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Oyu Tolgoi underground: mine production modelling of a coupled material handling system

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Abstract

The Oyu Tolgoi underground mine has a coupled material handling system that is comprised of multiple fixed plant machinery and heavy mobile equipment that aims to minimise delays using an integrated asset management calendar. Realising throughput across the coupled value chain to ensure that forecasting accurately reflects operations offers its challenges to the mine planning process.

Throughput forecasting focuses on 2 primary crushers located approximately 1,300 m below the Gobi Desert, which feed either a conveyor system or a shaft hoist to surface. Ore is sourced from multiple production panels, with Panel 0 currently in steady-state production and Panel 2 North in ramp-up, while additional panels are under development. Each panel comprises hundreds of drawpoints that are mucked by loaders into orepasses. Material flows through truck chutes where road trains are loaded. The trucks then haul the ore to one of the 2 primary crushers.

The material handling system is tightly coupled, comprising a combination of parallel and series components whose individual capacities collectively govern overall system performance. Each link in the chain is subject to specific capacity constraints that directly influence system throughput. The cave systems themselves impose additional operating rules and objectives, including panel-specific draw control and cave draw strategies.

As production ramps up through the ongoing construction and commissioning of additional drawpoints, the actual throughput performance of each system component is statistically evaluated to inform planning and forecasting input parameters. This paper outlines the structured process used to identify and map system connections and constraints, integrate maintenance calendars, apply time usage models for each sub system, and develop schedules that are compliant with the governing cave rules and draw strategies for each panel.

Keywords: *material handling system, constraints, time usage model, cave production planning, asset management calendar*

1 Introduction

The Oyu Tolgoi (OT) underground mine operates a highly integrated and tightly coupled material handling system (MHS), comprising of both fixed plant infrastructure and heavy mobile equipment, coordinated through an asset management calendar. Accurately forecasting throughput across this interconnected value chain is complex, as overall system performance depends on the combined behaviour of multiple subsystems operating in both series and parallel, each with distinct capacity constraints and operational dependencies.

At the core of the system are 2 primary crushers, located approximately 1,300 m below the Gobi Desert, which crush ore delivered from multiple production panels and feed it to the surface via either a conveyor network or a shaft hoisting system. Production is currently driven by Panel 0 (P0), which is in steady-state

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operation, while Panel 2 North (P2N) continues to ramp up, and preparing Panel 2 South (P2S) and Panel 1 (P1) for future production. Within each panel, hundreds of drawpoints are mucked by loaders into orepasses, with material transferred through truck chutes to road trains that haul ore to the crushers.

The cave mining environment introduces further complexity through panel-specific draw control requirements and cave draw strategies, which impose operational constraints on extraction and material flow. As production expands through ongoing development and commissioning of new drawpoints, the performance of each subsystem must be continuously evaluated and calibrated to reflect actual operating conditions.

To address these challenges, this paper presents a robust mine production modelling framework for the OT underground MHS. The approach integrates a unified capacity model across the loader–orepass–truck–crusher–hoist/conveyor chain, supported by statistical calibration of subsystem performance using historical data. Key elements include the application of time usage models (TUM), the incorporation of unscheduled loss factors, downtime modelling, and probability rate analysis to quantify realistic system performance (e.g. P50 throughput).

A structured process is used to map system connections and constraints, integrate maintenance schedules from the asset management calendar, and develop production schedules that comply with governing cave rules and draw strategies. Importantly, the framework incorporates a feedback loop that continuously reconciles planned and actual performance, enabling progressive refinement of forecasting accuracy.

By capturing the interactions between mining, material handling, and maintenance systems, this methodology supports improved prediction of production potential, clearer identification of system bottlenecks, and the development of effective mitigation strategies for unplanned downtime. Ultimately, it provides a foundation for more reliable throughput forecasting and informed operational decision-making in a complex, evolving underground mining environment.

2 Mine layout and material handling system

OT Underground Hugo North Lift-1 (HNL1) extraction level is approximately 1,300 m below the surface, the footprint is approximately 1,800 m long and 300 m wide, and is split into 4 sub panels; P0, P1, P2N, and P2S. Each panel has an apex, undercut and extraction level.

At the time of writing, Panel 0 cave construction had been completed. 124 drawbells had been blasted by the end of 2024. Currently cave production from P0 is steadily producing nameplate daily targets. Panel 2N is in the drawbell establishment stage and cave production is in the early stages of ramp-up, with critical hydraulic radius modelled to be achieved within months.

From the extraction level, the drawpoints are mucked by loaders which then dump ore onto a tipple which is connected to the Haulage level via an approximately 35 m long orepass. At the bottom of each orepass is a truck chute that feeds 160 t capacity road trains. In total there are 11 truck chutes commissioned and 27 more to be commissioned as the panels come online.

The road trains haul ore to one of the 2 gyratory crushers. Each crusher has double sided tipping points and a bypass loop to enable higher efficiency of road trains. The crushers can feed material to a shaft hoist or to a conveyor to the surface. The primary material movement is to the conveyor, which is a 7.4 km long conveyor belt consisting of 5 transfer stations. In Figure 1, the underground MHS has been mapped for reference.

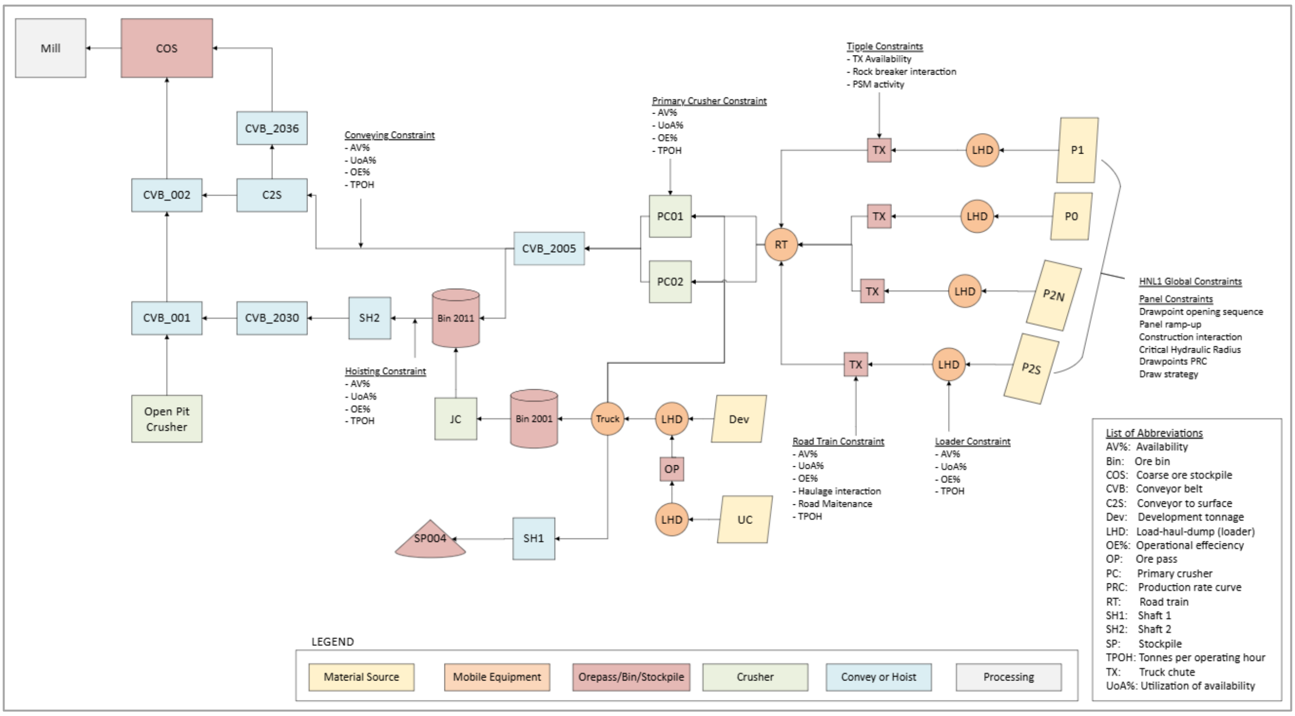

Figure 1 Underground system mapping of the material handling system

3 Approach to capacity modelling of a coupled material handling system

Most surface mining systems have large inventories or buffers to decouple the processing and MHSs (de Hennin 2024). This is not the case for the OT mine and most underground (UG) mines, as can be seen in Section 2. The context for the capacity modelling is outlined below:

- The MHS has limited or no buffers and is 'coupled' (de Hennin 2023).
    - A crusher going down will affect the road trains and the conveyor to surface (C2S) or shaft within a few minutes and the whole mine soon after.
- The system is ramping up and changing in multiple ways, so past performance needs to be projected for changes in the system.

There is no single TUM measure that represents the entire mine system; therefore, overall system capacity must be determined by combining TUM measurements from the relevant subsystems and nodes. Failure to account for the interaction between these components will result in an overestimation of achievable capacity. Where the system contains redundant equipment or pathways, such as Primary Crushers 1 and 2 (PC1 and PC2) or SH2 and C2S, the analysis should consider the proportion of time spent operating in each mode, as each mode has a different throughput capacity.

To avoid unnecessary complexity, the model should focus only on elements that are critical to the analysis and can be assessed with confidence. As a starting point, existing inventory buffers should be ignored, which provides a conservative estimate of capacity, and mode switching should not be assumed unless it is an established operational practice (for example, SH2 should not be considered a replacement for C2S during downtime unless this routinely occurs in practice).

In addition, as the mine continues to ramp up, there will be interface constraints and operational interactions that are not yet fully understood, such as the relationship between loaders, truck chutes and road trains. Developing a practical, high-level representation of how these interfaces and their capacity evolve over time will therefore be important to accurately reflect the ramp-up profile of the operation.

The steps in the process are:

1. Map the system: draw the value chain and understand the flow of the system and of the operating modes. What new elements are coming in (ramping up or ramping down).
2. Gather the data needed: shut schedules, maintenance plans, TUM and performance data for all of the subsystems. Understand the interactions between all of the system elements.
3. Project forward for change: understand what is changing over time (new loaders, truck chutes, crushers etc) and how it will impact the capacity of each of the subsystems.
4. Determine the operating modes of the mine (off, partially running, fully on): identify all of the fixed time losses and hence identify all of the modes of the mine. Factors that happen in a planned manner and/or at a consistent time of the day. An understanding of time that is spent attempting to run in each 'mode' of the mine is an output of this step.
5. Coupled performance of the system where it is attempting to run: assess all of the unplanned factors for the mine. Calculate the coupled performance of the mine and use reliability theory (Institute of Electrical and Electronics Engineer 2007) (Modarres 2016) in each of the modes (partial and full system running modes).
6. Review (sanity check and insights): highlight the most sensitive constraints according to the model and triple check those factors (rate and time), these are critical to the model accuracy.
7. Review/reconcile: sanity check against other plans, schedules – and ideally a simulation model – and invite peer review. Review the actual performance against the coupled system projections. If the mine is already running, A head start can be made by looking back over time and checking that the capacity is accurately predicted.

This paper will focus on describing the approach used from steps 1 and 4 to 6, to share the approach but to avoid sharing company confidential information (de Hennin 2025).

4 Determine the operating modes of the mine

4.1 Description

Mining systems experience scheduled downtimes that are predictable, such as:

- shift changeovers
- blast clearance
- daily, weekly, monthly maintenance windows.

These planned downtimes are deterministic, unlike random failures. Planned downtimes reduce overall availability even if equipment reliability is perfect during operating periods.

4.2 Mathematical foundations

Mean time between failures (MTBF) and the mean time to repair (MTTR) are both typically expressed in units of hours at a mine, and are used to calculate the random availability percentage of a piece of equipment or fixed plant asset (Table 1). If a mine is under study or newly put into operation, empirical or benchmark data can be used. For mines in operation it is common to perform statistical analysis on historical performance data and calculate a probability of future P50 (50^{th} percentile or median) performance.

The random availability percentage formula is calculated by utilising the MTBF and the MTTR as defined in Table 1, and fixed availability (%) is calculated using total time and fixed downtime, both in hours. It's important to note that because the time at which random downtime will occur isn't known or planned, the overall system availability (%) is calculated by multiplying the random availability and the fixed availability per Table 1.

Table 1 System availability formulations by type

Metric	Description	Formula
Mean time between failures (MTBF)	Mean time between failures	Historical/benchmark/empirical data
Mean time to repair (MTTR)	Mean time to repair	Historical/benchmark/empirical data
Random availability	From random failures	$A_{random} = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}}$
Fixed availability	From scheduled downtimes	$A_{fixed} = \frac{T_{total} - T_{fixed}}{T_{total}}$
System availability	Overall system availability	$A_{system} = A_{random} \times A_{fixed}$

4.3 Worked example

Below is a worked example of the way random availability and fixed availability are multiplied together to calculate the total system availability.

Given:

- $MTBF = 100$ hours, $MTTR = 2$ hours
- $T_{total} = 12$ hours, $T_{fixed} = 1$ hour

then:

$$A_{random} = \frac{100}{102} \approx 0.9804 \tag{1}$$

$$A_{fixed} = \frac{11}{12} \approx 0.9167 \tag{2}$$

$$A_{system} = 0.9804 \times 0.9167 \approx 0.899 \tag{3}$$

4.4 Additional insights

For deep underground mines, such as OT where material is transported via a conveyor or hoist to surface it is crucial to take note of the following:

- Not multiplying fixed availability by random availability can overestimate system capacity.
- Scheduled downtimes are controllable, offering opportunities to optimise shift scheduling.
- Strategies such as staggered shift changes can reduce simultaneous system downtimes.
- Use the same approach to assess operating time different ‘modes’. An example for OT would be when the conveyor to surface is on shut, but the shaft is still available to operate (different capacity and reliability implications in modelling capacity).

5 Coupled system: availability of a single system or node

5.1 Description

A mining subsystem – such as a haul truck, conveyor, or crusher – operates under random failures caused by mechanical breakdowns, wear, or environmental conditions. These failures are often modelled as exponential distributions, representing a constant failure rate.

Understanding and quantifying this behaviour is crucial because:

- failure frequency determines how often the system stops
- repair time determines how quickly it can return to service.

5.2 Mathematical foundations

Availability represents the fraction of time the equipment is operational. For steady-state availability, it is often assumed the failure and repair times are exponentially distributed. Systems with low MTBF or high MTTR have low availability and thus lower capacity. Even a highly reliable system can have low availability if it takes too long to repair. Formulas are referenced in Table 2.

Table 2 Summary of availability of a single node in the system

Metric	Description	Formula
Failure rate	Failures per unit time	$\lambda = \frac{1}{\text{MTBF}}$
Reliability	Probability system survives to time t	$R(t) = e^{-\lambda t}$
Random availability	Fraction of time system is operational	$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}}$

6 Coupled system: adding two subsystems in series

6.1 Description

In mining operations, many subsystems are arranged in series (e.g. haul trucks feeding a crusher). The system fails if any one subsystem fails, highlighting the weakest link effect.

6.2 Mathematical foundations

The availability and reliability calculations of 2 subsystems in series are shown in Table 3.

Table 3 Availability and reliability of system in series

Metric	Subsystem A	Subsystem B	System in series
Availability	A_A	A_B	$A_{series} = A_A \times A_B$
Reliability	$R_A(t)$	$R_B(t)$	$R_{series}(t) = R_A(t) \times R_B(t)$

6.3 Risk of overestimation

Analysing only one subsystem's reliability or availability can lead to overly optimistic capacity estimates. For example, given:

$$A_A = 0.95 \text{ and } A_B = 0.90 \tag{4}$$

then:

$$A_{series} = 0.95 \times 0.90 = 0.855 \tag{5}$$

Failing to consider subsystem B would overstate capacity by nearly 10%.

6.4 Additional insights

A few additional key considerations when adding two subsystems in series are listed below.

- Critical path analysis can help identify which subsystem most constrains throughput.
- Upgrading the weakest subsystem often has the largest impact on overall system performance.
- Sensitivity analysis can quantify how small changes in subsystem reliability affect the entire chain.

7 Coupled system: adding two subsystems in parallel

7.1 Description

Some mining systems use redundant subsystems (e.g. a conveyor and a hoist). Here, the system operates as long as at least one subsystem is running.

7.2 Mathematical foundations

The availability and reliability calculations of 2 subsystems in parallel are shown in Table 4.

Table 4 Availability and reliability of system in parallel

Metric	Subsystem B	Subsystem C	System in parallel
Availability	A_B	A_C	$A_{parallel} = 1 - (1 - A_B)(1 - A_C)$
Reliability	$R_B(t)$	$R_C(t)$	$R_{parallel}(t) = 1 - (1 - R_B(t))(1 - R_C(t))$

7.3 Capacity limitation

Redundancy improves reliability in parallel systems but does not necessarily increase throughput if only one path can carry the load. For example; 2 conveyors each with 1,000 tonnes per hour capacity, if only one runs at a time, system throughput is capped at 1,000 tonnes per hour.

7.4 Additional insights

A couple of additional considerations of adding two subsystems in parallel are listed below.

- Load-sharing strategies can allow both subsystems to operate simultaneously.
- Maintenance strategies can prioritise redundancy during critical periods.

8 Coupled system: generalising series and parallel systems

8.1 Description

Most mining systems combine series and parallel subsystems.

8.2 Mathematical foundations

The availability and reliability calculations of a series and parallel subsystem being combined into a system availability or reliability are shown in Table 5.

Table 5 Series and parallel subsystems combined

Metric	Subsystem A	Subsystems B and C (parallel)	Overall system
Availability	A_A	$A_{B\|\|C}$	$A_{system} = A_A \times A_{B\|\|C}$
Reliability	$R_A(t)$	$R_{B\|\|C}(t)$	$R_{system}(t) = R_A(t) \times R_{B\|\|C}(t)$

- Step 1: parallel block

$$A_{B||C} = 1 - (1 - A_B)(1 - A_C) \tag{6}$$

- Step 2: combine in series

$$A_{system} = A_A \times A_{B||C} \tag{7}$$

8.3 Additional insights

A couple of key additional learnings from combining series and parallel systems together.

- Simulation tools (e.g. Monte Carlo) can help model more complex configurations.
- System bottlenecks often reside in series segments; improvements there yield the highest gains.

9 Coupled system: examples

To demonstrate the principles, a simple set of examples where constructed. Three processes, labelled A, B and C are modelled for their availability as well as demonstrating how they can be added in series, parallel, or both, as can be seen in Figure 2 below. The ‘Calc Avail’ references the results of the maths performed, and the ‘Sim Avail’ references the results of a Monte Carlo simulation.

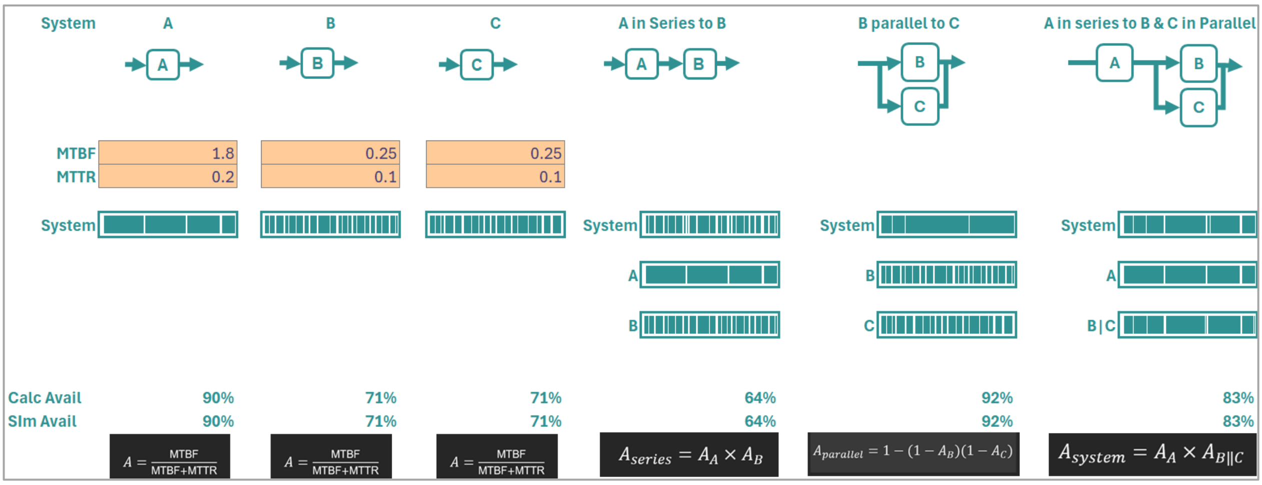

Figure 2 Simulation of 3 simple processes, and a demonstration of how they can be added in series and parallel. Results are compared to a Monte Carlo simulation of the processes

The example shown in Figure 3 shows how adding coupled systems in series, produces a total system with much lower availability. This effect is the core purpose for inventories or buffers to be installed in production systems and is often misunderstood in production analysis (de Hennin 2023). To improve this result, work is needed on the reliability of either of these systems, with higher leverage of system B, or a second system could be added in parallel to system B (system C) (Modarres 2016).

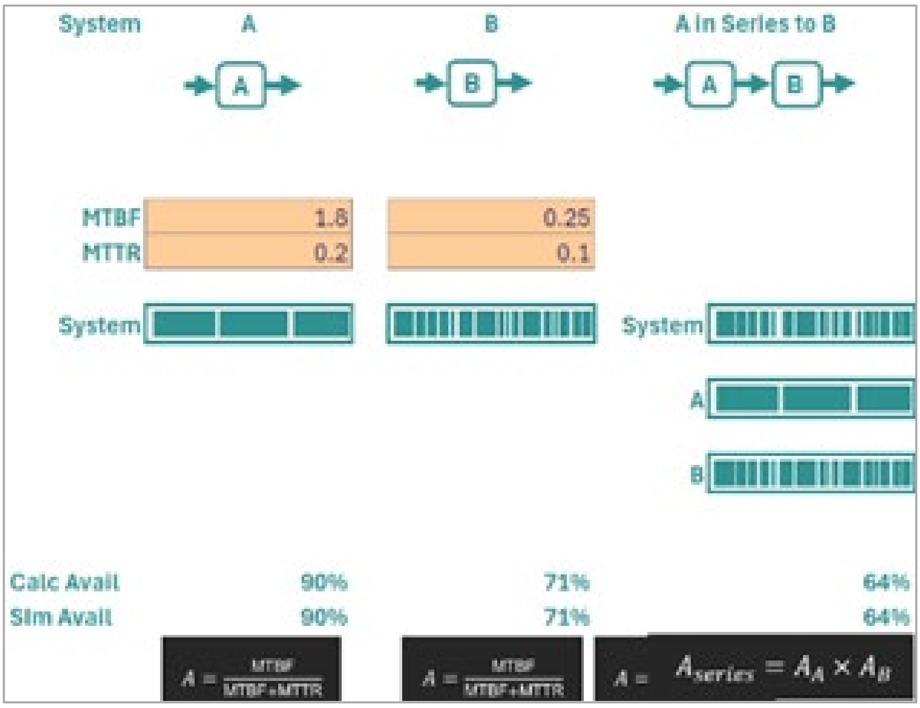

Figure 3 Simulation of two systems in series. Results are compared to a Monte Carlo simulation

In Figure 4, System B or C alone has a reliability of 71%. Putting both systems in parallel, the reliability is now 92%, which is a huge increase in the availability of the overall system. This redundancy can massively improve the operation of a mine and the continual flow of material through the system.

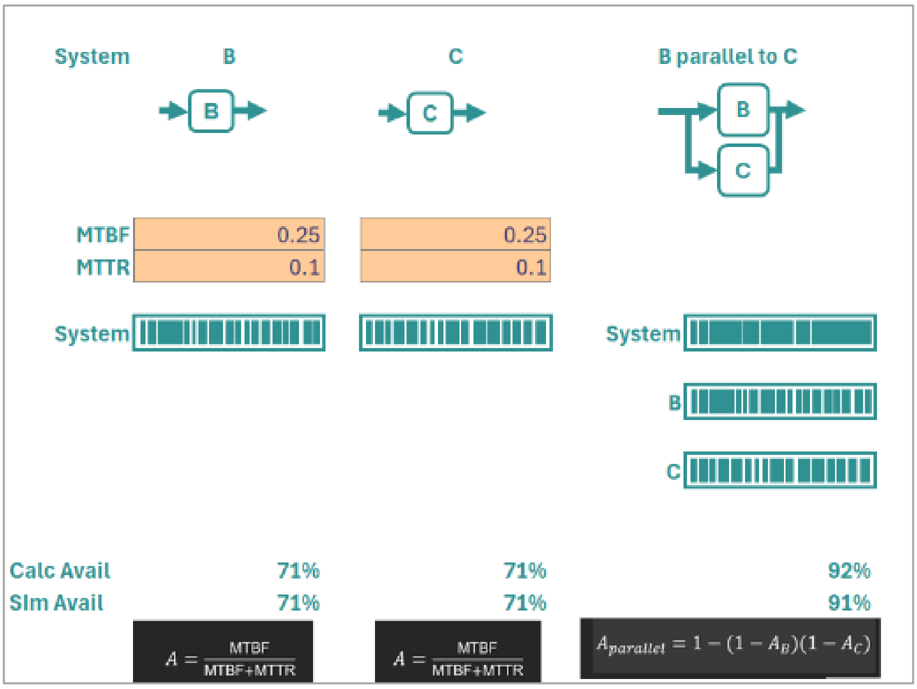

Figure 4 Simulation of two systems in parallel. Results are compared to a Monte Carlo simulation

By combining both approaches (Figure 5), full system can be modelled (A, B and C) and the overall rate and reliability of the total system can be seen – the full capacity of the system in each of the modes can be assessed. This parallel processing can also be used to create the rate needed to run the full system (if systems B and C are only half the capacity of A). In this case, there are 3 operating modes:

1. system off
2. A running, both B and C running, and (full rate)
3. A running, and one of B or C running (half the rate).

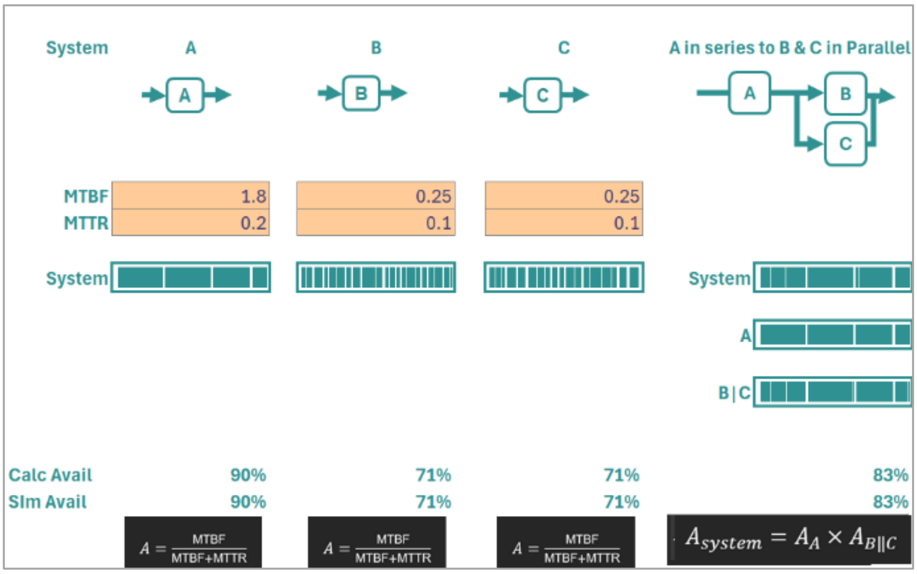

Figure 5 Simulation of a series and parallel system combined, compared to a Monte Carlo simulation

Notice that the reliability of the overall system is still lower than A alone, but it is higher than A and B combined. By example, this is the type of analysis that was performed on the overall OT MHS to improve the accuracy in reconciliation and prediction in capacity planning of the system.

10 Conclusions

As typical of deep underground mines, Oyu Tolgoi Underground mine operates a coupled MHS, where production potential is defined not by individual asset performance but by the collective behaviour of interconnected loaders, truck chutes, road trains, crushers, hoists, and conveyors. In such an environment, traditional modelling approaches that treat subsystems independently or rely on historical averages, risk significantly overestimating system capability and masking critical bottlenecks.

This paper presented a structured, data driven framework to overcome these challenges by unifying capacity modelling, subsystem availability analysis, scheduled downtime modelling, and cave draw rules into a single coherent methodology. By mapping the full value chain, quantifying both fixed and random availability losses, distinguishing operating modes, and applying series versus parallel reliability principles, the approach provided a transparent and mathematically grounded means of forecasting production under realistic operating conditions.

The examples demonstrate how even highly reliable components can drive down total system availability when arranged in series, and how targeted redundancy can dramatically improve performance. These insights reinforce the necessity of understanding the true interaction of subsystems within a coupled material handling chain rather than focusing on isolated key performance indicator (KPI) improvements. Integrating forward-looking ramp-up assumptions allows the model to adapt as new loaders, chutes, or road trains enter service, providing a dynamic tool suitable for OT's rapidly evolving production environment.

Ultimately, the strength of this approach lies not only in more accurate P50 throughput forecasts, but in its ability to guide operational planning and strategic decision-making. By identifying high leverage constraints, quantifying the value of maintenance and redundancy, and establishing a feedback loop between plan and actuals, the framework supports continuous improvement of mine performance. As the OT cave continues to mature and new panels come online, such a coupled system capacity model becomes essential to achieving predictable, reliable, and optimised material flow from drawpoint to surface.

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