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INTEGRATING OPTIMIZATION AND SIMULATION - A COMPARISON OF TWO CASE STUDIES IN MINE PLANNING

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ABSTRACT

This paper describes the benefits of integrating optimization formulations within simulation models. Two different case studies in mining are presented, both requiring a blending optimization. The primary problem at hand is to model a complex supply chain involving blending of multiple inputs to produce a number of potential products for customers. The first approach involves solving an optimization model to produce a long term plan, then simulating this plan over time without the ability to change the plan as time progresses. The second approach involves a more integrated system where multiple instances of an optimization model are run throughout the simulation using updated inputs. A description of the problem is supplied, providing the need for both optimization and simulation, and then the two case studies are compared to show the benefits of integrating the optimization within the simulation model.

1 MODELING OF A MINING EXPORT SUPPLY CHAIN

An export supply chain - beginning with the extraction of ore from a pit and ending with the loading of this ore on to vessels at a port - is a key component of many mining ventures. These supply chains are comprised of a series of complex operations, such as mining, ore processing, transportation, stockyard management and vessel loading. Two differentiating features of mining supply chains are the length of time over which they operate, and the many degrees of uncertainty that affect each link in the chain. Mining, by its very nature, is a capital intensive industry with relatively long investment cycles. Mine production life can typically last 30 years or more, which itself is preceded by significant lead times between orebody discovery and initial production. Added to this, two key areas of uncertainty play a driving role in any mining project: uncertainty in the geology of the orebody (supply) and uncertainty in the market price of the final product (demand). These factors - coupled with the size of the capital and operational investments required in any mining project - make risk analysis and management a core function for any company participating in the mining industry.

Typically, the operation and performance of each component of a mining supply chain is analyzed in isolation, with little consideration given to its interaction with upstream and downstream processes. In reality, stochastic and dynamic influences that affect one component of the chain can have significant flow on effects to other sub-systems in the supply chain. Hence, evaluation of the performance of the total integrated system needs to capture the interaction of these sub-systems. Discrete Event Simulation (DES) has proven to be a powerful tool in modeling supply chains, capturing the system dynamics and interactions, and allowing the overall performance of the integrated system to be rigorously evaluated (Chang and Makatsoris 2001). The construction of a DES supply chain model enables extensive capacity and risk analysis to be undertaken prior to any major investment decision.

The application of DES to model mining supply chains is particularly beneficial when used in the strategic planning process, to aid decision making for the long-term. These decisions are typically associated with significant capital expenditure, and may form part of a Pre-Feasibility or Bankable Feasibility Study. In a greenfield environment, strategic planning focuses on project design, including issues such as infrastructure requirements, plant design, equipment configuration and capacity, and evaluation of different options for operating principles and processes. Once a project is up and running, strategic planning is used to consider and evaluate major capacity expansion options, and identify system bottlenecks.

While the primary objective of mining export supply chains is typically to maximize production capacity, that is, tonnes of ore loaded on to vessels at the port, in some mining operations, the extracted ore is blended into a variety of products with differing characteristics before being exported. This can be the case for ores such as coal, iron and manganese. In these operations, an additional objective, in the form of achieving a pre-determined quality of material on the vessels, is an equally important measure of system performance. Blending is also of prime concern in chemically driven ore extraction processes such as gold and nickel. In these cases, maximizing throughput requires the creation of an optimal blend of inputs.

In a blended product supply chain, the objective of delivering a certain quality of product often directly conflicts with the objective of maximizing production capacity, resulting in an increased level of complexity across the supply chain. In supply chains such as these, the decision making process of planning the movement and blending of ore through the system is paramount to the overall system performance. Capturing this complex planning process in a DES modeling language is possible, but proves to be a very difficult and time consuming task (Anderson and Evans 2008). Since planning problems are often modeled and solved using an optimization framework, an alternative approach is to decouple the decision making process from the simulation model, develop a stand-alone optimization model for it, and then integrate the two to create a holistic model of the supply chain. The optimization model is constructed to replicate the planning activity that is regularly performed on site by experienced practitioners. The integration of this optimization model into a DES framework results in the creation of a supply chain model that captures the effect of system uncertainty across multiple time horizons. This enables deeper insight to be gained into the system behavior under different configurations of infrastructure and operating philosophies.

An example of a generic mining export supply chain that incorporates a blending component is presented in Figure 1. The supply of ore is determined by the mine plan, which typically contains a number of potential sources of ore that will be available during pre-determined windows of time. The demand for the final blended product is given by the shipping plan, which can include vessels currently anchored and waiting to be loaded as well as any nominated vessels that are yet to arrive at the port. The raw ore contained in the mine plan must be moved from pit to ship via a series of intermediate sub-systems that can include processing plants, transportation systems (rail networks or conveying systems) and stockyards. A feature of export supply chains in the mining industry is the inclusion of buffers (stockpiles and queues) between these sub-systems to mitigate the impact of sub-system performance variability on overall system performance. In the case of a multi-pit, multi-product blended ore mining operation, intermediate stockpiles are also used for blending the ore into products to be shipped that meet the specified quality parameters, as well as for buffering purposes. The modeling process described in this paper is applicable to a mining export supply chain such as that presented in Figure 1.

2 THE SIMULATION COMPONENT

Discrete Event Simulation (DES) modeling is the process of emulating real world operations in a controlled environment on a computer. This technique provides a rational and quantitative process for increasing understanding of the potential consequences of alternate proposals. These may range from a change in operational philosophies through to the commissioning of new infrastructure. Hence DES modeling is a useful tool for both long-term strategic decision making and short-term planning and operational decisions.

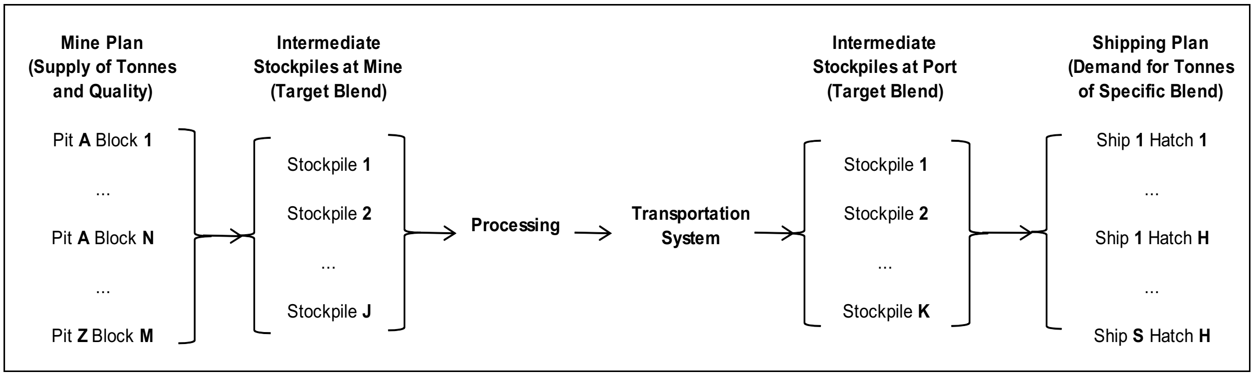

Figure 1: Generic mining export supply chain

A DES model is constructed by considering each physical item as a discrete entity, with its own uniquely defined set of properties or attributes (Zeigler, Praehofer and Kim 2000). These entities act out the operational activities that make up the processes being modeled. Activities take finite periods of time to execute thus imposing delays to the modeled entity. Processing time or delays can be random in nature thus stochastic methods are used to generate randomly induced delays, all of which are dependent on the data and operational rules that are defined for that particular process or piece of equipment. This combination of logical and random events is designed to reflect the most likely operational environment.

Each system within a DES model has individual operating rules and parameters which need to be accurately defined. In the context of a mining operation, an export supply chain involves the movement of ore from pit to port, via any number of sub-systems. In many mining supply chains, the operational rules regarding the movement of ore are simply defined (for example, lump material goes to a lump stockpile and fines material goes to a fines stockpile). The lack of product diversification in these instances means that there are little or no blending requirements throughout the supply chain. These simple operational rules are able to be incorporated into DES models of the mining supply chain relatively easily, allowing the DES model to provide a realistic representation of the export supply chain as a whole. However, in some mining supply chains, the process of moving ore from pit to port is significantly more complicated. This is particularly the case when the ore is blended into a variety of products with differing characteristics before being exported, which can be the case for ores such as coal, iron and manganese. For operations such as these, day to day movements of ore are typically planned and executed by groups of experienced individuals, who match current mining stocks and stockpile levels with a shipping plan. The decision process by which they do so is complex, and cannot be described using a simple set of rules. This limits the ability of a DES modeling language to precisely replicate the decision making process that is used in practice, and hence provide an accurate representation of the export supply chain.

3 THE OPTIMIZATION COMPONENT

Optimization modeling is ideally suited for analyzing complex decision making processes, where any number of (possibly conflicting) objectives have been identified as being desirable, subject to constraints such as system capacity, operational limitations and time (Winston 1987). One of the most powerful features of an optimization model is its ability to consider hundreds of thousands of possibilities and determine the optimal decision in a very short period of time. In the mining industry, optimization modeling has been widely applied in long-term mine planning, particularly production scheduling problems and ultimate pit design (Hustrulid and Kuchta 2006). It is also possible to apply optimization modeling to the problem of planning the movement and blending of ore through a complex export supply chain, such as that presented in Figure 1. This optimization component can then be integrated into a DES model of the entire supply chain, enabling a holistic model of the system to be developed. There are a number of advantages to modeling a complex export supply chain in this manner. Automating the process of generating the plans and carrying them out in the simulation reduces the need for human input, and aids in the process of knowledge capture and retention. In addition, a stand-alone optimization model provides the ability to easily modify and test alternative planning strategies in isolation. Optimization models also have the ability to evaluate multiple criteria (for example product quality, demurrage, quantity of stockpile tonnes re-handled), as well as to explore the effect of changing the priority of each of these objectives.

An optimization component of a DES model of a generic mining export supply chain such as that presented in Figure 1 is included to plan the movement of material through the system over a short-term time horizon; for example, on a fortnightly, weekly, or daily basis. It follows that inputs to the optimization model are short-term mine and shipping plans and the current levels and blends in the intermediate stockpiles. The model outputs direct the movement of material through the system over time via the intermediate buffer stockpiles to attempt to satisfy the shipping plan, in terms of both the quantity and quality of the final products shipped.

The optimization model is formulated as a multi-time period linear program of the form:

$$\max \{cx : Ax \leq b, x \geq 0\}$$

where A is an m by n matrix, c an n-dimensional row vector, b an m-dimensional column vector, and x an n-dimensional column vector of decision variables (Wolsey 1998). The time horizon to be covered by the model is divided into discrete units, for example, the model output may be a plan of ore movements on a shift-by-shift basis for the next week. The key decision variables for each individual time period include:

- For each individual mining pit or face, the tonnes of ore to extract and which mine stockpile to send them to;
- For each mine stockpile, the tonnes of partially blended product to transport to the port, and which port stockpile to transport them to;
- For each ship to be loaded during the time period, the quantity of blended product to load from each port stockpile.

The primary objective of the linear program is to maximize the throughput of ore achieved by the system over the time horizon under consideration. Secondary objectives are also included to force the quality of the product loaded on to ships and the blend of the intermediate stockpiles to be as close to target as possible, and are included through the use of penalty weightings in the objective function.

A wide range of constraints can be applied in a model of an assignment problem such as this, and can be tailored to the specific operation being modeled (Winston 1987 and Wolsey 1998). Most typically in the context of a mining application, constraints are included to limit the capacity of each item of equipment in any time period, to monitor the blend of the intermediate stockpiles, and in some instances to enforce a precedence order or sequence on certain activities or events. Note that a direct formulation of a planning problem involving blending will typically feature a number of non-linear constraints, which can lead to overly complicated mathematical formulations and impractical solution times. To overcome this issue, a small number of simplifying assumptions may be made to enable the formulation to be linearized, and hence reduce the solution time of the optimization model considerably, without losing significant detail or accuracy in the plans produced. Furthermore the effect of these simplifying assumptions can be directly measured and evaluated through the results of the simulation system.

4 COMPONENT INTEGRATION

Generally, a DES model of a mining export supply chain will consider the performance of the system over a one year time period, using a mine plan and shipping plan developed for that year as inputs. The optimization model is used to plan material movements on a more frequent basis, such as fortnightly, weekly, or a number of days in advance. The time horizon used for the planning process is an important factor in determining the complexity of the planning problem, and hence the computation time required to solve an individual problem instance.

When the time horizons to be used have been decided upon, for example a simulation time frame of one year, with ore movements planned on a fortnightly basis, a simulation model run can be commenced by running the optimization model to produce an initial plan of ore movements for each two weeks of the year. The output is a short-term plan which is then translated into discrete 'tasks' to be carried out by the simulation model. The DES model then attempts to carry out these tasks as close as possible to the plan, subject to random events and variability. A small amount of intelligence is required within the simulation model for dealing with unexpected occurrences such as bad weather causing the operation to be shut down, or the unplanned failure of individual items of equipment.

This is where our two case studies diverge in approach. While the first study continues on for the entire year with the initial plan, in the second study, at the end of the defined short-term planning period, control is passed back to the optimization model with an updated set of inputs for the next planning horizon. This allows a plan that is specific to the simulated circumstances of each planning period to be developed. This process is then repeated for each individual planning horizon throughout the simulation run. The two case studies now presented compare the results of running a long-term simulation using a single, fixed plan generated by an optimization model at the commencement of the simulation run, with a more advanced, integrated model that regularly re-solves the optimization formulation with updated inputs as the simulation time progresses.

5 CASE STUDIES

5.1 Decoupled Optimization and Simulation – Lihir

Lihir Gold Limited (Lihir) is the owner and developer of one of the world's premier gold mines, located on Lihir Island in the New Ireland province of Papua New Guinea. Lihir has one of the world's largest gold resources and ranks among the top gold producers in the world.

TSG Consulting (TSG) were commissioned by Lihir to undertake a simulation study as part of a Feasibility Study examining the addition of a separate 3Mtpa grinding line, together with flotation cells and ancillary equipment, to treat low grade ore. One of the primary objectives was to investigate whether the existing conveyor linking the crushers to the processing plants would be able to supply both mills with sufficient material. Figure 2 shows a simplified diagram of the supply chain.

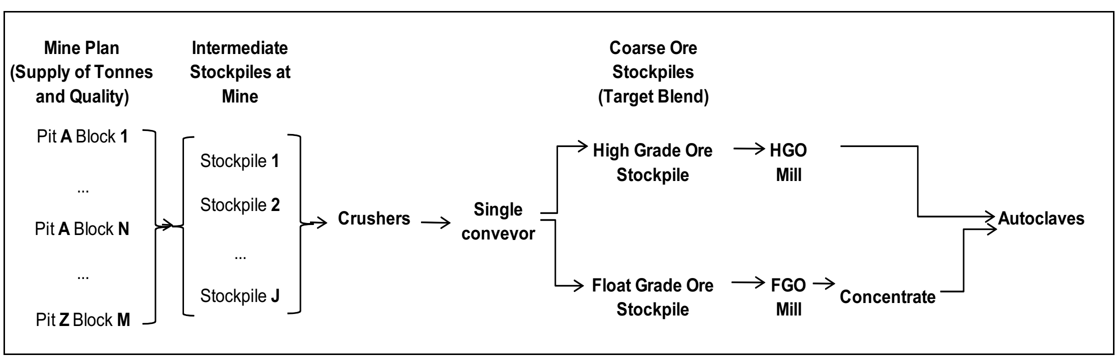

Figure 2: Simplified representation of Lihir's supply chain

The key driver of the performance of the system is the autoclaves. Autoclave throughput is dependent on a complex mix of material constituents, primarily based on sulphur levels. The mix of High Grade Ore (HGO) to Float Grade Ore (FGO) in the autoclaves can be modified instantaneously to maintain an optimal mix of constituents; however this is in turn influenced by the previous choices of which stocks have been used to make up the HGO and FGO stockpiles. As the two case studies presented in this paper are quite similar in nature, a simplified overview will be provided for this case study, with more focus being placed on the second case study.

5.1.1 Optimization Component - Lihir

The optimization component is solved at the commencement of the simulation run, with the objective to maximize the throughput of the autoclaves across the year, given the available stocks expected for each individual short-term time period. The model assumes the optimal plan is carried out exactly in each period, so that at any time all stock levels are known exactly, and can be updated with new material made available in the mine plan to give an expanded set of available stocks for the next period. The resultant plan (list of material movements) provides an optimal sulphur level to the autoclaves in each time period.

5.1.2 Simulation Component - Lihir

Each time period will have a required list of stocks to be crushed and transported down to the mills, producing a given level of sulphur to the autoclaves. The simulation will attempt to carry this out subject to all of the variability that occurs in real life (equipment reliability, fluctuation in ore grade, weather impacts etc.).

A large part of a simulation model involves mundane tasks such as moving ore from A to B, ensuring bins mix material, etc. These processes work the same way in every model and can be simplified using templates. The interesting part of each model is the operating logic. The two main areas of operating logic within the Lihir simulation model were:

- keeping the coarse ore stockpiles (COS) full, and;
- keeping the autoclaves running at an appropriate sulphur concentration.

These two sections of the model were referred to as the two ‘brains’. They handled the decisions from a high level, analogous to a control room operator who has a high-level view of the operation and is able to make decisions based on many pieces of information.

5.1.3 Stockpile Brain

The stockpile brain controlled the level of the COS by changing which material was being mined and batched via the crushing and conveying circuit. Of primary interest was the relative level of HGO to FGO in the COS. The stockpile brain was simplistic in nature. A number of breakpoints were placed on the levels of each stockpile, allowing them to be defined in terms of zones (full, half full, empty for example). If one stockpile was in a lower zone than the other, it would attempt to send all trucks to haul that material and then campaign it down the crushing and conveying circuit to the COS. A minimum campaign length was enforced to ensure the model did not constantly switch between HGO and FGO.

5.1.4 Concentration Brain

The concentration brain controlled the concentration of sulphur in the pre-oxidation tanks that feed the autoclaves. It did this by varying the rate of the HGO Mills and the amount of FGO concentrate added. The transfer system on the concentration tank only allowed one transfer rate, effectively on or off, so the concentration of sulphur in the pre-oxidation tanks ‘bounced’ between acceptable ranges.

5.1.5 Results

The primary objective of determining whether the conveyor system could supply both mills was met, even under worst case scenarios. However there were two further important findings.

First, a key assumption of the optimization model is that all available stocks in a period are blended to produce a single average grade to feed to the autoclaves. In reality, the actual grade of sulphur varies considerably over time, depending on the method of choosing blocks to feed to the COS. Figure 3 shows the variation in actual % sulphur level compared to expected level over time in the simulation model. The instantaneous fluctuations of sulphur level can have serious impacts on the operation of the plant, and hence throughput. This highlights the benefit of simulation in understanding the impact of real life variability.

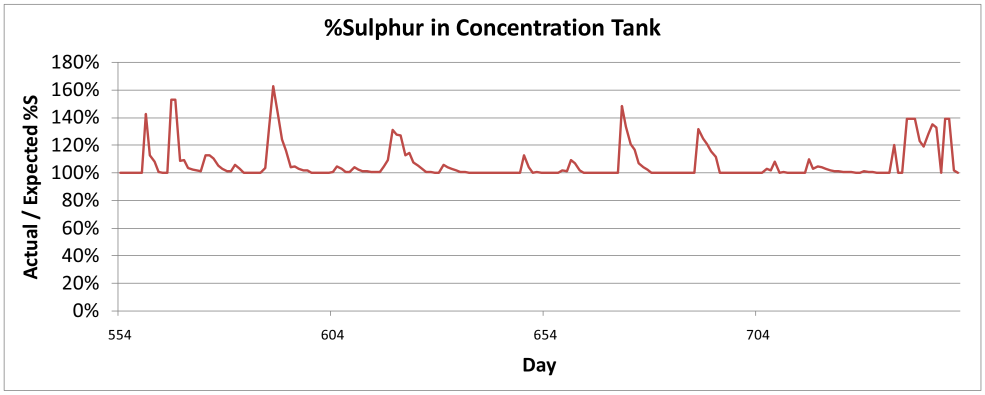

Figure 3: % Sulphur in concentration tank

Secondly, the optimization model assumes the plan for each period will be carried out precisely, leaving a known quantity of stocks for the subsequent time period. In reality, equipment reliability along with grade uncertainty means that as time goes on, the actual stocks available to feed into the autoclaves will drift further and further away from the original plan. As a result the optimal sulphur level that the optimization model has planned for is no longer optimal given the current stocks available. This is illustrated in Figure 4. The mixture of HGO to FGO is modified by the concentration brain to maintain the 'optimal' sulphur level as determined by the optimization model. As time goes on, the actual sulphur concentration in the blocks that make up the HGO and FGO stocks varies increasingly, so that the actual ratios of HGO to FGO required to maintain a given sulphur concentration drift further and further away from the plan.

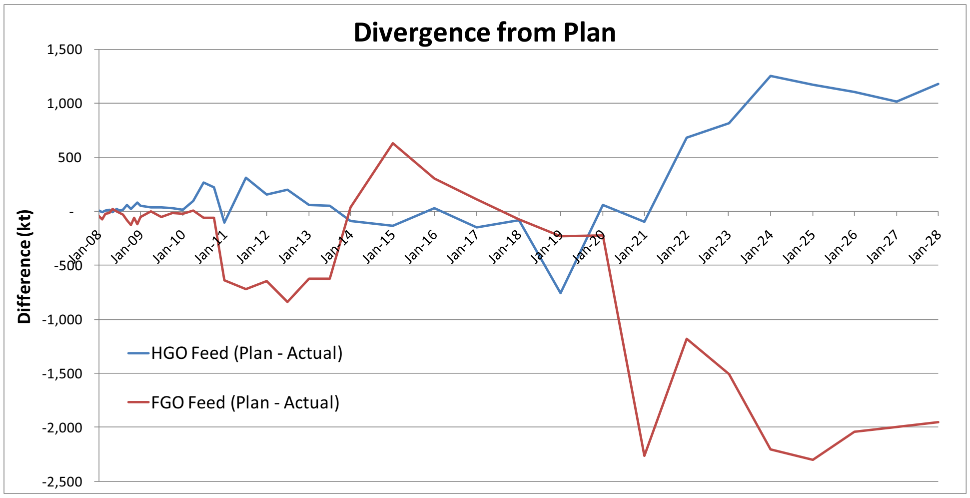

Figure 4: Divergence from plan

In order to provide more realistic results with the simulation in later years, simplifying assumptions had to be imposed to ensure stockpiles more closely mirrored what was in the original plan.

5.2 Integrated Optimization and Simulation - KPC

PT Kaltim Prima Coal (KPC) operates a coal mine near Sangatta in East Kalimantan, Indonesia. Coal is mined at various grades and blended through a series of intermediate stockpiles that are linked by a 13km overland conveyor (OLC) before being loaded as multiple products on to vessels. To determine the potential consequences of increased production and alternative production scenarios, KPC required an understanding of the interaction between throughput and quality, and how these are impacted by any changes in infrastructure and / or operating policy.

As a starting point, a DES model of the KPC export supply chain was constructed. Initial evaluation found that the modeling results did not reconcile closely enough with the actual performance of the operation. Further investigation found that the planning activity that is regularly performed on site to assign ore movements from the pit to meet product demand at the port was not able to be captured with sufficient accuracy within the DES framework. As a result, an optimization model of the planning process was developed to be incorporated within the DES model of the entire supply chain. The nature of planning the KPC operation to achieve the contracted coal qualities involves multiple objectives including throughput, blending and on time delivery on to ships. As a result, the optimization model that was constructed needed to incorporate these multiple objectives, as well as have the ability to interact with the DES model. The integration of the optimization component within the DES model allowed KPC to link the effects of real life uncertainties to the strategic plans being developed.

The addition and integration of the optimization component within the DES model was a complex task. In isolation, the three key elements of this model (quantity model, quality model and planning) are well established; however the incremental addition of each of these elements into an integrated DES and optimization framework greatly increases the model complexity.

5.2.1 Simulation Component - KPC

The KPC Coal Chain integrated DES model is a large, complex model that incorporates many features to enable it to accurately replicate the real operation. The inputs for this model include:

- Key plant and equipment capability and capacity;
- Equipment configuration;
- Equipment reliability (planned and unplanned downtime);
- Mine plan;
- Shipping plan (forecast).

Equipment capacity and reliability is determined through analysis of the historical performance of the existing operation. Equipment configuration is based on the current operation and may be manipulated to simulate different operating conditions or capital expansions. Mine and shipping plans are supplied by KPC in the form of mine log files and the current shipping program spreadsheet. Scenarios are arranged by manipulating these key input parameters to test the system under different conditions.

5.2.2 Optimization Component - KPC

The primary objective of the optimization is to determine a sequence of tasks to deliver the required coal to the waiting vessels in the short-to-medium term. The key difference between this optimization formulation and that developed for Case Study 1 (Lihir) is that rather than producing an optimal blend of inputs for a chemical process, this optimization model produces an optimal blend for each ship. The model is formulated in Lingo using a combination of well-known modeling techniques (Schrage 2000 and

Wolsey 1998). The DES model then follows the list of tasks produced until such time that the tasks are completed or replanning is required.

Planning horizon. The planning horizon used in the optimization model is able to be varied. Following a testing phase it was established that a planning horizon of 21 shifts (7 days), with plans updated every 9 shifts (3 days), provided realistic results and did not require excessive solution times. In addition, this approach ensured that the DES model was unlikely to become significantly out of synchronization with the plan.

Objective function. The following is a list of objectives included in the optimization model. The importance of each of these objectives is controlled by weighting multipliers in the solver.

- Maximize throughput. Primarily this is to maximize the tonnage down the OLC however it is extended to also maximize tonnes mined and tonnes shipped.
- Minimize the deviation of the quality of all mine and port stockpiles from their assigned lower and upper bounds. Quality deviation is calculated by creating a variable to record the difference between the desired and actual quality, and then including this variable in the objective function with a negative value to penalize the deviation.
- Minimize the deviation of each vessel's target quality (product demand).
- Load each vessel as quickly as possible.

Constraints. The following is a list of the constraints that the optimization model must respect each time it is called on to construct a plan.

- *Pits*
  - Only mine blocks that are available at each pit.
  - Blocks must be mined in a sequence that respects safety constraints in the pits.
  - Do not exceed shovel capacity in any pit and across all pits in any shift.
  - Do not mine more than the tonnage of any given block.
- *Mine stockpiles*
  - Do not exceed transfer rates.
  - Physical configuration constraints regarding which pits are able to feed to each mine stockpile.
  - Do not exceed the capacity of each mine stockpile.
  - Do not exceed the maximum reclaim rate from each mine stockpile.
  - Attempt to maintain the quality of each mine stockpile within its nominated quality range at all times.
- *Overland conveyor*
  - Do not exceed the maximum conveying rate.
- *Port Stockpiles*
  - Do not exceed the capacity of each port stockpile.
  - Attempt to maintain the quality of each port stockpile within its nominated quality range at all times.
  - Do not exceed total port capacity.
- *Vessels*
  - Load vessels to their stated tonnage.
  - Do not load vessels prior to their arrival time.

- o Do not exceed the rated capacity of the ship loader.
- o Attempt to load each vessel with its nominated quality of each required product.

5.2.3 Results

Scenario Analysis. The integrated DES model has been used to evaluate the consequences of strategic long-term decisions, short-term planning decisions and operational decision-making when creating and evaluating weekly plans. In any application, DES modeling is a complex process that has the ability to generate a significant quantity of output results. The interpretation of these results requires an in-depth knowledge of the model and its outputs. To best describe the performance of the operation under varying operating scenarios, a reduced number of Key Performance Indicators (KPIs) have been identified that enable a simplified and manageable understanding of the model outputs.

System performance is a combination of the KPIs that describe the ability of the system to load coal on to ships in the correct quantity and quality within reasonable time frames. Hence system performance cannot be described alone by any one performance indicator but rather is a combination of KPIs. Furthermore, testing the system at a single throughput is not sufficient to enable the successful identification of system bottlenecks and inefficiencies. Rather, to establish system performance sensitivity, the model is run with a range of throughput levels, that is, using mine and shipping plans with differing levels of demand for, and supply of, coal. This establishes a response curve for the system, which describes the system performance as the demands on it are increased.

To enable a complete understanding of the system performance the combination of the following two KPIs is the focus of the integrated DES model of the KPC operation:

- *Quantity:* tonnes moved from mine to ship and the utilisation of the intermediate stockpiles.
- *Quality:* the match between the customers' contracted shipments and the coal that is actually loaded on to their vessels. Quality is measured by the gross calorific value (GCV) of the coal.

Quantity: DES modeling allows the user to quantify the amount of extra production from a proposed capital expansion, as well as providing valuable insights into the auxiliary effects from any actions. This is particularly valuable in systems that contain many interacting components, such as the KPC operation. Testing the sensitivity of the system performance to varying equipment rates allows the potential benefit of changing the operating philosophies used in this area of the supply chain to be determined, and also provides a means of evaluating whether each piece of equipment is or could potentially be a restriction or bottleneck on the overall system.

Quality: In the KPC operation, the quality of coal is measured by gross calorific value (GCV). The integrated DES model incorporates the tracking of coal quality through the system and hence has the ability to measure the quality of coal loaded on to ships. To quantify the effectiveness of the operation under various scenarios, it is necessary to compare the contracted consignment quality of coal with the loaded quality.

Example: The following is an example of the analysis that is able to be undertaken using the integrated DES model of the KPC Coal Chain. This example examines the effect of a potential capital investment to upgrade the ship loader to enable it to operate at an increased rate, both in isolation and in conjunction with the option of making an additional investment to upgrade the OLC to enable it to also operate at a higher rate.

Figure 5 examines the impact of the proposed capital upgrades on the quantity achieved by the operation, measured by the KPI of tonnes shipped across a year. The Base Case line shows the current operation has little excess capacity to cope with any increase in demand. Upgrading the OLC or the ship loader in isolation enables some gains to be achieved in throughput, while spending the additional capital to upgrade both items clearly has the greatest impact for the potential throughput of the operation when shipping demand is increased by 5%. The tailing off in improvement in all scenarios when shipping demand is increased by 10% indicates that the requirement to meet the contracted quality on each vessel has mitigated the benefit of the increased production rate at this level of demand, since vessels demand tonnes of a nominated quality rather than simply tonnes. This may indicate a mismatch between the quality provided by the mine plan and the quality demanded by the shipping plan, or that the bottleneck constraining the operation has shifted, possibly to mining rate or stockpile size. With this knowledge, the integrated DES model can be used to investigate a new set of scenarios that consider alternate capital upgrades and input plans in these areas of the operation. Price and cost estimates are applied to determine which of the potential capital upgrades are financially viable and provide the greatest return on investment.

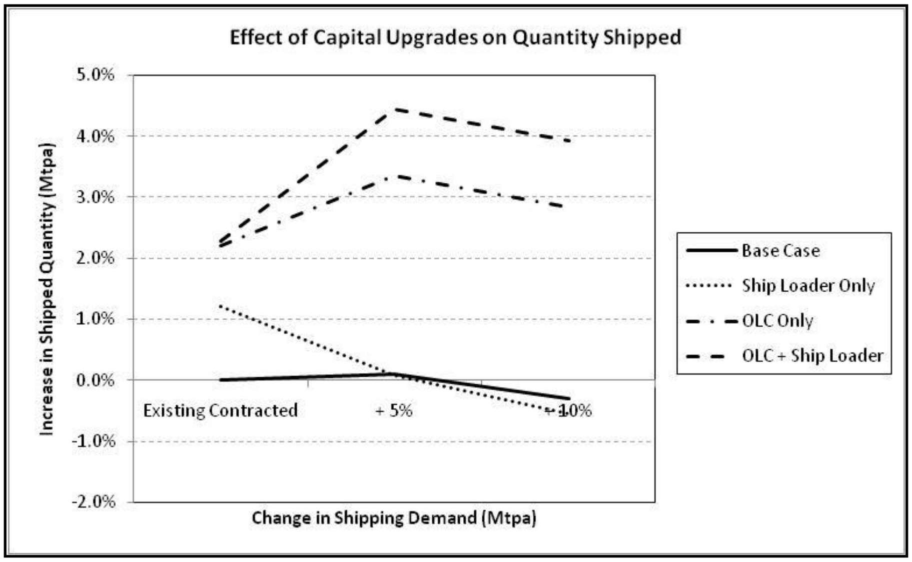

Figure 5: Effect of capital upgrades on quantity shipped

To assess the impact of the proposed capital upgrades on coal quality, a chart such as that presented in **Figure 6** is produced for each combination of demand and equipment configuration. This chart compares the contracted consignment quality of coal with the actual loaded quality. Each point on the chart represents a loaded vessel. The y-axis measures the difference between the contracted and actual quality of coal loaded by each vessel. Therefore a positive y-value indicates that the model has exceeded the contracted coal quality for that particular vessel. The increase in the magnitude of coal quality error towards the end of the year indicates a mismatch between the mine plan and the marketing (shipping) plan developed for the year. At the end of the year, there is a potential for a majority of the existing stocks as defined in the mine plan to become depleted, which flows through to the quality of each intermediate stockpile in the system, making it harder to produce the required blend for each vessel. Since there is more than one final product, each with a unique blending recipe, and many intermediate stockpiles, the depletion of raw product stocks means that the quality of certain final products may be above the contracted level at the same time as the quality of other final products is below their contracted level.

A KPI measuring the percentage of vessels loaded to within a defined percentage of their contracted coal quality is used to assess the performance of the operation with regards to coal quality. The benefits of capital upgrades such as increased stockpile capacities can be demonstrated in a chart such as **Figure 6** by a reduction in the events across the year where coal quality error exceeds a predetermined level, for example +/- 10%.

By integrating the optimization within the simulation, more than 95% of the ships' quality targets have been met. Without the benefit of continually updated information, these targets are extremely difficult to hit.

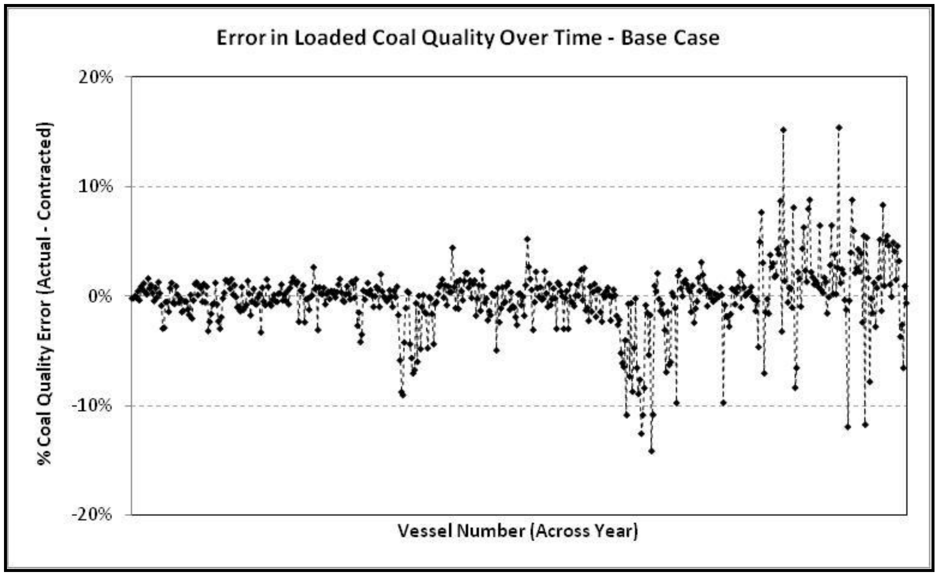

Figure 6: Error in loaded coal quality over time

6 CONCLUSIONS

The application of a properly developed DES model provides a range of significant benefits in assessing an integrated export supply chain. These benefits include the ability to examine the trade-offs between different options for capital expenditure, as well as to assess alternative operating practices, including maintenance options, through quantification of potential performance.

In the case of mining operations that have multiple, conflicting objectives, such as delivering a certain quality of product while also attempting to maximize production capacity, it is possible to decouple the decision making process of planning the movement and blending of ore through the mining supply chain from the DES model, develop a stand-alone optimization model for it, and then integrate the two to create a holistic model of the supply chain.

Integrating optimization within a simulation allows a more accurate representation of the system, providing a more optimal solution. The tradeoff of this is that run times can become problematic, potentially requiring simplifying assumptions to the optimization.

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