Progress towards geometallurgical digital twins[1]

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Abstract

A digital twin should capture the behavior of a process. However, most geometallurgical steps have uncertain inputs, and uncertain responses, since the ore properties are variable and not fully known, and the physics and chemistry involved in the processes may be too complex to fully understand them. Despite these challenges, uncertainty can be managed and a geometallurgical digital twin can be built, incorporating this uncertainty as a random variable. The response is therefore variable but can be optimized. In this note, some insights are provided about the steps taken in the research community to create the building blocks of what can become an integrated digital twin of the geometallurgical processing of the ore in a mining system.

1. Introduction

A digital twin can be defined as an ultra high-fidelity simulation of a real object or process, and that can be connected to this physical object or real process. Digital twins originated in the manufacturing industry and were later adopted by NASA for applications such as testing a vehicle under extreme conditions for space exploration and military applications [Glaessgen and Stargel, 2012]. In most applications, a concrete object or process is considered, thus limiting the modeling effort to a relatively limited number of physical laws or chemical reactions that are well understood.

Mining is moving towards Industry 4.0, incorporating concepts of interconnectivity, through Internet of Things (IoT) and smart automation [Loow et al., 2019]. The true digitalization of the mining industry will happen only when automated decision-making can be implemented. Currently there are many efforts in progress to implement integration, predictive modeling, and automation in the mining industry [Dominy et al. 2018], but the idea of a fully integrated and fully automated operation is far from practical at this point.

In the coming sections, approaches that are already available are discussed, that could be integrated into a geometallurgical framework, to provide the basis for automated decisions. Some of the missing components needed to achieve the idea of a geometallurgical digital twin of a mining operation are also identified. In particular, the focus is on uncertainty management and decision-making.

2. Geometallurgical framework

A geometallurgical digital twin (GDT) can be created by combining realistic models of the different stages of the mining value chain, where particular inputs lead to outputs that feed other processes downstream (Figure 1).

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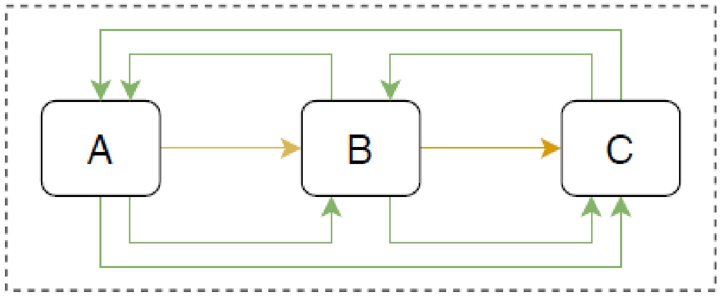

Figure 1: Illustration of connected processes [Avalos, 2021].

What is important, is that the outputs include all the relevant attributes that will influence the response of the process and of all subsequent processes (depicted as forward green arrows in the previous figure) [Ortiz et al., 2015; Avalos, 2021]. This means that the model must integrate many variables and if these variables cannot be measured, they must be incorporated through "soft sensors" or non-regressive predictive models (for example, stochastic models) that can realistically capture the associated uncertainty around an unbiased estimate of the true value. Furthermore, the components must be interrelated to account for the interactions between processes and feedback (backward green arrows in previous figure). Real time measurements can help maintain a stream of information used to calibrate and control the system [Benndorf and Jansen, 2017].

3. Building blocks

A mining system can be seen as a sequence of stages or processes. Broadly, Figure 2 shows a simplified depiction of the parallel between the actual ore deposit, mine and operation (at the top) and the modelled resources, reserves and extraction (bottom). Ideally, in a GDT the model (bottom) should be constantly fed with information from the real operation (top), and the stages and processes in the model should follow the systems approach presented in Figure 1.

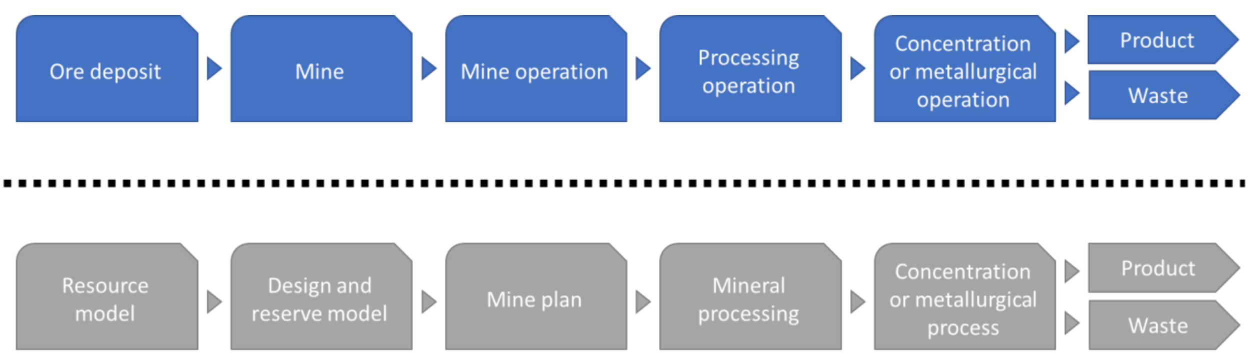

Figure 2: Mining system: actual (top) vs model (bottom).

Given the complexity of stages and processes in mining, the behavior of each component of the system can only be approximated. Real time sensors, composited measurements, and soft sensors can be used to update the status of the twin (model). This requires smart sensors and measurements, high speed communication to transfer this information in real time, and models that can predict the response and assess the potential variability linked to the uncertainty in rock properties, and in the process performance. This predicted output must be compared to other measurements of the actual output, for the models to learn. Once properly calibrated and trained, a smart agent can take over the decision-making process, to: (1) Optimize each process and (2) Optimize the system. It should be emphasized that today, automatic control systems exist, but are limited to specific processes, particularly in processing plants.

4. Examples

Each stage in Figure 2 has seen significant progress with the use of geostatistics, machine learning, deep learning, and other statistical modeling techniques. Table 1 reviews some examples where these techniques are applied and references where these methods and models are developed.

Table 1: example applications of modeling into different stages of the mining value chain.

Stage	Step	Technique	References
Resource model	Domaining	Unsupervised geochemical classification for domaining	[Faraj and Ortiz, 2021]
		Machine learning to model alteration	[Berube et al., 2018]
		Geostatistical clustering	[Fouedjio at al., 2017]
	Geological modeling	Pluri-Gaussian simulation with local proportions	[Emery et al, 2008]
		Indicator simulation with locally varying directions	[Gutierrez and Ortiz, 2019]
		Deep learning for geological modeling	[Avalos and Ortiz, 2020]
	Attributes modeling	Multivariate modeling of geometallurgical attributes	[Deutsch et al., 2015]
		Compositional data modeling	[Tolosana-Delgado et al., 2019]
		Projection Pursuit multivariate transformation	[Barnett et al., 2014]
	Upscaling	Non-linear modeling of geometallurgical attributes	[Deutsch, 2015]
		Uncertainty assessment at any block support	[Riquelme and Ortiz, 2021]
		Change of support of non-additive variables	[Garrido et al., 2019]
Design and reserve model	Design optimization	Risk-based selection of ultimate pit limit	[Jelvez et al., 2022]
		Underground design optimization	[Sari and Kumral, 2020]
		Surface and underground optimization under uncertainty	[Montiel et al., 2015]
	Classification	Resource and reserve classification with machine learning	[Cevik et al. 2021]
Mine plan	Extraction sequence	Stochastic optimization for planning	[Dimitrakopoulos, 2011]
	Schedule	Stochastic integer programming accounting for uncertainty of geometallurgical attributes	[Morales et al., 2019]
	Demand-side management	Managing energy consumption via DSM for integration of renewable energy sources	[Diaz et al., 2016]
		Cutoff grade optimization based on stochastic resource models with stockpile for long-term planning	[Asad and Dimitrakopoulos, 2012]
Mineral processing	Crushing and grinding	Hardness prediction with deep learning	[Avalos et al, 2020a]
		Data-driven grinding processing modeling	[Lv et al., 2020]
	Particle size classification	AI driven air classification of particles	[Otwinowski et al., 2021]
Concentration or metallurgical process	Flotation	Deep learning to determine froth flotation performance	[Pu et al., 2020a]
		Deep learning froth flotation recovery prediction	[Pu et al., 2020b]
	Leaching	Recovery prediction in leaching using machine learning	[Flores and Leiva, 2021]

From this list, it is easy to see that, if these methods are wrapped appropriately to be connected into a larger and integrated system, the first steps towards automatic prediction, learning and automatic decision-making are possible. Encouraging results in the design of intelligent agents with reinforcement learning have already been developed [Avalos, 2021] and demonstrate that a data-driven approach that continuously learns and refines its results is possible, leading to a twin of the actual deposit and operation.

The uncertainty caused by the limited sampling, can be compensated with real-time feedback loops to ensure the model remains calibrated and close to the actual state of the operation.

Each one of the stages described above has a broad variety of problems, hence models are available for specific circumstances and need generalization. There are also many other aspects of the “towards full automation and integration” vision that can be considered, including: product control, environmental footprint control, energy and water use. See for example [Avalos et al, 2020b; Ortiz et al., 2020].

Finally, it is important to mention that these technologies can only be integrated if a proper high-speed and low latency communication protocol, such as the 6G technology [Boxall and Lacoma, 2021], and adequate computer power or algorithmic efficiency [Peredo et al., 2015; Peredo et al., 2018] is developed.

5. Conclusions

A digital twin of an operating mining operation is possible if advanced predictive technologies are used to put in place a model of each stage that accounts for the proper inputs and outputs that have an impact in the entire value chain. Tracking materials and measuring properties becomes essential to capture the system’s behavior and learn from it, through data. Enabler technologies, such as high-speed data communication and high-performance computing are essential to achieve a fully automated and integrated model, that matches the operation state, while handling the forecasted uncertainty at every step and optimizing decisions, under these circumstances.

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