Predictive modelling workflows in geometallurgy[1]

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Abstract

Geometallurgy requires the integration of multiple data sources that are interrelated in complicated ways. Its aim is to provide models that link the spatial characterization of materials with process performance. These processes can be linked both to the mining extraction or ore and waste materials, as well as the processing of the ore, and even the disposal of the waste.

In this paper, a review of the methods and tools used to create predictive models in geometallurgy is provided. Different modelling workflows are presented and some case studies are included to illustrate how to tackle problems related to geological modelling, resource estimation, mine planning and mineral processing modelling. The workflows provide a map of how to face a modelling problem. The tools used at each step can be adapted to the type and quantity of data available, as well as the complexity of the problem. More importantly, these workflows can be integrated in a model of the entire system.

A review of the tools provided by statistical learning and geostatistics is included emphasizing the types of problems that can be tackled with each method. Also, the data requirements, challenges and limitations of the methods are described. Finally, these concepts are illustrated with practical applications, where the potential benefits obtained are highlighted as well as the assumptions and limitations.

1. Introduction

The sustainable management of mineral resources and reserves must maximize the benefits of the extraction of raw materials. These benefits involve economic revenues, as well as environmental and social aspects and ensure the continuous supply of metals and materials needed by society. Any mining operation combines diverse interconnected processes to go from in situ geological resources to final products that can be sold or used in the production of other materials and goods. In current operations, these processes are treated separately, managed independently, mostly predicted with deterministic models and updated in discrete time steps [Avalos, 2021]. This means that risks associated to the heterogeneity of these natural resources, as well as uncertainties linked to our incomplete knowledge of their properties and the associated processes, are not accounted for [Montiel et al., 2016]. The uncertainty is caused by the limited sampling information available to characterize the flows of materials in the mining system, as well as the complex nature of the physical and chemical processes these materials are subjected to recover the metals and materials of interest.

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The sequential modelling of the processes in a mining system (resources, design, planning, drilling, blasting, loading, hauling, crushing, grinding, metallurgical processing) does not lend itself to their joint optimization [Ortiz et al., 2015]. In this paper, we present specific workflows for different stages of a mining system, and then discuss their possible integration and the advantages of this systemic modelling approach to geometallurgy.

2. Geometallurgy: an expanded definition

Geometallurgy aims at creating spatially-based predictive models by combining geological, mining and metallurgical information. These models are subjected to the mining, mineral processing and metallurgy processes and can be used anticipate their performance, control the processes and optimize the parameters and decisions involved [Ortiz et al., 2015]. Geometallurgy must be understood beyond process mineralogy, which has been the traditional context in which the term has been used [Dominy et al., 2018], and should account for the processes involved in the ore excavation.

Geometallurgical modelling aims at characterizing these processes in an interconnected framework that transfers properties of materials from one process to the next, accounting for their time of extraction, local (space and time) properties (grades, mineralogy, physical properties), blending that occurs in each process, residence time distribution, mass balance, etc. Each process can be modelled to obtain a prediction of the properties of the output, including estimated values and uncertainty quantification. Importantly, the transference of this uncertainty from one stage to the next should be modelled, accounting for correlations, interactions and blending. These models can have different levels of sophistication and complexity from simple statistical predictions to phenomenologic models.

A geometallurgical predictive model (which can be seen as a digital twin of the operation) 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. The resulting outputs can be calibrated with production information and be used to feedback into the models to enhance them [Benndorf and Jansen, 2017]. Optimization and control of the entire system is only possible if a complete understanding of all the components and their interactions is achieved.

3. Modelling workflows

In order to put together a geometallurgical predictive model, each process must be modelled as a stand-alone step, but all relevant inputs and outputs must be accounted for. Understanding which variables must be incorporated in each model is a result of specific domain knowledge.

Examples of modelling workflows can be found in the literature, linked to specific conditions or problems solved through modelling. These workflows will change depending on the type of data available and the specific conditions of the operation. However, typically mining projects need to deal with the following steps:

- Domaining
- Block model construction
- Mine planning and scheduling
- Processing and recovery

Although this is a high-level classification of the typical steps, the workflows can be adapted to specific constraints or requirements of the operation, including, for example, blending, economic constraints, water and energy management, environmental constraints, etc.

In the next sections, we review some possible workflows for each stage separately, and illustrate their modelling approaches, providing some real life illustrations of the results.

Domaining

The idea behind domaining is to identify subsets of samples with similar properties that can help create a spatially connected volume for a specific modelling purpose [Faraj and Ortiz, 2021]. Domains can be defined for resource, structural, or geometallurgical modelling, just to name a few. In each case, the relevant features change and the modeller must decide what aspects are relevant for the modelling goal, which is referred in **Error! Reference source not found.** as "domain knowledge". Multiple tools can be used in the clustering stage [Fouedjio et al., 2018]: constrained optimization, k-means, Gaussian mixture models, geostatistical clustering, etc. In real projects, this is often done manually, by checking which geological properties of the samples control the mineralization (or any other attribute of interest being modelled). This is an ill-posed problem, since in reality, the mineral resources are not divided into true domains, so there is no way to check that our definition of clusters (and later of domains) is appropriate, other than by a posterior validation.

For spatial modelling, once the samples have been labelled into one of K clusters, any categorical geostatistical estimation or simulation method can be used to define the extent of the domains. For instance, indicator approaches, truncated Gaussian or pluriGaussian simulation, or multiple-point simulation [Chiles and Delfiner, 2012], can be used to generate one or more domains models. If a single "expected" domain model is generated the approach is termed **deterministic**. If multiple possible scenarios are built that depict the possible extent of these volumes, then this is called a **stochastic** model.

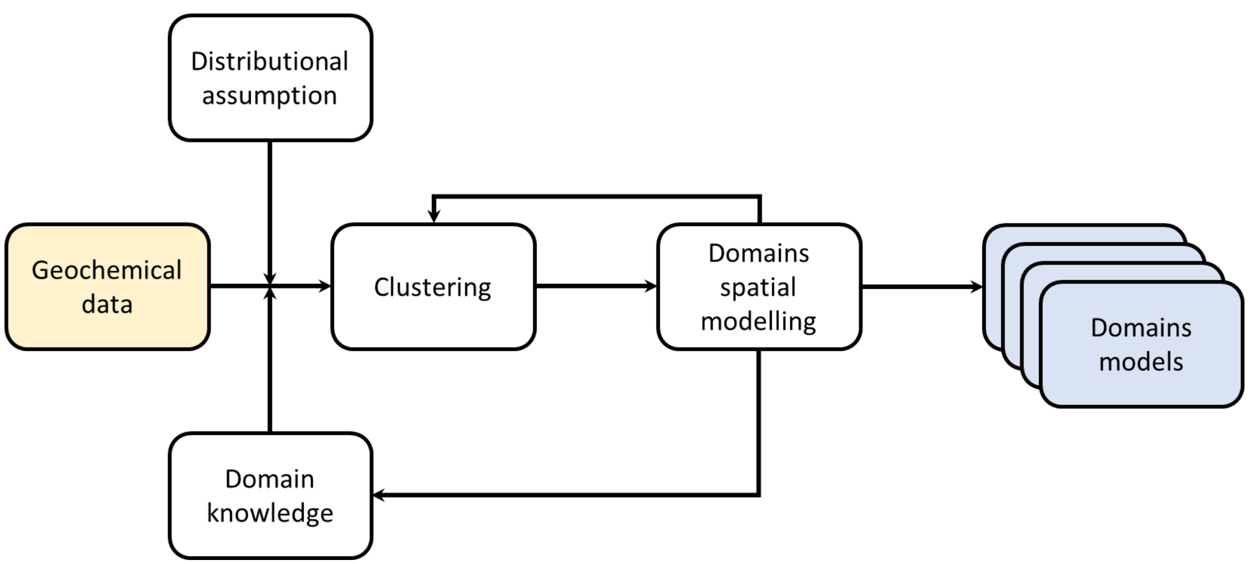

Figure 1: Example workflow for domaining.

An example of the results of an automated domaining approach is provided in Figure 2**Error! Reference source not found.**, where sample data are labelled according to their alteration domains, inferred from geochemical data. These labelled samples are then used to determine the domains, with uncertainty, through an ensemble support vector classification [Koruk and Ortiz, 2022]. This approach combines domain knowledge (used in the determination of which geochemical variables are relevant to the model at hand), a simplified optimization technique to assign samples to each cluster, controlled by a match to the parametric distribution of these variables in each domain, and a machine learning method for classification, which in this case is extended to provide multiple scenarios of the extent of the volumes classified in each domain. The output of this workflow, can be a stochastic model, represented by an ensemble of models of the domains, or as a single probabilistic model, i.e. where for each block, the probability of belonging to each category is quantified, or a deterministic model, represented by the most likely category in each block, determined through majority voting over the ensemble of models, or some other consensus.

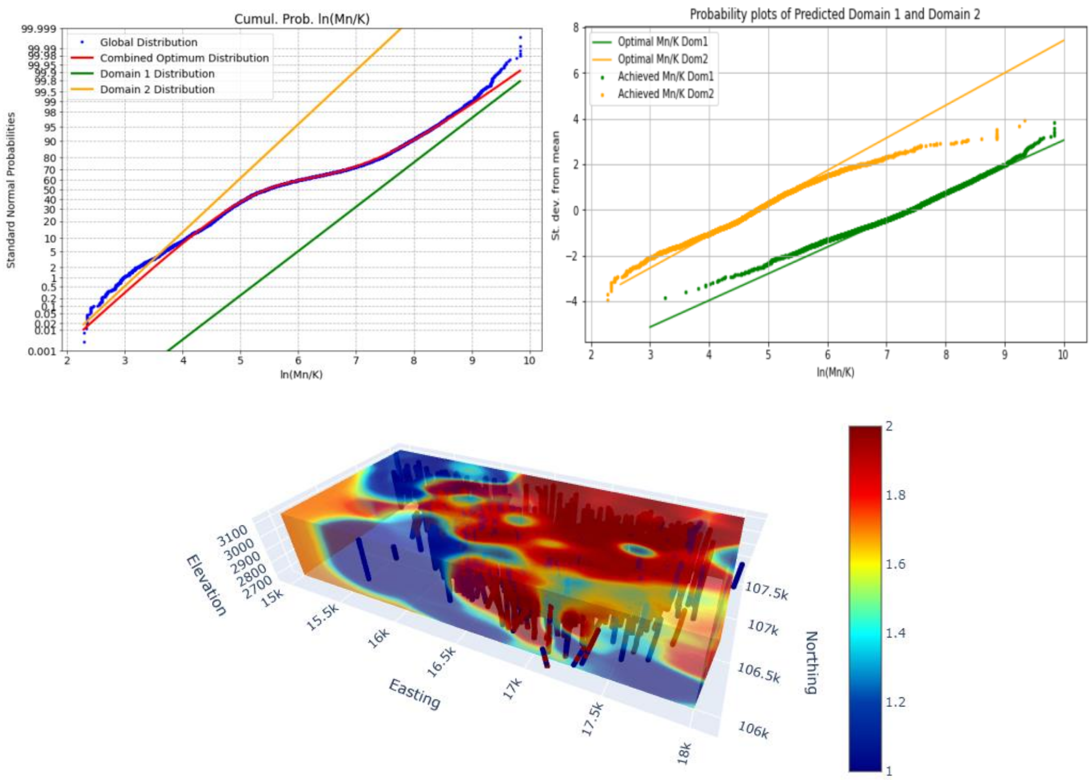

Figure 2: Samples are assigned to categories: distributional assumption (top left), clustering (top right). A probabilistic model is built with SVC using resampling and bagging (bottom).

Block model construction

Once the domains have been established, the construction of a spatial block model follows, by estimating or simulating the different attributes within each domain volume, constrained by the sample information belonging to that same domain. This is conventionally done with geostatistical tools such as kriging or conditional simulation. Accounting for multivariate relationships is key to capture interactions that are relevant for process modelling downstream. These multivariate relationships are both statistical, i.e. correlations between variables collocated, and spatial, measured through direct and cross-variograms between the different variables within each domain.

There are well established techniques for multivariate modelling, including geometallurgical attributes [Deutsch et al., 2015], compositional data (such as elemental or mineral proportions) [Tolosana-Delgado et al., 2019] or multiple variables with complex relationships [Barnett et al., 2014; Avalos et al., 2022].

Workflows for this stage are well-established and thoroughly documented in the literature. As an example, a typical workflow using a transformation into factors that can be modelled independently in space, is provided in Figure 3**Error! Reference source not found.**. The input considers multiple domain models (that account for uncertainty in the extent of the domains) and multivariate sample data representing grades. The result is a set of block models with the spatial distribution of the grade models, respecting their complex relationships, and their spatial continuity, and honouring the data.

A bivariate example of this is illustrated in Figure 4, for two synthetic variables with a complex non-linear correlation. The original variables are transformed to "morphing factors", which are spatially uncorrelated and can be simulated independently with any geostatistical simulation method. The back-mapping provides realizations that honour the data, and spatial and statistical relationship between the two attributes [Avalos et al., 2022]. This technique has been tested with up to 10 variables, providing excellent reproduction of the statistical and spatial correlations.

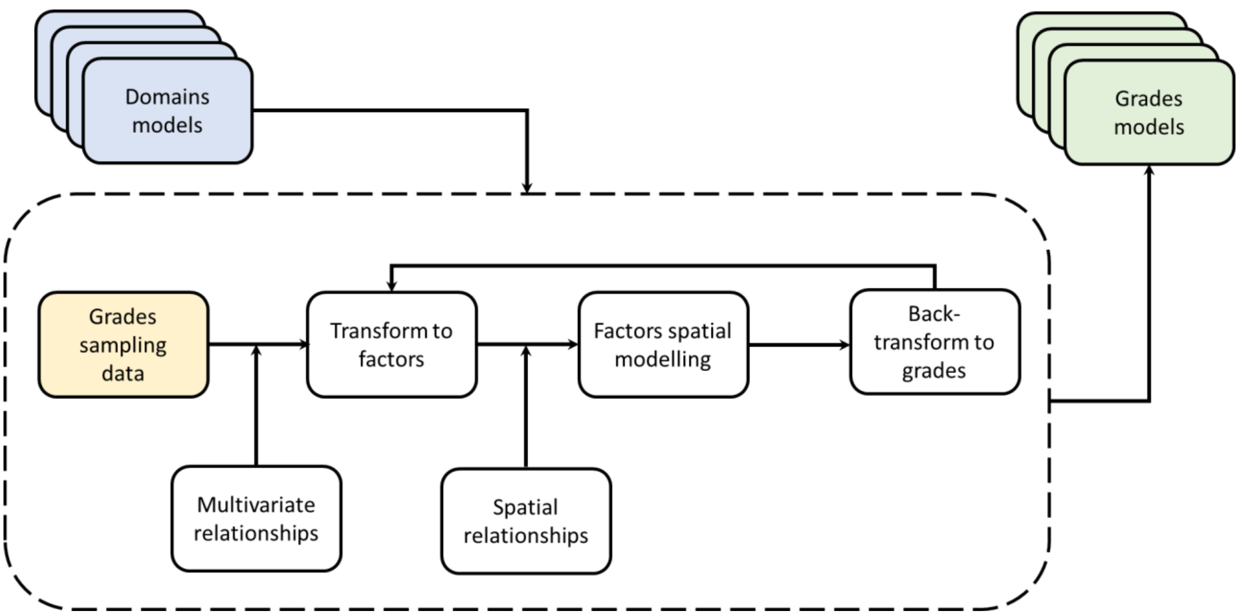

Figure 3: Example workflow for block model construction.

As with the domaining approach, the block model construction workflow allows for the generation of a deterministic or a stochastic output. The deterministic model, which is similar to an estimation, is obtained by locally averaging the realizations obtained through simulation. This is known as an E-type model. Alternatively, the realizations can be used to determine a local probability distribution at every location, or the full ensemble of realizations can be kept to input in subsequent steps.

Finally, it is important to note how stochastic input domain models are used. Rather than propagating uncertainty by using each domain input model and creating an ensemble of realizations of grade distributions within these domains, a cascade approach is taken, where a single realization of the grades is generated for each domain model. In this fashion, if we have 100 domain models at the beginning, the product of the block model construction stage is 100 models of grade distributions, each constrained by a different domain model. This allows us to sample the space of uncertainty with a limited number of models, avoiding the explosion in the number of models if these are nested.

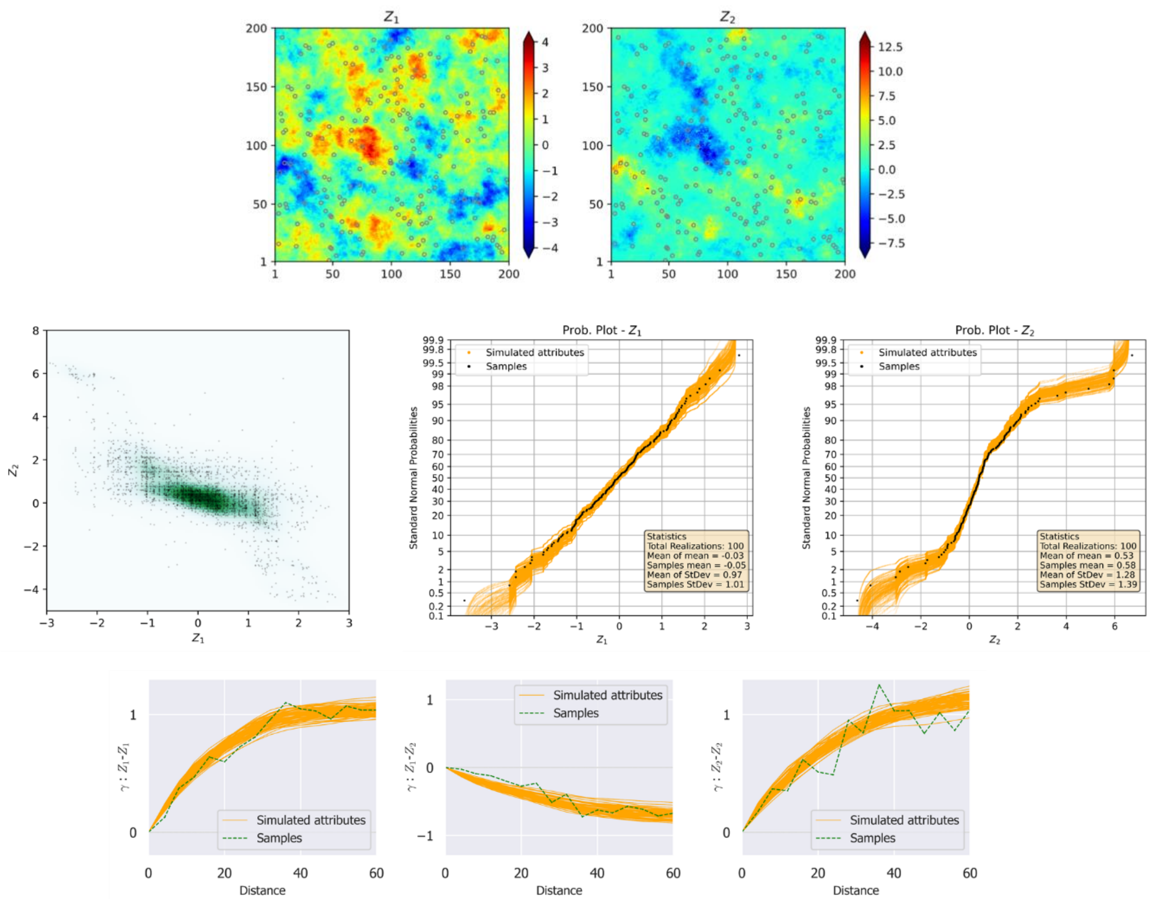

Figure 4: Multivariate block model construction.

Mine planning and scheduling

Mine planning and scheduling define the decision of extracting blocks and the sequence over time and space of this process. Planning must account for the uncertainty in the spatial distribution of the attributes of interest and multiple constraints related to their extraction (economic, operational, environmental, geometric, etc.). There are multiple approaches to optimizing the mine plan, including stochastic optimization [Dimitrakopoulos, 2011]. Scheduling can be done with stochastic integer programming accounting for uncertainty of the attributes [Morales et al., 2019], and constraints can be inputted in the model (see for example an approach to account for demand-side management for energy consumption [Diaz et al., 2016]). Some of the newer proposals involve reinforcement learning approaches to train the system optimizing sequential decision making [Avalos and Ortiz, 2021]. A workflow for a trained Deep Q-Learning neural network is shown in Figure 5. A set of grades models are combined to provide a grades model with uncertainty, which along with production data is used to train a Deep Q-Network. The grades models, in this particular workflow, are processed into an E-type model and a model of the local variance, thus representing the block uncertainty distribution by these two parameters. The network then learns the probability of extraction for each feasible block. Based on these probabilities, a decision about the next block to extract is made, and this is used to assess the quality of the decision and update the probabilities for the remaining blocks. The neural network evolves from a stage where different trials are applied (called exploration phase) so that it can learn what the effects of new decisions are, and slowly moves towards an exploitation phase, where mostly decisions whose outcomes are known, are applied. In this fashion, the network learns to make the best decisions and provides an optimized extraction sequence. Interestingly, this approach can also incorporate feedback from production, thus allowing a learning strategy that rewards decisions that in practice have a positive impact in the objective function.

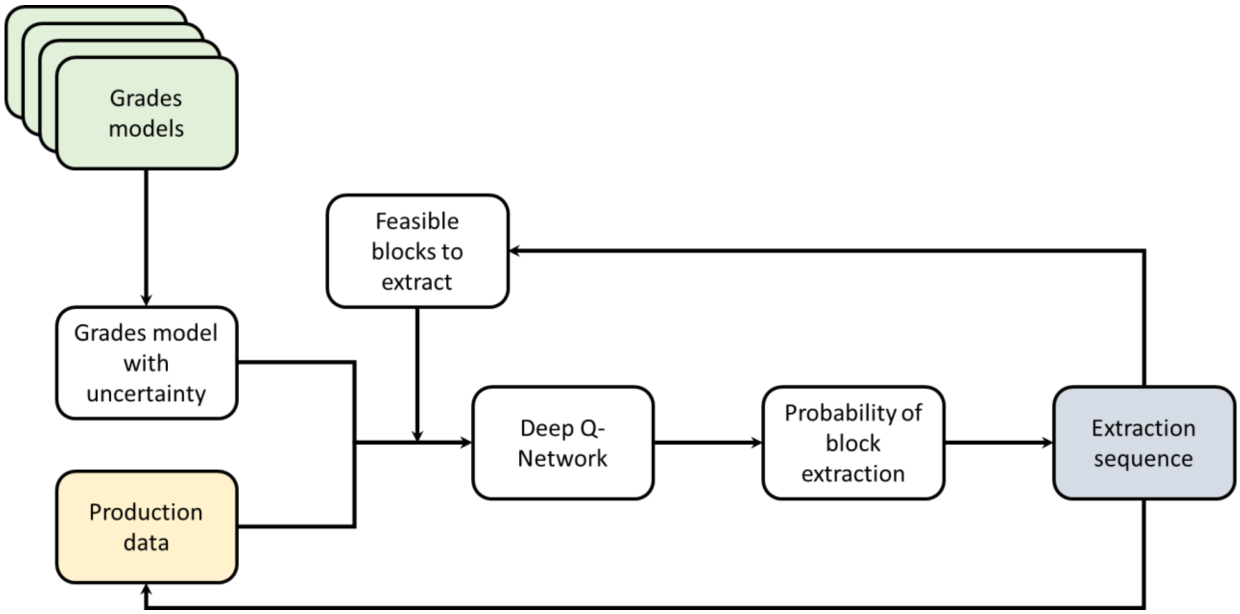

Figure 5: Example workflow for mine scheduling.

The results of the methodology are illustrated in Figure 6, where a schedule is defined randomly initially and after the neural network learns the probabilities of extraction, based on its training, decides a better schedule that increases value in about 5% [Avalos and Ortiz, 2021].

At this stage, the uncertainty from domaining and from the grades distribution is accounted for. The optimization of the plan, considers these two sources of uncertainty and comes up with a single strategy tailored to manage the possibilities given by the available information. The resulting plan can then be applied to each one of the grades models, in order to assess the impact of the domains and grades uncertainty in the production outcome from the mine. These time series of blocks extracted in a fixed sequence, for each realization of the grades distribution, can be used as the processing streams inputted into the crusher and the processing plant.

Processing and recovery

As mentioned, the sequence of extraction and schedule from the mine plan provide the transfer function to go from the spatial domain to the time domain. The blocks extracted from the mine become truckloads fed to the processing streams. Transferring the uncertainty can be done by use of simulation or considering a multiGaussian kriging approach [Riquelme and Ortiz, 2021]. Once the time series characterizing the materials in each processing stream are available, the processing performance can be predicted. Since there are many different processing flowsheets, models will vary. Examples of such models involve hardness prediction with deep learning [Avalos et al, 2020], AI driven air classification of particles [Otwinowski et al., 2022], deep learning froth flotation recovery prediction [Pu et al., 2020], and recovery prediction in leaching using machine learning [Flores and Leiva, 2021].

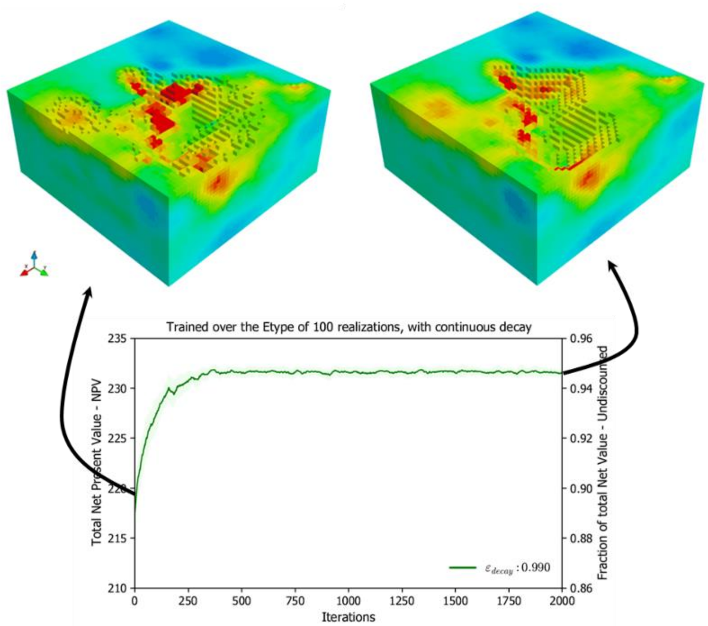

Figure 6: Illustration of the schedule before and after training.

An interesting compilation of models in mineral processing can be put together as a discrete event simulation [Moraga et al., 2022]. For each grades sequence coming from the expected schedule, the changes at each stage of the process can be modelled, in order to predict residence time distribution, particle size distribution and properties of the streams of concentrate and tailings in flotation. This is illustrated in Figure 7, where the processing stages are interconnected in a sequence, producing two outputs: concentrate and tailings. The models for crushing and grinding will vary depending on the equipment, type of circuit configuration and settings used. Similarly, flotation involves recirculation of streams, which have an effect on the resulting products. This can be modelled as well, for a particular configuration, as depicted in Figure 8.

Modelling the processing stage allows for the prediction of blends that occur during grinding and flotation, and are an important input if the processing stage is to be controlled for optimum output.

Integrated model

From the workflows presented earlier, it is possible to create an integrated model from the original drilling data, to the processing stage, considering the concentrate as a product, and also allowing the management of the tailings. This is illustrated in Figure 9.

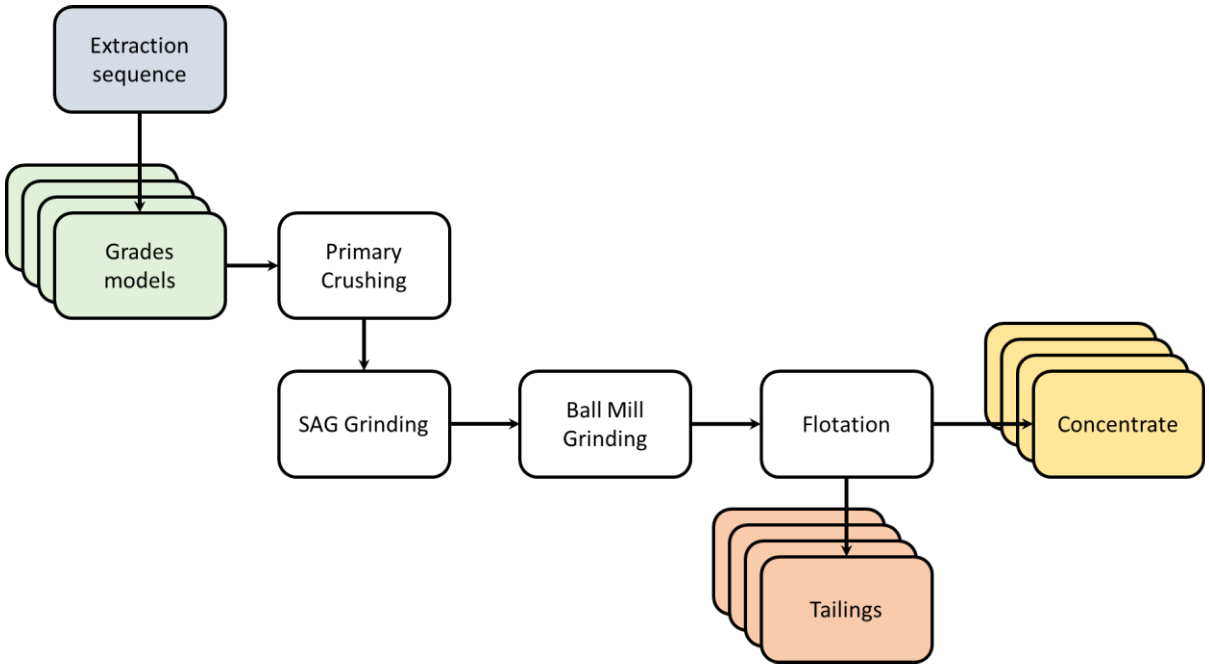

Figure 7: workflow for modelling performance during processing.

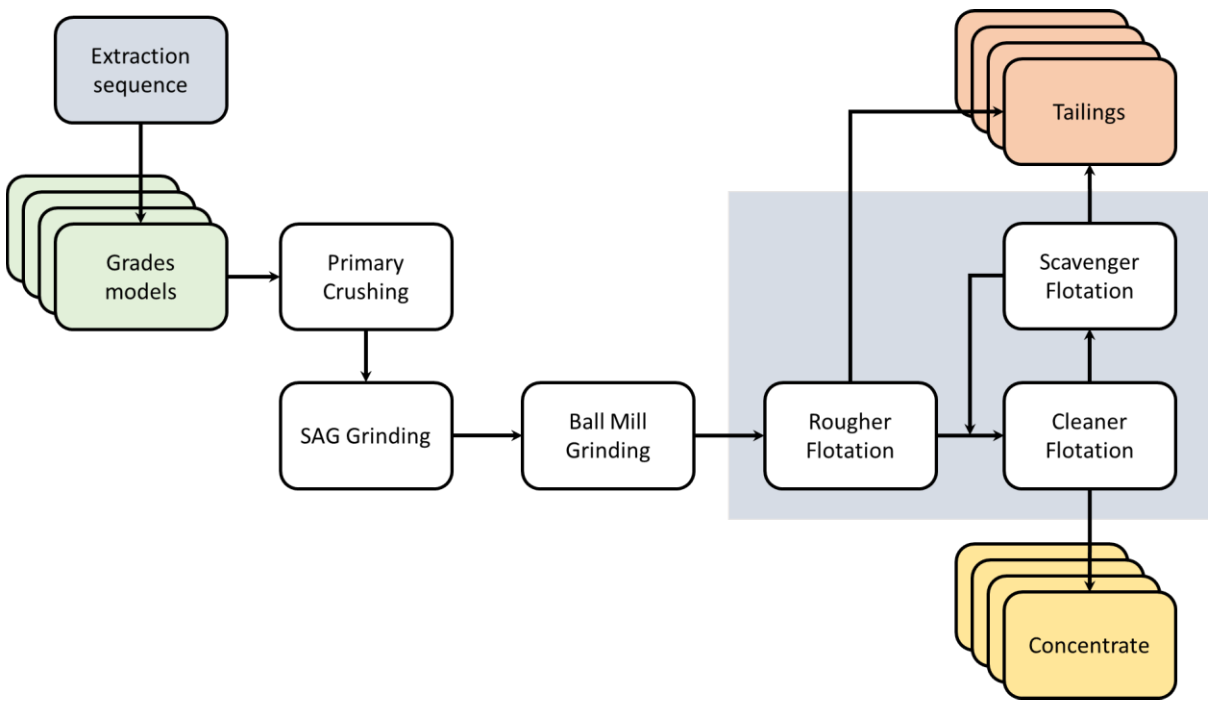

Figure 8: workflow for modelling performance during processing, for a particular flotation circuit configuration.

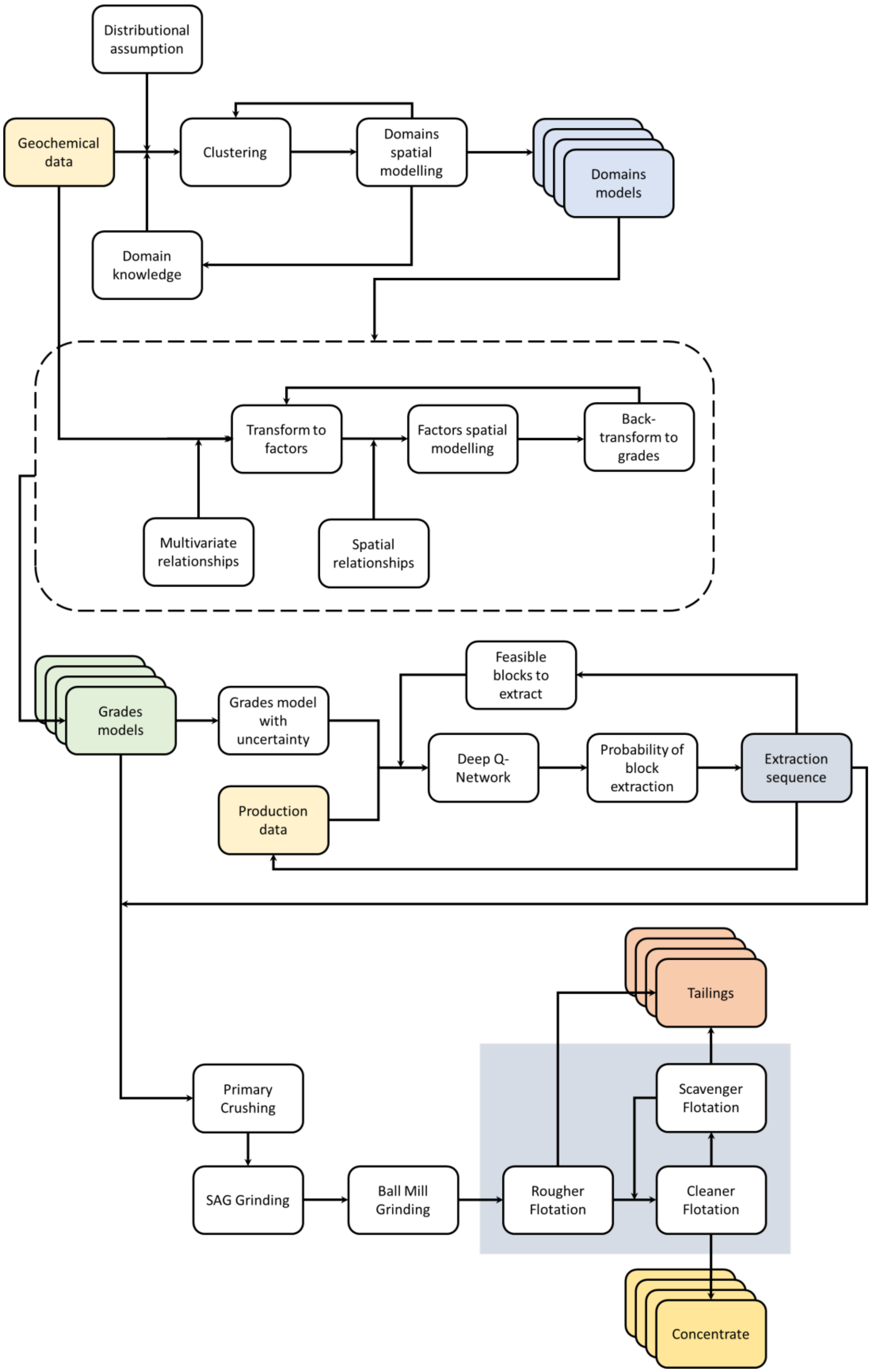

Figure 9: Workflow of integrated process, from drillholes to concentrate.

4. Conclusions

A mining system can be seen as a sequence of stages or processes. The actual ore deposit, mine and operation is modelled through the block model for resources, reserves and the mine extraction schedule. Mineral processing and the metallurgical process can also be modelled, accounting for the variability and uncertainty in the feed and in the corresponding process. All this information can be used to perform optimization and control over each stage of the process, but, most importantly, once the geometallurgical model is fully implemented and connected, the model can be optimized globally and multiple constraints can be incorporated in the decision making process.

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 model. This predicted output must be compared to other measurements of the actual output, for the models to learn. Feedback must be constant to keep models updated at a time scale relevant to decision making. Prediction should incorporate uncertainty as a key factor, to ensure the properties of the final product and the waste are anticipated. This approach ensures all considerations are accounted for when extracting raw materials and recovering the elements of interest, thus making this process more sustainable.

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