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IRON ORE VALUE CHAIN OPTIMIZATION USING SIMULATION MODELLING AND RESPONSE SURFACE METHODOLOGY

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ABSTRACT

Simulation modelling has long been established as the long term planning tool of choice for large bulk material value chains such as coal and iron ore. These methods have been used to great effect over the past twenty years to help improve their capital efficiency and productivity. However, as these value chains have grown, so too have the complexity, expectations and computational requirements of the models that represent them. Despite spectacular increases in computing capability and power, all too often we find ourselves in the position where a traditional experimentation process becomes the bottleneck and only a portion of the solution space can be explored.

This paper presents a case study on the use of experimental design using the response surface methodology to improve the efficacy and solution space coverage of simulation modeling applied to a capital growth optimization project for a major Australian iron ore producer.

1 CONTEXT

There is increasing pressure being placed upon iron ore mining ventures to deliver improved capital and operating productivity. In the Pilbara region in Australia, these are huge vertically integrated operations that extend across mines, processing plants, railways and ports. In these operations, multi-billion dollar revenues and long operating lives creates a high opportunity cost for sub-optimization in system design and operation. In these operations, simulation modelling has long been the tool of choice for long-term capacity planning and project evaluation (Glassock and Hoare, 1995).

In some of these operations, the process of moving product from pit to port is complicated. A high degree of flexibility in the day-to-day operations combined with expert planners and planning systems embed a complex decision-making process. Replicating the performance of this process in a simulation model requires significant programming and computational expense. For some of these simulations, a single replication of one year of operations can take in the order of one to three hours, depending on the scenario. With high variability between replications and large experiment sets, scale becomes an issue very quickly.

In the case study presented here, the iron ore producer was evaluating a wide portfolio of options to increase port capacity under three layers of uncertainty. There was uncertainty about the performance of next-generation equipment, uncertainty about expected upgrade costs as the range of cost estimates narrowed as more detailed work was conducted and uncertainty in the future system baselines assumptions due to a number of concurrent business improvement initiatives. Together these factors created a solution space that was incomputable within the study timeframe using a fully factorial design. This would typical-

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ly be resolved by limiting the solution space by grouping options based on engineer intuition or high level analysis. However, for a complex set of upgrades, this risks leaving global optima out of the solution space.

2 METAMODELLING

To preserve optionality in the decision-making process, a metamodel of the simulation model was developed. While there are a number of different modelling techniques that can be used (Simpson et al, 2001), for this study a response surface approximating the relationship between the simulation model and its key operating assumptions was developed similar to a previous approach for risk and uncertainty analysis (Fricke, Velletri and Wood, 2014). The metamodel surface, characterized by multiple linear regression, can then be evaluated instantly. Using this metamodel, multivariable optimization can then be used to determine the optimized upgrade options for the system.

A total of 58 independent variables were identified for the metamodel. A full two-level factorial design for this experiment would have required 2^{58} runs. Instead, a resolution V fractional factorial base design was used, requiring only $2^{12} = 4096$ runs, and complemented with a center point and 58 x 2 = 116 face-centered axial points. This is known as central composite design. Using this experimental design, the simulation model was run using a computing cluster and system capacity was estimated using multiple linear regression to create a full second-order model. Goodness-of-fit was evaluated and the model was pruned to avoid overfitting. This was then overlaid with option cost data to create a function of benefit and price for optimization.

3 IMPACT

There were two broad categories of benefits of the development and use of the metamodel. On one hand was the impact upon the concurrent engineering study, on the other the definition of the final optimized design of the system.

For the engineering study that ran in parallel with this work, there were a number of benefits to on-time delivery and overall study costs. It allowed the simulation modelling and engineering design to occur simultaneously, with the engineering design scope informed by early simulation analysis. As the design iterated and more detailed information, particularly related to costs, became available it allowed the option selection and sequencing to be rapidly reassessed. Further to this, when key objectives such as capacity requirements or capital constraints were changed during the study, the study team could adapt with minimal impact on schedule.

For the resulting cost-optimized system design, the approach used added some key analysis capabilities that would not otherwise have been possible. Firstly, it enabled the analysis of all potential combinations and sequences of upgrade paths, greatly expanding the solution space. Within this enlarged solution space, it provided the ability to identify synergies between upgrades, translating into groupings around localized bottlenecks which could then be packaged and pursued within the engineering stream. In addition to this, it allowed the sequence of upgrades to be evaluated against a number of baseline states, depending on the state of other improvement initiatives and creating an overall robust capital project outcome.

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