use of ML and Artificial Intelligent (AI) create the conditions for the development a Digital Twin in mineral processing. Organizations, such as GTK, ABB, Metso:Outotec, have already developed and implemented Digital Twin applications with the purpose of digitalization and automation of mineral processing activities, online visualizations, testing of processing parameters before going live, co-working with partners/customers, big data analytics, reinforcement learning, dynamic simulation, and process optimization (GTK, 2019; ABB, 2022; Metso:Outotec, 2022) (McCoy and Auret, 2019).

Consequently, the use of a Digital Twin in the mineral processing area has got three clear benefits, namely, enriched decisions, calibrated performance, and tangible solutions (Nad et al., 2022). These three aspects allow safe environments, material traceability, science-based model calibration, and fast and easy solutions to be implemented. It goes without saying that a Digital Twin helps study processes in real-time by observing and diagnosing them. It is also important to indicate that Digital Twin provides an environment for operator training, and new scenarios testing.

3.2. Structure of the Digital Twin implementation

It is expected that the Digital Twin should provide an optimal plant model that captures the process background accurately. In other words, a well-instrumented physical process (MPP) generates process information that will constitutes the database needed to tune process model dynamically which help explore new processing scenarios, and then validate them in the physical system. This two-way communication is like having a mirror image of the physical system that is represented digitally. In order to validate new scenarios and improve process performance, the Digital Twin of the physical system should identify appropriate process conditions to be used.

Figure **6** illustrates the above-mentioned description, and clearly depicts the two-communication protocol, i.e., experimental data ↔ prediction.

In the implementation of the Digital Twin, an important aspect to be considered is the process monitoring and control based on significant and/or critical parameters and variables. To determine the significant variables of the process, it must be established the benefit level that would be reached through each measurement. This must be in the metallurgical context of the physical system and the process modelling/simulation (i.e., MPP Digital Twin). The identification of these parameters and variables allows implementation and calibration to be addressed correctly in the physical system. Besides, by identifying the critical information to be obtained, it is possible to prevent unnecessary complexities (Koistinen et al., 2020) which may impact the control strategy associated to the operation of the MPP, and therefore, affecting the development of the Digital Twin.

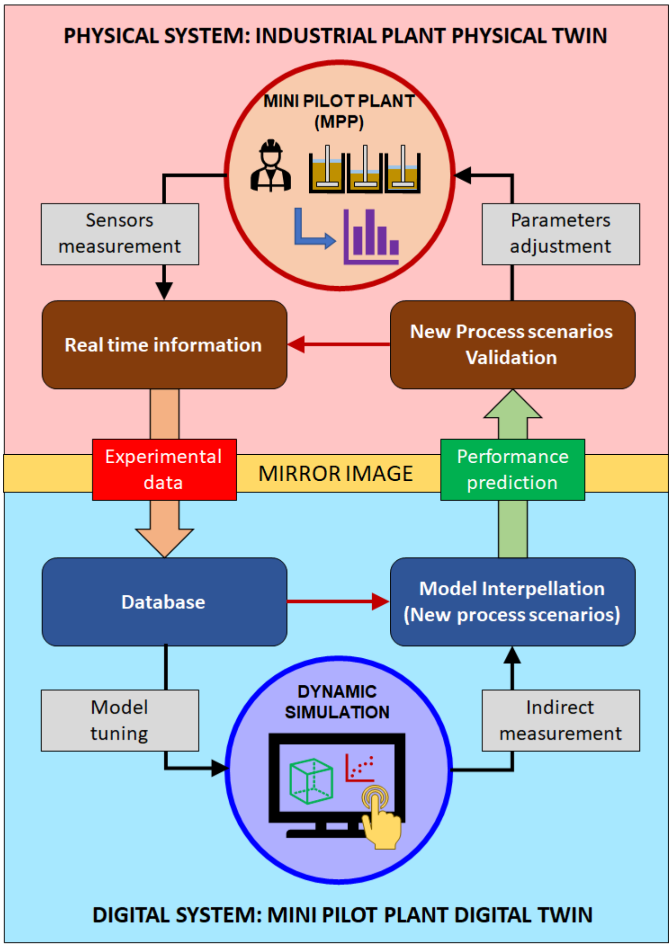

Figure 6: MPP – Dynamic modelling/simulation data exchange in the Digital Twin implementation.

The use of smart instrumentation not only is associated to measurable variables directly, but also to combine different measurements to infer an aspect of the process that cannot be measured (i.e., soft-sensor, e.g., bubble size). The modelling and simulation required to develop a Digital Twin must be tuned. This process also helps infer parameters that are difficult to measure experimentally. As a result, the MPP Digital Twin considers direct and indirect measurement of key variables to generate the two-way communication through automated data exchange (see Figure 6).

4. Innovative and enhanced geometallurgical characterization

4.1. SGS geometallurgical flotation characterization

Geometallurgy is an integration of fundamental economic geology and deposit mineralogy into process, i.e., mine plans and resource recovery schemes. A geometallurgical model considers three sub-models: geological model (minerals, elemental grades, and lithology), process model (forecasting, metallurgical response for geological units), and production model (timeframe and different scenarios for ore mining and processing). The application of the geometallurgical model helps reduce operations risks and optimize production. It is important to realize that a utilization of a geometallurgical model is a long-term commitment (Lishchuk, 2018; Fustos, 2017; Parian, 2015).

Consequently, the generation of reliable geometallurgical information is required to populate a geometallurgical model. SGS has a proven record developing and measuring ore characteristics in order to capture ore attributes to be included and distributed in a geometallurgical model.

Figure 7 depicts a comprehensive approach developed by SGS to carry out an advanced geometallurgical flotation characterization. This approach consists of five complementary steps:

1. Geometallurgical approach.
2. Phenomelogical representation of flotation process.
3. Kinetic flotation model.
4. SGS MFT batch flotation characterization.
5. Mini Pilot Plant and Digital Twin.

Step 1: An integrated geometallurgical approach that considers ore attributes distribution in order to establish resource recovery schemes. Note that SGS has got the capabilities to quantify many different attributes associated to the ore.

Step 2: A phenomenological description of a flotation separation process is devised considering that there are two well-defined zones: Collection zone (pulp) and Froth zone. It goes without saying that there is a dynamic interaction between both zones as indicated in the diagram (see Figure 7). Note that diagram was designed for steady-states conditions and true flotation. Nonetheless, it is important to realize that flotation recovery also has a non-selective component associated to it, i.e., entrainment (Montes, 2015).

Step 3: Since a flotation cell is a separation reactor, this needs to be described kinetically. A kinetic model that considers hydrodynamic aspects of the flotation process (i.e., air injection mechanism and mixing characteristics), zones efficiencies (i.e., froth recovery and pulp recovery), and ore intrinsic attributes (i.e., floatability determination based on mineralogical assemblage). In addition, it is also needed to include in the process kinetic description nature of the flotation reactor (i.e., flotation cell type, either mechanically agitated, CSTR[1], or pneumatic driven, PFR[2]).

Step 4: Mineral Flotation Testing (MFT) is a laboratory batch flotation test devised by SGS to capture ore floatability characteristic considering the mineralogical features of the ore (Turner-Saad, 2010). MFT has become a referent in order to characterize flotation response for geometallurgical purposes. MFT is a comprehensive laboratory characterization procedure which generates as a result a kinetic rate constant distribution based on particle size distribution and mineralogy of it. It also captures floatability response based on the degree of the induced hydrophobicity. MFT can be used to characterize different process streams to capture ore floatability depending upon processing stages.

Stage 5: Dynamic modelling and simulation of MPP, machine learning training of operating data generated allows a Digital Twin description to be obtained. The utilization of the MPP infrastructure provides process evaluation in a contextual manner (i.e., flowsheet configuration operated continuously). The use of MPP Flotation Digital Twin facilitate capturing ore variability which is an advanced integration of the different aspects of the process, i.e., advanced geometallurgical flotation characterization.

One important aspect to take into account is that the phenomenological description of the flotation process has generically been obtained considering the system in steady-state condition. However, to develop the MPP Digital Twin an adaptation of the steady-state models to dynamic models needs to be utilized (i.e., sensor-based process is essential). At the same time, it is also important to realize that well-known MFT is a laboratory batch flotation characterization which will require an adaptation to be used in the context of MPP operation. Lastly, the integration of all these steps relies on having a well-instrumented and connected MPP system, so that real-time information is available to be transferred.

Note that the value of the interconnection of these five steps creates the conditions for advanced geometallurgical flotation characterization. In other words, distribution of resources recovery information coming from a contextual process evaluation that includes mineralogical characterization combine with the right kinetic and dynamic description, represents the advanced geometallurgical flotation characterization approach. It is believed that this way of evaluating geometallurgical performance will enhance the reliability of the geometallurgical prediction capabilities in terms of future process performance.

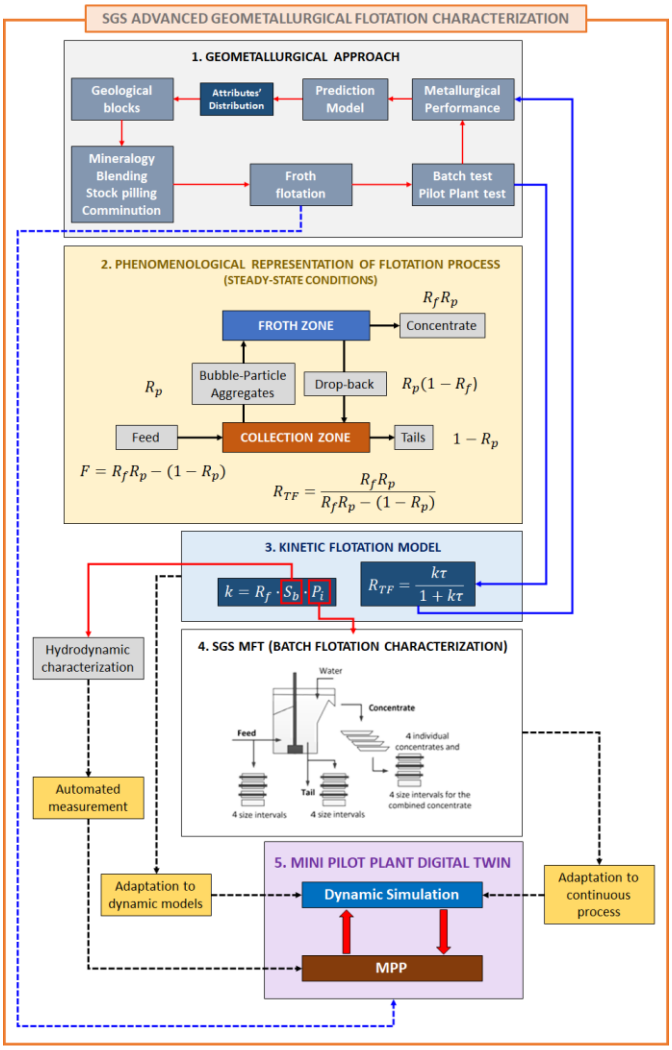

Figure 7: SGS advanced geometallurgical flotation characterization. Approach consists of five complementary steps, namely, (1) Geometallurgical approach, (2) Phenomenological representation of flotation process, (3) Kinetic flotation model, (4) SGS MFT batch flotation characterization, and (5) Mini Pilot Plant and Digital Twin.

Improved monitoring and process planning can be achieved by smart sensors that generate the information required for a Digital Twin. The primary flotation parameters are air flow rate, pulp level, and rotor speed. Chemical reagent addition is also important to carefully control to achieve the desire metallurgical performance. In order to address

[1] CSTR : Continuous Stirred Tank Reactor (https://en.wikipedia.org/wiki/Continuous_stirred-tank_reactor)
[2] PFR : Plug Flow Reactor (https://en.wikipedia.org/wiki/Plug_flow_reactor_model).

metallurgical performance optimization in terms of recovery and grade, the MPP Digital Twin is the ideal tool to map out different processing scenarios and identify the optimal recovery-grade trade-off. The exploration of processing scenarios utilizing the MPP Digital Twin is a safe low risk approach which allows process conditions to be discovered efficiently (Hatton and Hatfield, 2013).

Figure **8** depicts a schematic representation of the recovery grade optimization approach to be used with the MPP Digital Twin. This diagram shows that by operating the MPP, metallurgical data is generated, and an operational recovery-grade trade-off can be determined. Having obtain these metallurgical results, it is possible using the MPP Digital Twin approach to identify an optimized a recovery-grade performance. The latter is then validated by the feedback provided to the MPP operation. Ultimately, the process knowledge produced at the MPP scale needs to be scaled-up to implement the optimized process scenario at industrial scale.

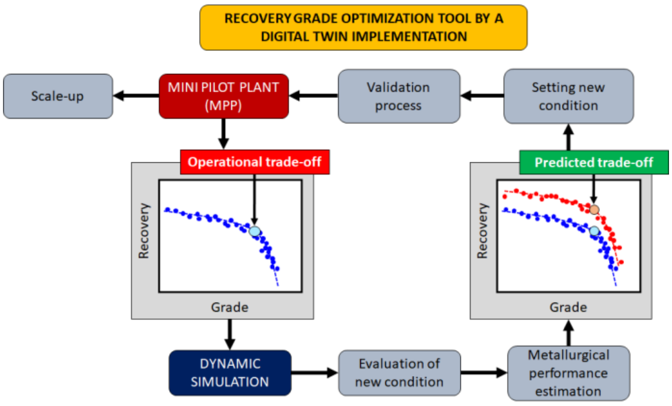

Figure 8: Schematic representation of the recovery grade optimization approach to be used with the MPP and Digital Twin, which allows knowledge transfer with industrial plant to be achieved through a robust scale-up methodology.

4.2. Enhanced geometallurgical characterization

The flotation process is the most common separation approach used in mineral processing. The fourth industrial revolution has allowed mineral process plants, in particular flotation cell, to be well-instrumented (smart sensors) (Schach et al., 2019). This state-of-the-art instrumentation has enhanced monitoring and process control initiatives providing in real-time relevant process information. In addition, characterization equipment (i.e., composition) is also available to provide frequent chemical assays of dry solid particles and slurries. This information helps determine metallurgical performance quickly and effectively creating a system capable of integrating itself in a major optimization process initiative (i.e., MPP ↔ Digital Twin ↔ Industrial Plant).

Figure **9** describes a holistic integration of the MPP and Digital Twin in the geometallurgical optimization on an industrial flotation process. As previously described, the dynamic simulation is the basis for the Digital Twin development which represents a "virtual image" of the MPP. The use of smart instrumentation and sensors, the MPP is capable of transfer experimental data of key process variables to a depository database. The digital system processes this data in order to generate a dynamic simulation of the physical system. As a result, the Digital Twin allows a MPP metallurgical performance to be predicted under operational conditions that are measured on-line. Model prediction must be validated by contrasting experimental data with predicted results. In this context, the communication routes transfer automated simulated results to the physical system. Note that, in order to secure a Digital Twin, communication must occur in two-ways (i.e., physical ↔ digital system).

At the same time, the SGS proposed approach relies on considering the MPP as a physical twin of the industrial plant (emulation of flotation circuit configuration). The connectivity between the industrial operation and the MPP is assured through a robust scale-up methodology. The latter allows the MPP conditions to be implemented to achieve the optimized metallurgical performance (validated by MPP digitalization) at industrial scale.

Figure **9** also indicates a potential two-way communication route between industrial plant and Digital Twin. This interaction is possible due to Digital Twin training, and the understanding of the scale-up methodology. Knowledge generation and transfer of it may help adjust and control equipment variables at industrial scale based on the learning embedded on the Digital Twin. It is believed that the triangle established among the MPP, Digital Twin, and Industrial Plant represents an advanced approach to capture ore metallurgical performance variability in context with plant flowsheet configuration and assess in the Mini Pilot Plant at a low risk by means of the utilization of the Digital Twin. Consequently, this approach represents an advanced geometallurgical evaluation of process performance.

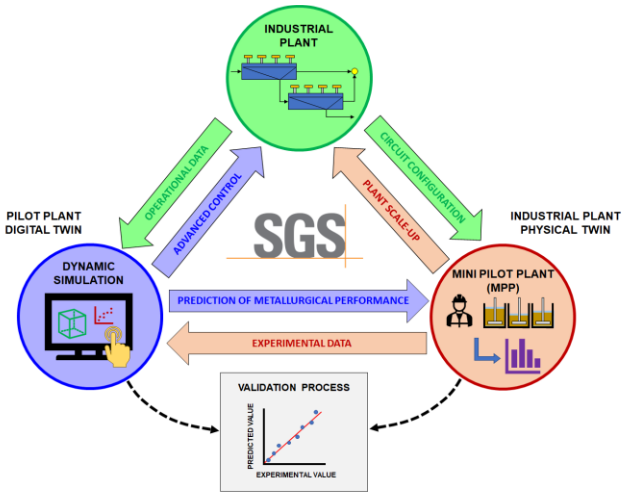

Figure 9: Enhanced geometallurgical characterization. MPP leveraged by Digital Twin. Advanced process optimization of an industrial flotation process.

5. Observations and General Discussion

The combination of geological and mineralogical information, and metallurgical performance create a geometallurgical based-predicted model.

Ore metallurgical features have been historically captured through well-designed bench-scale tests (i.e., usually batch testing) (Amelunxen, P.A. and Amelunxen, R.L., 2013). Nonetheless, these tests heavily rely on the ore representativity of the geological block being considered. The idea behind this characterization approach is to determine the inherent metallurgical performance associated to the ore sample being studied. Later, this information is geostatistically distributed through the geological model. Many modelling approaches are used to populate the blocks with ore related information. However, the quality of the ore characteristic information depends on procedures utilized to acquire ore characteristics (i.e., proper mineralogical characterization, ore energy requirements, and ore kinetic response to separation process) (Michaux and O'Connor, 2019).

In order to optimize a given ore processing configuration, the ore process performance variability must be accommodated in a contextual manner, i.e., high level of flexibility of flowsheet to be configured. Consequently, the use of a mobile equipment (Mini Pilot Plant, MPP), well-instrumented, and flexible in terms of accommodating different flowsheet configurations helps generate reliable process information which is dynamically used to produce a Digital Twin (DT). Having obtained a DT, this can be interpellated and used to explore new and optimized processing scenarios which are then validated in the MPP. Note that the MPP may become the "Physical Twin" of the Industrial Process if a robust well-conceptualized scale-up methodology is in place.

Finally, the integration of ore characteristic information, ore process response at pilot plant and industrial scale, and the Digital Twin provides a more sophisticated, but practical, approach to reduce operational risks (manage process uncertainty), and eventually optimize production.

6. Conclusions

This contribution addressed the use of a well-instrumented Mini Pilot Plant and the digitalization of the information generated from it. By doing so, a digital representation of the Mini Pilot Plant is obtained, which allows the exploration of new and enhanced processing scenarios. In particular, the focus of this article is on the flotation separation carried out in the Mini Pilot Plant. It goes without saying that the digitalization refers to digitalize data coming from the Mini Pilot Plant instruments (i.e., smart instrumentation). The real-time information is deposited in a database to develop dynamic models.

The Mini Plot Plant environment serves as a platform for testing different process design at low risk. A static and dynamic modelling/simulation of the mini pilot plant has been developed and tuned. Simulation of different process scenarios can be useful in process design and improvement, process knowledge, identification of key measurement, soft sensors, and control design. Last but not least, process simulation into a process Digital Twin allows model adaptation against unmodeled phenomena. Besides, real-time information integration enables the exploration of new scenarios

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Appendix

Figure 10 shows the mass balance and reconcile results for the open circuit configuration run in the MPP for a copper ore. It is observed that the treatment is approximately 9.5 (kg/h) at 0.94% of Cu. This open circuit represents a three-product configuration.

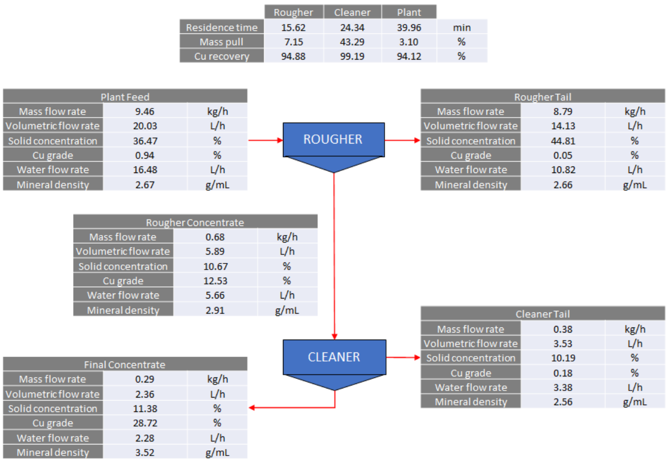

Figure 10: Open circuit flotation configuration (Rougher-Cleaner).

Figure 10 illustrates the type of real-time information generated out of the Mini Pilot Plant.

References

ABB. (2018). Case study: the use of a digital twin with Advanced Process Control at Boliden Aitik mine. https://new.abb.com.

Amelunxen, P.A., Amelunxen, R.L. Aminpro's Methodology for Applying Current Flotation Modeling Starting from Batch Kinetics (part 2 of 2). XXV Encontro Nacional de Tratamento de Minérios e Metalurgia Extrativa & VIII Meeting of the Southern Hemisphere on Mineral Technology.

Brandao, R., De Tomi, G., Assis, P. (2016). Mine/Mill production planning based on a Geometallurgical Model. Esc. Minas, Ouro Preto, 69(2), 213-218.

Fustos, M. (2017). Descubrimiento de unidades geometalúrgicas por medio de análisis de conglomerados geoestadístico. Universidad de Chile.

GTK (2021) Digital Twin of the GTK Mintec Pilot Plant – For Customers and for Us. https://www.gtk.fi.

Hatton, D., Hatfield, D. (2013). A Geometallurgical Approach to Flotation Process Design Using Optimised Grade-Recovery Curves. Canadian Mineral Processors Proceedings 2013.

Jooshaki, M., Nad, A., Michaux, S. (2021). A systematic review on the application of machine learning in exploiting mineralogical data in mining and mineral industry. Minerals 2021, 11, 816.

Koistinen, A., Ohenoja, M., Tomperi, J., Ruusunen, M. (2020). Adaptation framework for an industrial digital twin. Proceedings of SIMS 2020, 365-372.

Kortelainen, J. (2019). Utilization of digital twin in model-based control of flotation cells. University of Technology LUT.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. IFAC, 51-11, 1016-1022.

Lishchuk, V. (2018). Bringing predictability into a geometallurgical program An iron ore case study. Luleå University of Technology.

McCoy, J.T., Auret, L. (2019). Machine learning applications in minerals processing: A review. Miner. Eng. 2019, 132, 95–109.

Metso:Outotec. (2022). Metso Outotec launches Geminex™, a digital twin for efficient management of variability in mining and metallurgical operations. https://www.mogroup.com.

Michaux, S., O'Connor, L. (2019). How to Set Up and Develop a Geometallurgical Program. Geological Survey of Finland.

Montes, H. (2015). Modelación geometalúrgica del proceso de flotación basado en mineralogía y ensayos metalúrgicos. Universidad de Chile.

Nad, A., Jooshaki, M., Tuominen E., Michaux, S., Kirpala, A., Newcomb, J. (2022). Digitalization Solutions in the Mineral Processing Industry: The Case of GTK Mintec, Finland. Minerals 2022, 12, 210.

Parian, M. (2015). Development of the Mineralogical Path for Geometallurgical Modeling of Iron Ores. Luleå University of Technology.

Quintanilla, P., Neethling, S.J., Navia D., Brito-Parada, P. (2021). A dynamic flotation model for predictive control incorporating froth physics. Part I: Model development. Miner. Eng.

Ross, V. (2019). Key aspects of bench flotation as a geometallurgical characterization tool. The Southern African Insitute of Mining and Metallurgy.

Schach, E. et. Al (2019). Pilot Plant for the Processing of a Complex Tin Ore: A Contribution towards Geometallurgy in Beneficiation. Procemin-GEOMET 2019.

SGS. (2021) Mini Planta Piloto Móvil brochure. SGS Natural Resources.

Turner-Saad, G. (2010). Vision for a risk adverse integrated geometallurgy framework. SGS Mineral Services, Technical bulletin 2010-1.

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