WHITE PAPER

Production Forecasting for Mining Operations with Simulation

A case study with SIMEC

MathWorks®

Introduction

Effectively managing the delivery of ore through the “pit-to-port operations” from the mining pit, through the plant, to the port where it is loaded onto a ship is a difficult task. It involves the management of discrete teams from the mining operation, plant operations, loading hauling, rail, port operations, marketing, and shipping. Most of these teams are driven by key performance indicators (KPIs) that focus on the group's performance that in some cases is not aligned to the overall efficient pit-to-port operation. For instance, the objective of minimising rehandling cost at the run of mine (ROM) could impact final product quality when loaded onto a ship. For efficient and effective pit-to-port operations it is important to effectively balance the trade-off between each groups operations to maximise profit whilst minimising risk.

Production forecasting is a crucial tool used to optimise mining operations through data-driven decision making. These techniques are equally applicable to the forecasting of both precious metals and bulk commodity production output. The forecast is based on a model of the process or supply chain. This model is simulated into the future using inputs such as the mine production, plant capacity, and scheduled downtime. Parameters can be varied between simulation runs to qualify the impacts of feed uncertainty, and unplanned outages. Once production output and risk have been quantified, the business can make informed decisions and manage threats to the production output.

This paper discusses how SIMEC Iron Ore Mining Division operating north of Whyalla, South Australia, started the transition of their pit to port operations from a pull to a push model using planning supported by a production forecasting model. In this case, the production forecast allowed the timing and quality of the product to be shipped to provide insight used by the marketing team. The mining and operations team then reused the model to evaluate the impact of different plant feed schedules. As a result, the push model allowed the operation to avoid compromises of chasing shipment grades, which resulted in a reduction in penalties and maximise value per shipment loaded.

Pit-to-Port Model

Central to production forecasting is a model of the operations. A model should be developed to answer specific questions. In the case of SIMEC Iron Ore Mining Division, a model of the entire Pit-to-Port operations was developed so that they could forecast product quality and timing of ore shipments leaving the port-based upon mining plan inputs and pit-to port configuration. The timeframe of the model simulation was anywhere from quarterly plan through to the life of mine.

The development of the model was a collaborative effort that allowed the different stakeholders or groups from the entire pit-to-port operations to provide input. Each group was able to include relevant assumptions and validate their component against production data where available. This was a key step that allowed the stakeholders to take ownership of the model and have confidence in the results.

It is important to balance the detail and fidelity of the model so that the core primary factors are included whilst the time to develop the model and computational effort required to execute are limited. For instance, a complex model of ore truck’s movement and dynamics are not important when considering the life of mine models where these details could be represented by typical travel, loading, and unloading times. Considering these factors, a discrete event-based simulation environment was selected that allowed the movement of entities such as trucks, trains, ships, and parcels of ore to be modelled as delays. The modelling and simulation environment used was [Simulink®](#) and [SimEvents™](#) both products of MathWorks.

The high-level model, shown in Figure 1, includes 4 mining areas Iron Knob Mining Area (IKMA), Iron Baron Mining Area (IBMA), South Middleback Ranges North (SMRN), and South Middleback Ranges South (SMRS) and their rail connection to the Port. The model of the global short-term scheduler is also included.

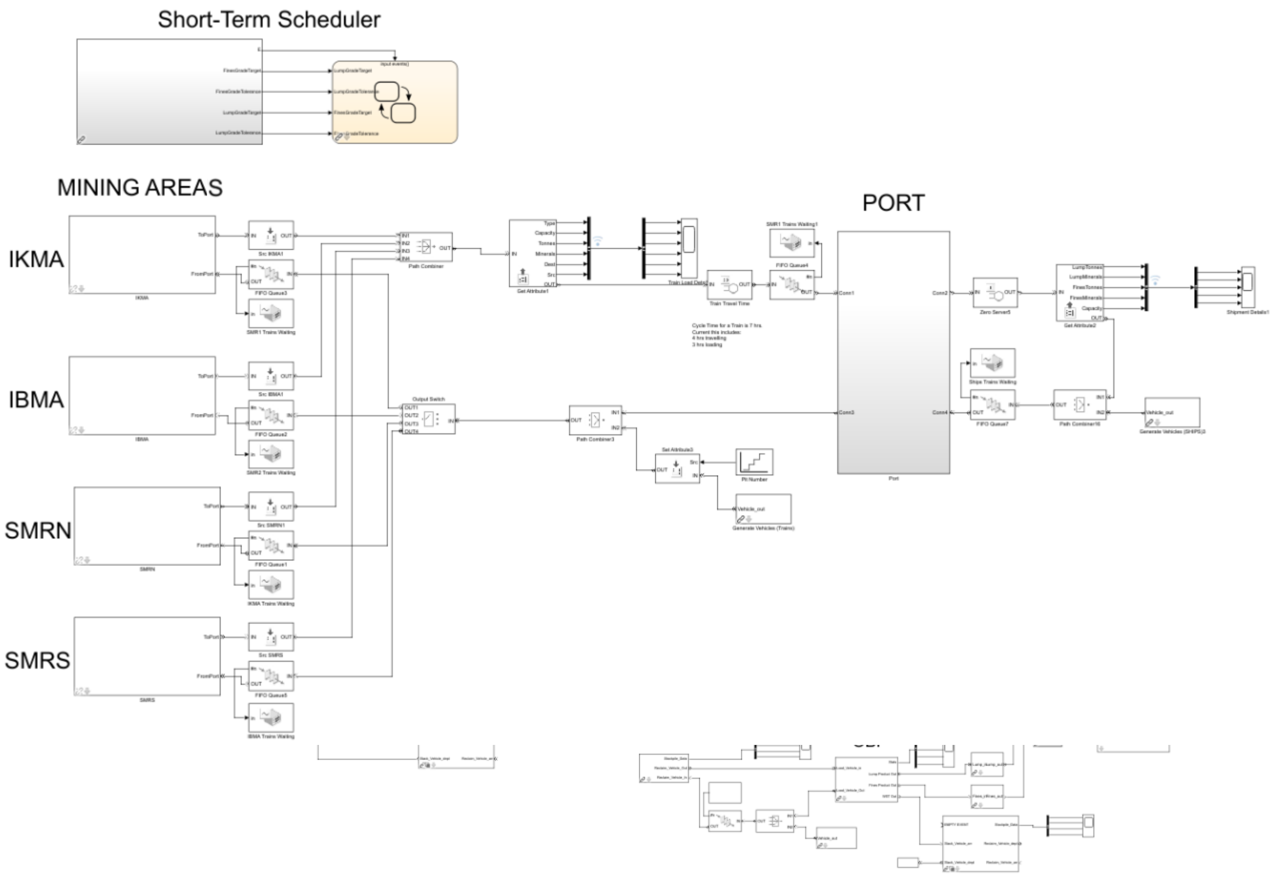

Figure 2 – IKMA mining area model

Pit Model

The model for the pit is based on the mine plan. Each row in the mine plan includes block details and blast timing. As the simulation progresses a blast is scheduled, and the block material is ready for hauling. These blocks act as the primary input to the model.

Stockpile Model

The stockpile is one of the most essential elements and is reused throughout the Pit-to-Port operational model. To quantify the impacts of product quality, it was important to include grade variation throughout the pile. The stockpile was modelled using a mesh that provides the capability for different quality material to be stored at each of the mesh locations. It was also important to allow different stacking and reclaiming methods to be included to simulate their impact on product mixing. This flexible component allowed it to be reused throughout the pit-to-port model for instance the plant feed fingers, ROM piles, and conveyor load out piles.

Plant Model

The OHP and OBP elemental recovery was determined from prior plant operational data. This historical data was used to train a regression model. This model was used to simulate the separation of the feed material into the Lump and Fines products and in the case of the OBP the rejection of waste.

Short-Term Scheduler

Equally important to modelling the physical elements of the Pit-to-Port operations is to include models of the human decision-making process. To implement the human decision-making process, it is important to distil the human decision making into a set of rules that can be programmed. In some cases, this requires some solver or optimisation engine to be executed to solve the problem. For instance, scheduling plant feed requires a solution to a mixing problem to be solved that achieves grade targets whilst minimising undesirable gangue elements such as phosphorus.

In this case, the continuous stockpile model (CSM) which has been successfully used in other mining operations and detailed in Kamperman (2002), Howard (2007), and Wills (2011) was implemented. The CSM assumes continuous mixing throughout the process and replaces more traditional batch scheduling for plant feed. The CSM focus on removing short-term grade variations, whereas long term grade control is best implemented by making changes to the mine plan.

The grade control was achieved by scheduling plant feed ore at each of the 4 mining areas. Before running the simulation, the mine plans are assessed to determine how the material should be sorted and placed onto the ROM. This sort would change over the simulation period and be based upon the largest spread of mineral grade found in that period. Once the sorting mineral was determined the cut grade was found that split the material into two equal amounts. This allowed the minerals to be sorted into two equally size piles in the ROM area. Considering these two ROM piles from each of the 4 mining areas an optimisation problem was solved to minimise short term grade variations. The optimisation problem was based on solving a quadratic program (QP) problem that would reorganise the schedule to minimise variations of the target grades. The QP solver used is included in Optimization Toolbox™.

To simulate the human decision-making process this QP solver would be run once daily determining the schedule over the next period. This was periodically launched and run within the simulation environment.

Data-Driven Decision Making

The production forecast based on the model of the pit-to-port operations provides an environment to simulate the performance of the operations based on a particular configuration. The performance could be quantified using metrics such as the net present value (NPV), or adherence to shipment timing and grade schedule. The forecast supports both planning activities and to explore process improvement opportunities. This model-based environment forms the basis of a data-driven decision-making process.

The results of the model were used for planning purposes. For instance, the marketing team used it to determine the timing and quality of shipments. This information allows contracts to be sold based upon the forecast availability of material. This allows the pit-to-port operations to operate in a push mode as opposed to pull mode where the operations are chasing grades that might compromise overall NPV performance.

The results of the model were used to evaluate operational and capital changes to the pit-to-port operations. The different options could be modelled and simulate to determine the opportunity and potential risks. Due to the large budget opportunities and risk, it is important to evaluate the option prior to implementing them. Simulation offers an opportunity without committing substantial amounts of capital.

For instance, this data-driven decision-making approach was used to evaluate the potential impact of the CSM based grade control on the NPV. In this case both the configuration with and without grade control were evaluated over a life-of-mine simulation. The NPV per shipment for the two cases is shown in Figure 3. A small per shipment value is shown when the grade control is switched on as the short-term product variations are reduced. The total simulation results show an 1.1% improvement in the shipment revenue over the life-of-mine.

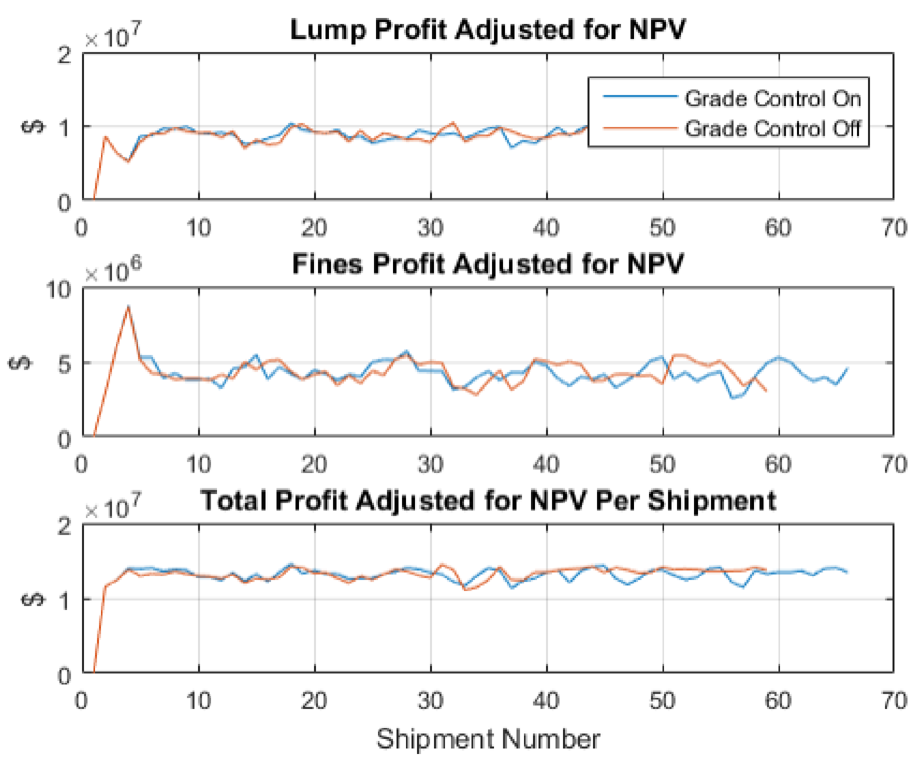

Figure 3: NPV values per shipment comparing grade control on and off.

The model was also used to quantify risk. In this model the uncertainty of the resource model and therefore the mine plan was a potential risk. This was addressed by generating multiple mine plans based on different realisations of the resource model. For each of these mine plans a new model simulation was performed. To speed up the computation of the many simulations, [Parallel Computing Toolbox™](#) was used to run them parallel leveraging the multiple cores of the compute environment. In the case of the grade control algorithm, it was able to demonstrate that a consistent increase in NPV was achieved across the different simulations.

Conclusions

This project has provided an important data-driven decision-making capability based on a pit-to-port production forecast to assist in both planning and evaluating process improvement initiatives. The pit-to-port model allowed SIMEC to evaluate the impact of different initiatives and to inform their decision-making process. The model also provided a mechanism for communication and collaborate amount the different teams across the pit-to-port operations.

As a tangible example the case study shows that the CSM grade control strategy was used to manage short term grade variations provided value when compared to pure push model with no grade control. The risk introduced by resource model uncertainty was evaluate and deemed to be low.

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