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HYBRID MODELLING OF DISCRETE-CONTINUOUS INTERFACES IN MINING SYSTEMS

Modelagem híbrida de interfaces discretas-contínuas em sistemas de mineração

Modelado híbrido de interfaces discretas y continuas en sistemas de minera

Lúcio Fábio Dias Passos [1], **Thalles Vinicius Frade Mota** [2], **Samuel Vieira Conceição** [3], **Noel Torres Júnior** [4], & **João Flávio de Freitas Almeida** [5*]

[1 2 3 4 5] **Universidade Federal de Minas Gerais**

[1] lucio.passos@gmail.com [2] thallesvfmota@gmail.com [3] samuel.svieira@gmail.com [4] noelface@gmail.com [5*] joao.flavio@dep.ufmg.br

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*** Corresponding Author**: **Almeida, J. F. de F.**

ABSTRACT

Mining supply chains often involve interfaces between discrete and continuous processes, such as the interaction between mine truck traffic and crushing systems, where operational variability can propagate through production stages and affect system performance. However, most studies analyze these subsystems separately, with little attention to the integrated dynamics between discrete and continuous processes, present at various points along the production chain. This study investigates the propagation of variability at the mine-plant interface of an iron ore mining and processing plant, using a hybrid modeling framework that combines discrete event simulation (DES) and analytical queuing models. The DES component represents the stochastic dynamics of mine operations, while an analytical G/G/1/b model evaluates the behavior of the downstream crushing system. The models are calibrated using 13 months of operational data and applied to evaluate alternative operational plans, including fleet expansion, safety stock implementation, and micro-downtime reduction. The study demonstrates that a hybrid modeling approach provides an effective and scalable solution for analyzing the propagation of variability in complex mining systems with discrete-continuous interfaces.

RESUMO

As cadeias de suprimentos da mineração frequentemente envolvem interfaces entre processos discretos e contínuos, como a interação entre o fluxo de caminhões da mina e sistemas de britagem, onde a variabilidade operacional pode se propagar pelas etapas de produção e afetar o desempenho do sistema. No entanto, a maioria dos estudos analisa estes subsistemas separadamente, com pouca atenção à dinâmica integrada entre processos discretos e contínuos, presente em diversos pontos ao longo da cadeia produtiva. Este estudo investiga a propagação da variabilidade na interface mina-usina de uma planta de extração e beneficiamento de minério de ferro, utilizando uma estrutura de modelagem híbrida que combina simulação de eventos discretos (DES) e modelos analíticos de filas. O componente DES representa a dinâmica estocástica das operações de mina, enquanto um modelo analítico G/G/1/b avalia o comportamento do sistema de britagem a jusante. Os modelos são calibrados utilizando 13 meses de dados operacionais e aplicados para avaliar cenários operacionais alternativos, incluindo expansão da frota, implementação de estoque de segurança e redução de micro paradas. O estudo demonstra que a modelagem híbrida fornece uma abordagem eficaz e escalável para analisar a propagação da variabilidade em sistemas de mineração complexos com interfaces discreto-contínuo.

RESUMEN

Las cadenas de suministro mineras suelen implicar interfaces entre procesos discretos y continuos, como la interacción entre el tráfico de camiones mineros y los sistemas de trituración, donde la variabilidad operativa puede propagarse a través de las etapas de producción y afectar el rendimiento del sistema. Sin embargo, la mayoría de los estudios analizan estos subsistemas por separado, prestando poca atención a la dinámica integrada entre los procesos discretos y continuos, presente en diversos puntos de la cadena de producción. Este estudio investiga la propagación de la variabilidad en la interfaz mina-planta de una planta de extracción y procesamiento de mineral de hierro, utilizando un marco de modelado híbrido que combina la simulación de eventos discretos (DES) y modelos analíticos de colas. El componente representa la dinámica estocástica de las operaciones mineras, mientras que un modelo analítico G/G/1/b evalúa el comportamiento del sistema de trituración posterior. Los modelos se calibran utilizando 13 meses de datos operativos y se aplican para evaluar planes operativos alternativos, incluyendo la expansión de la flota, la implementación de existencias de seguridad y la reducción de micro tiempos de inactividad. El estudio demuestra que un enfoque de modelado híbrido proporciona una solución eficaz y escalable para analizar la propagación de la variabilidad en sistemas mineros complejos con interfaces discretas-continuas.

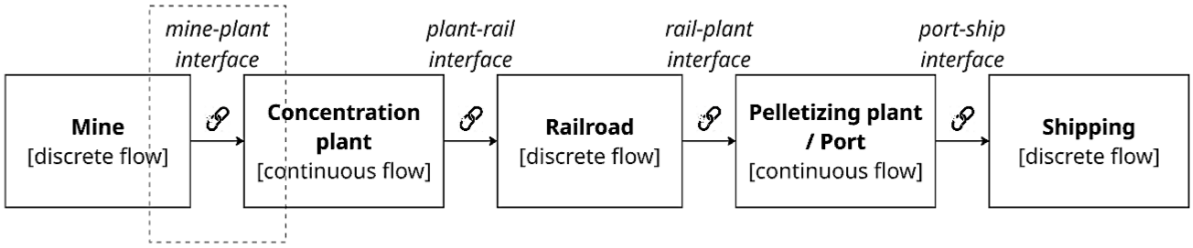
INTRODUCTION

Multi-stage production chains are inherently sensitive to the propagation of variability, since disturbances can be amplified as material flows through interconnected processes. For example, a temporary interruption at one stage can reduce the supply of material to downstream processes, resulting in idle resources, and cause queuing upstream, with additional variability throughout the system (Buzacott & Shanthikumar, 1993; Hopp & Spearman, 2011).

Modeling how this variability propagates is a complex task. The difficulty lies in capturing the stochastic interactions between sequential processes, as well as the nonlinear effects introduced by constraints such as limited buffer capacities and varying levels of resource utilization (Gershwin, 1994). These challenges become even greater in production systems where material flows alternate between discrete and continuous processes across successive stages. Indeed, the operational behavior differs significantly across stages. Discrete systems are typically characterized by random arrivals, routing decisions, and queue dynamics, whereas continuous processes are governed by flow rates and processing capacities. When these two regimes interact, additional sources of variability emerge, making it considerably more difficult to model system performance, particularly in large-scale production chains.

A typical mining supply chain, Figure 1, is a clear example of such systems, with several interconnected subprocesses in which material flows alternate between continuous operations (processing plants), and discrete operations (mining, rail transport, and shipping) in four interfaces: mine–plant, plant–rail, rail–port, and port–ship.

Figure 1. Mining overall process with interfaces between continuous and discrete flows



Source: Authors (2026).

Queueing-based approaches have long been used to analyze stochastic behavior in multi-stage manufacturing systems (Papadopoulos et al., 1996; Gershwin, 1994), offering rapid performance estimates into system behavior, especially for studies that can be simplified into structures with unidirectional flow of continuous operations with deterministic parameters. Therefore, a detailed representation of complex stochastic systems, such as the mine-to-plant interface, is better addresses by more accurate approach, like discrete-event simulation (DES).

Indeed, the development of DES models enables the representation of stochastic dynamics without restrictive assumptions (Law, 2015). Nevertheless, analytical models remain relevant due to their tractability, since the exclusive application of DES to large-scale systems can be computationally demanding and difficult to manage.

As a result, the analysis of large-scale supply chains with discrete and continuous interaction dynamics requires combining different modeling approaches to achieve a balance in the trade-off between accuracy and tractability. This integration, commonly referred to as hybrid modeling, has been increasingly applied in the simulation literature (Brailsford et al., 2019).

This study proposes a hybrid modelling framework that explicitly links discrete-event simulation outputs to an analytical queueing model, enabling the evaluation of variability propagation across the mine-plant interface, illustrated by a case study in a large open-pit iron ore operation in Brazil. The main contributions of this work are threefold: (i) the development of an integrated DES-analytical modelling approach tailored to discrete-continuous systems; (ii) an empirical application based on 13 months of operational data from a large-scale mining operation; and (iii) the evaluation of operational scenarios that reveal structural trade-offs between capacity, variability, and buffering.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on mining simulation and hybrid modelling approaches. Section 3 presents the case study and the proposed methodology. Section 4 describes the hybrid modelling framework and simulation design. Section 5 reports and analyses the results. Finally, Section 6 concludes the paper and outlines directions for future research.

Literature Review on Mining Simulation

Studies on mining systems are usually classified into two main methods: traditional and integrated. The traditional angle decomposes the complex system into smaller subsystems for individual analysis, whereas the included approach seeks to capture the system, reflecting the interdependence with subsystems as well as the multiple sources of variability.

A founding work by Hoare (1998) supports the application of a "fully integrated system" in the mining industry as a prerequisite for achieving sustainable improvements in productivity and profitability. Although such a system may be subdivided for analytical purposes, this practice imposes significant limitations on performance improvement, since traditional approaches often fail to adequately represent intrinsic system characteristics, such as the coexistence of continuous and discrete flows within the same operational environment.

Fioroni et al. (2007) modelled a large conveyor network (in the steel industry, but like mining applications), incorporating both discrete and continuous flows. Similarly, Hong et al. (2020) analyzed the primary transport system in an underground longwall coal mine, where discrete extraction systems (e.g., trucks and skip units) feed continuous conveyor systems. In both studies, the continuous components were discretized and analyzed within a DES framework. For open-pit mining operations, several applications of DES are presented by Fahl and Askari-Nasab (2017). In a related context, Elijah et al. (2021) applied classical queuing theory techniques to optimize the productivity of a shovel-truck haulage system by estimating the inter-arrival and service rates for different fleet sizes.

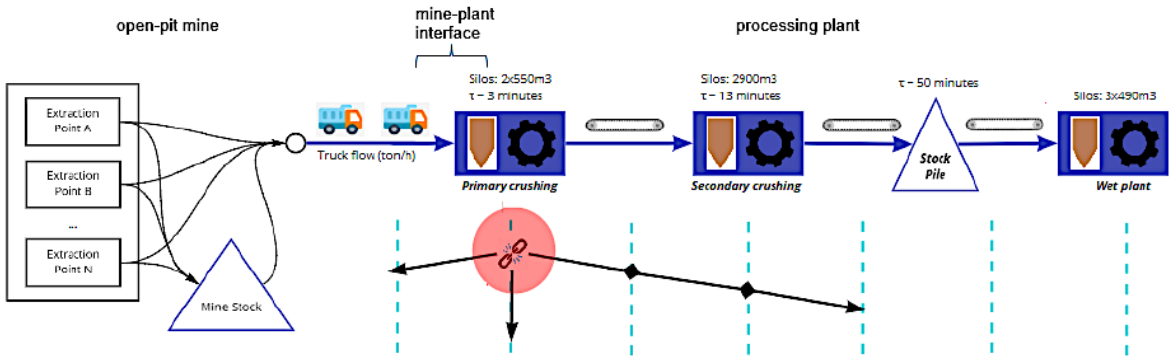
Although prior studies have significantly advanced the application of simulation and queueing techniques in mining systems, most approaches either rely on full discrete-event representations or purely analytical approximations. Consequently, they often fail to adequately capture the interaction mechanisms between discrete logistics operations and continuous processing systems. Also, the propagation of variability across such interfaces remains insufficiently explored, particularly in real-world, large-scale systems. In this context, there is a clear opportunity for hybrid approaches that combine the strengths of both modelling paradigms, enabling scalable yet accurate representations of complex production chains. This study contributes to this emerging research direction by proposing and empirically validating a hybrid DES-queueing framework focused on variability propagation at discrete-continuous interfaces.

Case Study

The mining supply chain exerts a significant influence on the global economy, and managing a mining business is challenging due to the large scale of its operations and logistics, as well as the capital intensity involved (Matlaba et al., 2017).

In this work, we focus on the mine-plant interface, where the intermittent and discrete flow of haulage trucks feeds the continuous flow of a crushing plant (Figure 2). It shows a branched flow of haulage trucks coming from different areas of the mine and converging at the unloading point of the primary crushing silos. From this point onward, the material flows continuously along a single path through conveyor belts to the secondary crushing and screening plant and is finally stored in a buffer stockpile. On the plant side, even brief interruptions may lead to queues of trucks waiting to unload at the primary crushing silos. These queues disrupt mine operations and may subsequently cause another stoppage in the crushing process, this time due to a lack of ore. As a result, variability emerges and propagates through the system with complex dynamics. Thus, the buffer size and capacities were extracted from the equipment technical data sheets (Table 1).

Figure 2. Process flow and flow break diagram from open-pit and processing plant



Source: Authors (2026).

Table 1. Process and variability measures for primary and secondary crushing

	Buffer Size (tons)	Capacity (tons/min)	r_e (tons/min)	σ_e	c_0	c_e
Pri.Crushing	1000	108.0	72	18.38	0.21	3.33
Sec.Crushing	4000	92.5	72	12.58	0.55	4.55

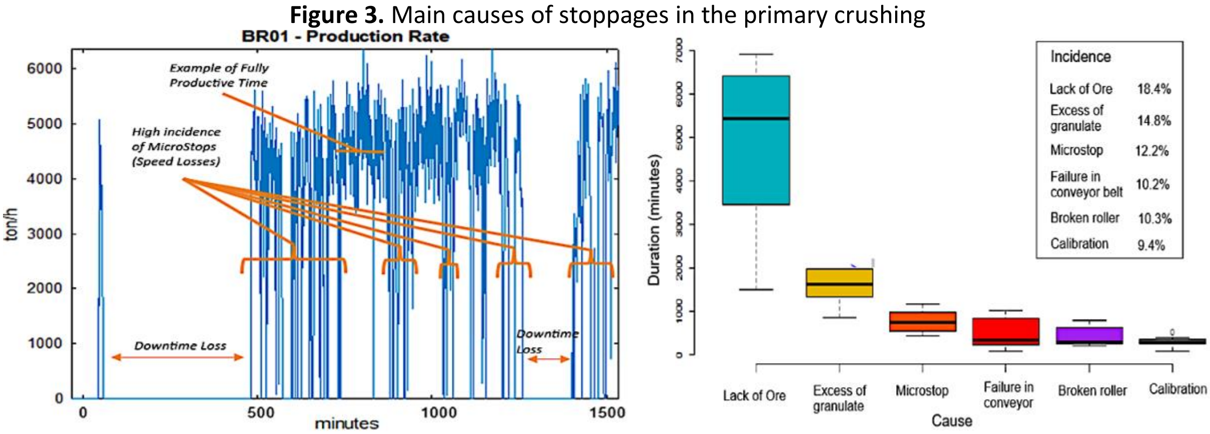
Source: Authors (2026). Flows are measured in tons per minute.

Based on historic data samples, effective processing time t_e was assessed as 0.0138 min/t and relates to the mean time required to process one ton of material. The effective rate $r_e$is defined as the ratio among the amount of parallel processing lines and t_e. As expected for serial production units, from a long-term view the effective rate of primary crushing meets to the effective rate of secondary crushing. Too, the effective variability coefficient c_e was computed as σ_e/t_e, where σ_e implies the standard deviation of the effective processing time. The natural variability coefficient c_0 relays to the value of c_e calculated after removing operational detractors. This indicator was assessed from production rate samples filtered to signify stable operating conditions (i.e., minus speed losses or downtime).

The results suggest that both crushing stages show very high variability related with the reference level of 1.33 proposed by Hopp and Spearman (2011). Also, although the primary crushing stage has a slightly higher nominal capacity, all variability indicators are significantly larger at this stage. This finding is consistent with previous bottleneck analyses, which identify the frequency of stoppages in primary crushing as the main limiting factor for production. The high variability observed in secondary crushing can therefore be interpreted since of the propagation of variability originating upstream, from the primary crushing unit.

Figure 3 presents a representative 25-hour operational sample from crushing line 1 (BR01), illustrating short intervals of stable full-capacity production surrounded by extended downtime periods caused by equipment failures and operational inefficiencies that lead to multiple micro-stoppages. The boxplot, on the right, presents the underlying causes of stoppages, indicating that *lack of ore* is the most frequent.

Figure 3. Main causes of stoppages in the primary crushing



Source: Authors (2026).

As mentioned earlier, it is important to note that a "lack of ore" event may, in fact, result from a mine shutdown. However, it can also be a misleading indicator, since logistical constraints at the mine may arise due to previous shutdowns at the crushing plant that caused truck queues. This fact is often the origin of disputes between mine and plant managers and reinforces the need for an integrated analysis of both sides of the interface.

For the presented case study, special scenarios were tested and analyzed. On the mine side, the implementation of a safety stock and an increase in the number of haulage trucks were considered. On the plant side, scenarios involved the reduction of micro-stoppages in the crushing area. All scenarios were evaluated using real operational data collected over a 13-month period, provided by a Brazilian iron ore mining company.

Hybrid Modelling for a Scenario-Based Study

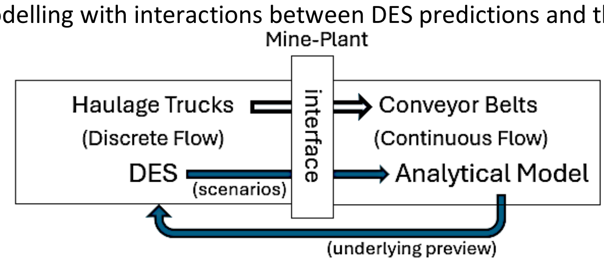
This study adopts a hybrid modelling approach to represent the interaction between discrete and continuous processes in a mining production system. The methodology combines discrete-event simulation (DES), used to capture the stochastic and operational dynamics of the mining and haulage system, with an analytical queueing model, used to approximate the behavior of the downstream continuous crushing process.

The integration between these modelling paradigms allows for a tractable yet realistic representation of the system, enabling the evaluation of variability propagation across process interfaces and supporting scenario-based decision analysis. The modeling procedure followed the **A-F** steps:

A - Collection of 13 months of operational data, including truck travel records, shutdown and production reports, and flow and level meter measurements used to estimate production rates and volumes stored in silos; **B** - Estimation of probability distributions for MTTF (mean time to failure) and MTTR (mean time to repair) of the main equipment, as well as truck travel times, based on downtime reports; **C** - Application of a discrete-event simulation model to reproduce queueing and processing dynamics in the mine and crushing plant; **D** - Creation and evaluation of alternative scenarios aimed at increasing production; **E** - Calculation of key production parameters, such as variability, availability, and nominal and effective capacities; **F** - Application of a G/G/1/b queueing model to assess the impact of the scenarios proposed in Step D on secondary crushing and to evaluate operational adjustments required to meet the projected production increase.

The interaction between these steps is illustrated by the hybrid modelling, Figure 4, where the DES results feed the analytical model, which, if necessary, provides feedback to the DES model for the evaluation of new scenarios.

Figure 4. Hybrid modelling with interactions between DES predictions and the analytical model



Source: Authors (2026).

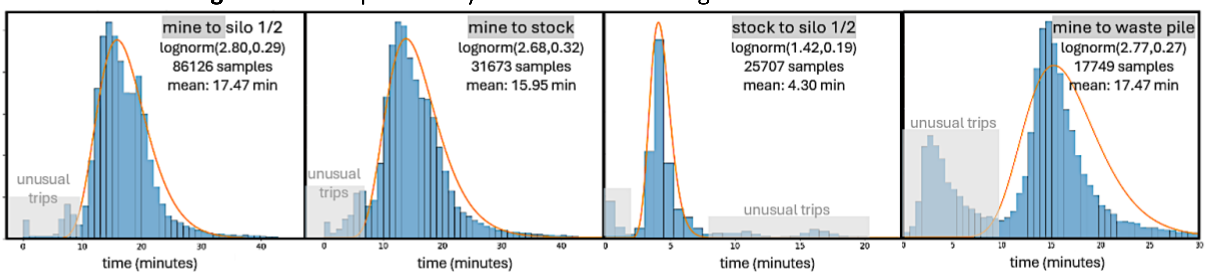
DES Model (Steps B, C, and D)

The open pit mine operates at full capacity, 24 hours a day throughout the year, and consists of 14 extraction points, each equipped with a loader capable of filling one truck at a time.

Trucks haul the material to three possible destinations: (a) crushing silos, when the ore meets the required quality specifications; (b) the mine stockpile area, when subsequent blending is required; or (c) waste piles, when the material consists of waste rock. The plant operates a fleet of 26 trucks, each with a capacity of up to 250 tons. Trucks can be loaded either directly at the extraction points or at the intermediate stockpile. Loads from the intermediate stockpile are transported directly to the primary crushing silos.

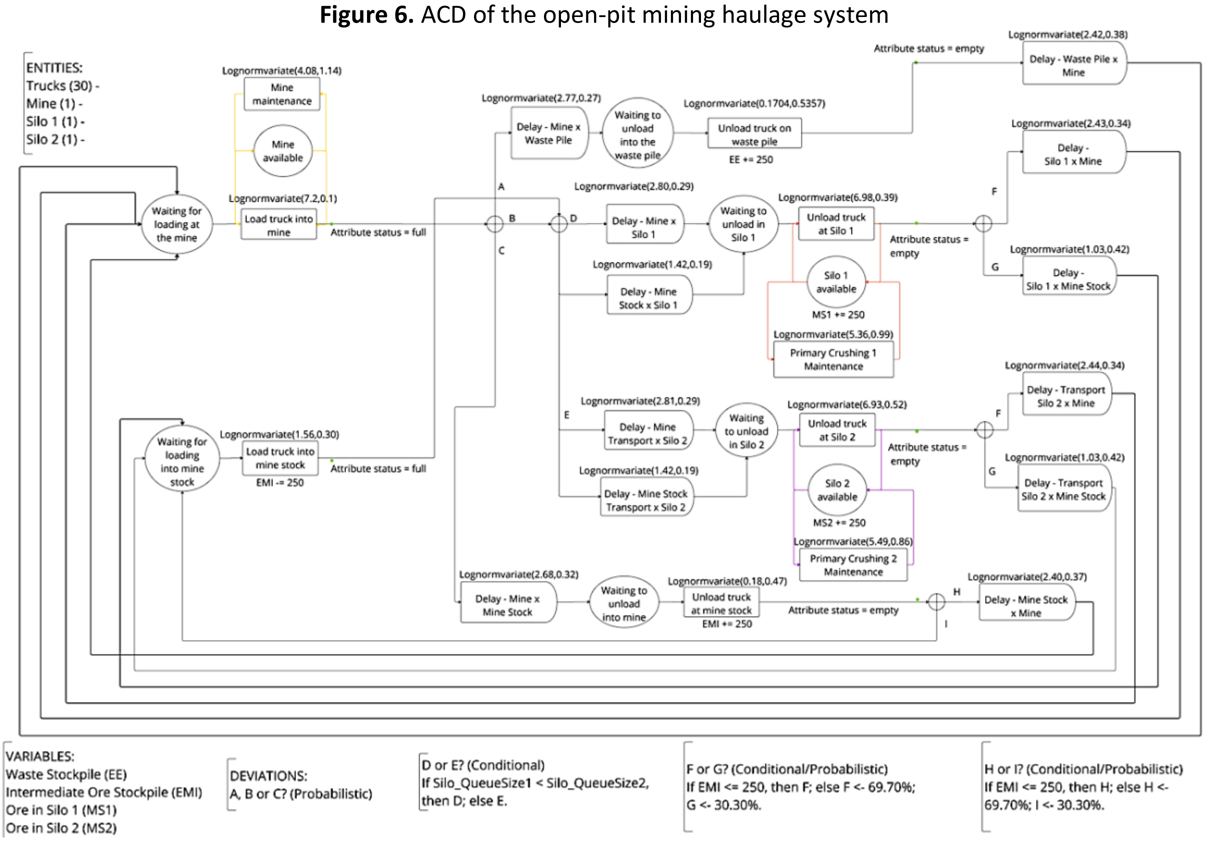
The Activity Cycle Diagram (ACD), Figure 5, describes the current dynamics of the open-pit haulage system. The lines represent the different routes travelled by the trucks, while the rectangles represent the activities performed along these routes, with curved rectangles specifically indicating transit times. Circles represent queues of trucks and resources required to process the activities. The routing probabilities for truck destinations were determined through an analysis of travel history records from the collected operational data. The label above the activities symbols indicates the probability distribution parameters estimated in Step B. This specification was implemented using SimPy (SimPy, 2024; Scherfke, 2024; Zinoviev, 2024), a Python-based library for process-oriented discrete-event simulation.

Figure 5. Some probability distribution resulting from best fit of DESK-DistFit



Operating and downtime data for equipment, such as mean time between failures and mean time to repair, were obtained from historical downtime records, while travel times were based on time intervals given by the differences between GPS positions of the trucks. Probability distributions curves to travel times are illustrated in Figure 6. Since the study focuses on regular operations, data from unusual trips, such as the use of auxiliary stocks, were disregarded. The functions were set using DESK-DistFit (Almeida, 2025), a Python tool for fitting probability distributions to empirical data using statistical tests, considering samples from the data provided.

Figure 6. ACD of the open-pit mining haulage system



Source: Authors (2026).

ANALYTICAL QUEUING MODEL (STEP E AND F)

The DES model covers operations up to the interface with the processing plant. The remainder of the crushing and screening circuit was represented in a simplified manner using an analytical queueing model, which provides useful approximations by generalizing several classical queueing models. Also, to estimate plant behavior under the new scenario conditions, a G/G/1/b model (using Kendall's notation) was implemented, considering the case in which the arrival rate is lower than the production rate $(u < 1)$. In this notation, "G" represents a general arrival distribution and "b" denotes the buffer capacity [Hopp and Spearman, 2011]. The model estimates the Factory Physics parameters by relating WIP_{nb} (work in process without blocking, Equation 1), ρ (corrected utilization, Equation 2), TH (throughput, Equation 3), and b (buffer size), as expressed in the equations below.

$$WIP_{nb} = \left(\frac{{c_a}^2+{c_e}^2}{2}\right)\left(\frac{u^2}{1-u}\right) + u, (1) \qquad \rho = \frac{WIP_{nb} - u}{WIP_{nb}}, (2) \qquad TH \approx \frac{1 - u\rho^{b-1}}{1 - u^2\rho^{b-1}} r_a, (3)$$

The remaining variables were obtained from Table 1. The parameter u, referred to as the utilization ratio, is defined as the ratio between the arrival rate r_a and the effective service rate $r_e (r_a/r_e = 72/92.5 = 0.778)$. Here, r_a corresponds to the effective production rate of the primary crushing stage, while r_e represents the nominal capacity of the secondary crushing stage. The arrival variability coefficient c_a is given by the effective variability coefficient of the primary crushing stage (3.33), whereas c_e corresponds to the natural variability coefficient of the secondary crushing stage (0.55).

ANALYSIS AND RESULTS

Mine and plant operators report three key issues that directly affect daily mining productivity: insufficient ore supply from the mine to the plant; the formation of truck queues at the crushing silos during plant stoppages; and the high number of micro-stoppages in the crushing process, defined as frequent interruptions of up to four minutes caused by control and operational issues. The application of simulation techniques enables the evaluation of alternative operational scenarios and supports decision-making on how to mitigate these problems in a feasible manner. Three solution scenarios were evaluated:

- **Scenario A:** creation of a safety stock between the mine and the plant;
- **Scenario B:** increase in the number of trucks in the haulage fleet;
- **Scenario C:** reduction of micro-stoppages in the crushing process.

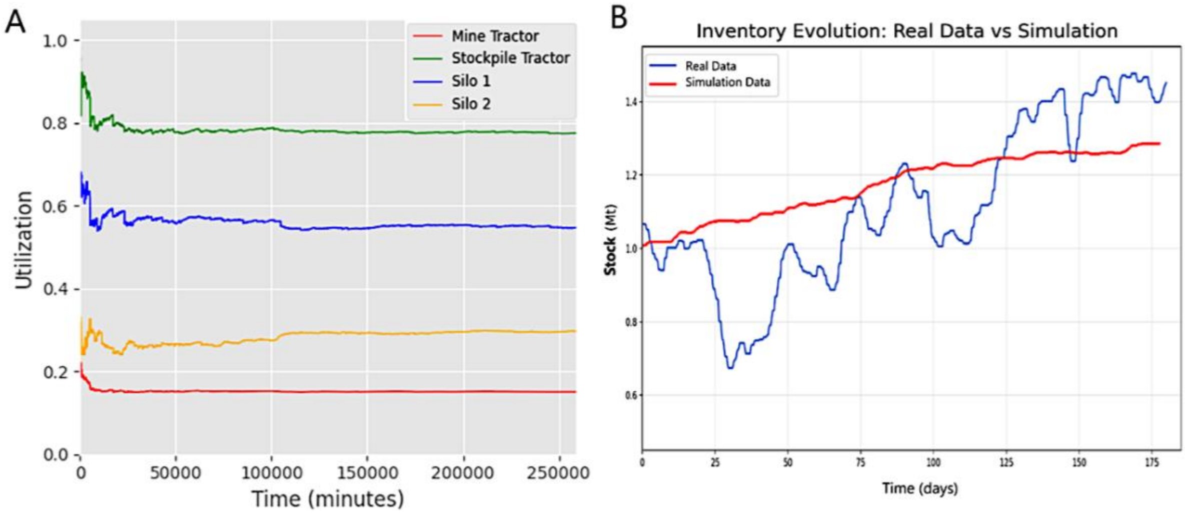
In addition, a **Current Scenario** was included, accurately simulated and calibrated to reflect current operating conditions, providing a baseline for comparison with the proposed scenarios.

DES SIMULATION

To ensure the statistical validity of the results with a 95% confidence level, 16 independent 180-day replications were performed, with system variables and statistics reset at the beginning of each cycle. To define the number of replications, the dispersion of the production rate was evaluated, and a maximum acceptable half-width of 1 was established. An initial sample of $n = 10$ replications yielded a mean value of $\bar{x} = 122$ and a confidence interval half-width of $h = t(n-1, 1-\alpha/2) \times s / \sqrt{n} = 1.24$. The required number of replications for a target precision of $h^* = 1$ was estimated as $n^* = [n \times (h / h^*)^2] = n^* \approx 15.4$. Finally, 16 replications were adopted to ensure a conservative margin and statistical robustness.

During the testing phase, a five-day warm-up period was established. It was observed that, during this interval, the monitored indicators, specifically the utilization rates for the mine and stockpile tractors, as well as silos 1 and 2, converged to values consistent with the collected real-world data. Consequently, data stabilization was achieved from the fifth day of the simulation, as evidenced by the convergence and stability of the time series (Figure 7-A).

Figure 7. Performance indicator: average resource utilization



Source: Authors (2026).

The simulation model was validated in two ways. First, the intermediate inventory level was observed throughout the 180-day simulation period. Figure 7-B compares the long-term trends of intermediate stock levels in simulated and real data and confirms that both present a slow ascending drift. The second way was to compare operational values, specifically, production rates, primary crusher availability, and average waiting times both at the crusher and in the inventory. A maximum tolerance margin of 10% for the relative error between the variables was adopted to ensure the necessary statistical rigor.

In the **Current Scenario**, the existing resource conditions of the mine were considered: 14 loaders at the extraction points and one loader at the intermediate stockpile; a fleet of 26 trucks transporting material daily; and two primary crushing lines, each equipped with a silo with a capacity of 550 m³.

To simulate **Scenario A**, the required capacity of a new safety stock between the mine and the plant was estimated based on historical data, considering the longest mine stoppage recorded during the 13-month observation period and the mine's processing capacity during that time. The resulting safety stock capacity was estimated at 123.58 kt. When the mine is operating, it supplies the crushing silos, and when the stock level decreases, the mine replenishes it;

In **Scenario B**, all parameters of the Current Scenario were retained, except for the number of trucks in action, increased from 26 to 30 (total number of trucks available, with spare ones);

In **Scenario C**, all parameters were also maintained, but a 50% reduction in micro-stoppages was considered, which altered the distribution of stoppage durations in the crushing process.

The simulated parameters of the primary crushing process at **Current Situation** are reasonably close to those observed in the collected data. The mean truck queue time in the real system is about 15 minutes, compared with 17.4 minutes in the simulation. The production rate is 72 in the real versus 67.8 in the simulation, while availability is 77% compared with 79% (Table 2).

Table 2. Current situation and scenarios A, B, and C, using Discrete Event Simulation

	Current situation	[A] Safety stock	[B] More trucks	[C] Less micro stops
Number of trucks in operation	26	26	30	26
Production rate tons/min (± 0.4)	67.8	68.4	72.2	69.0
Crushing availability (%)	77±1	77±1	77±1	79±1
Truck queue at crushing (min)	17.4±0.4	15.9±0.2	18.6±0.2	15.2±0.2
Truck queue at mine stockpile	11.3±0.1	12.4±0.1	19.0±0.1	11.8±0.1
Truck queue at mine (min)	1.4±0.1	1.3±0.1	1.3±0.1	1.3±0.1
Truck queue at safety stockpile	-	17.4±0.2	-	-
Total time in queue (min)	46.5±0.5	61.7±0.8	57.4±0.3	43.6±0.2
Average number of trucks in queue	5.2±0.1	5.3±0.5	7.4±0.1	5.0±0.1

Source: Authors (2026).

Improvements on The Plant Side to Fit Increased Mine Production

The G/G/1/b analytical queueing model (Equations 1-3) was applied to estimate the adjustments required on the plant side to accommodate the increased mine production flow projected for Scenarios A, B, and C. The respective production rates have been brought in ascending order (68.4, 69.0, 72.2) to the first column of Table 3 after the original rate (67.8). The adjustment parameters for the crushing operation are: *Primary Crushing Rate*, *Primary Crushing Variability* and *Secondary Crushing Buffer*. Their values are presented in a sequence set, where values are separated by "/", and adjusted parameter in parentheses.

Table 3. Adjusted values to fit increased mine production

New scenarios (mine rate)	Adjust primary crushing rate	Adjust primary crushing variability	Adjust secondary crushing buffer
Current scenario (67.8)	(74.6)/3.33/4000	74.6/(3.33)/4000	74.6/3.33/(4000)
Safety stock (68.4)	(75.4)/3.33/4000	74.6/(3.21)/4000	74.6/3.33/(4400)
Reduced micro stops (69.0)	(76.6)/3.33/4000	74.6/(3.08)/4000	74.6/3.33/(4600)
Increased trucks (72.2)	(82.4)/3.33/4000	74.6/(2.34)/4000	74.6/3.33/(7600)

Source: Authors (2026). Note: values separated by "/", with the adjusted parameter in parentheses.

For example, in the first parameter set "(74.6)/3.33/4000", the variability coefficient and the buffer capacity were kept at their original values ($c_a = 3.33; b = 4000\ tons$). The primary crushing production rate $r_a$was then adjusted until the predicted secondary crushing throughput (TH, Equation 3) matched the mine supply rate of 67.8 tons/min. This condition was achieved by assigning a value of 74.6 tons/min to r_a.

DISCUSSIONS

The predictions generated by the models enable the identification of the most appropriate operational recommendations and the assessment of their associated benefits and eventual costs. The most effective strategy to increase production is to expand the truck fleet used for material transportation. Adding four trucks increases production by 6.5%. However, for the crushing plant to absorb the resulting mine production rate, the primary crushing capacity must increase from 74.6 to 82.4 tons/min, or downtime must be reduced to decrease effective variability from 3.33 to 2.34 (Table 3). If improvements in primary crushing are not feasible, an alternative is to increase the secondary crushing buffer capacity from 4,000 to 7,600 tons. Besides the significant cost of operating four additional trucks, the proposed alternatives also require additional investments in the crushing system.

The scenario C, with a 50% reduction in micro-stoppages, is particularly noteworthy, as it offers the best cost–benefit ratio among the evaluated alternatives. Since most of these stoppages are caused by control and operational failures, they can be mitigated without major capital investments, primarily through improvements in instrumentation, control logic, and operator training, while still delivering significant performance gains for the plant.

In terms of productivity gains, and without considering financial aspects, Scenario A increases production by 0.88%, Scenario B by 6.49%, and Scenario C by 1.77%. Based on a one-year operational projection, the current production level of 44.54 Mt/year would increase to 44.94 Mt/year under Scenario A (+0.39 Mt/year), 47.43 Mt/year under Scenario B (+2.89 Mt/year), and 45.33 Mt/year under Scenario C (+0.79 Mt/year).

From a theoretical perspective, the results reinforce key principles from Factory Physics, particularly the relationship between variability, utilization, and system performance. The findings show that increasing capacity alone (e.g., through fleet expansion) may lead to limited gains if variability is not simultaneously reduced. Conversely, reductions in variability, such as those achieved by mitigating micro-stoppages, can produce significant improvements with relatively low investment.

Furthermore, the results highlight the role of buffers as a structural mechanism to decouple upstream and downstream processes. However, increasing buffer capacity introduces economic and operational trade-offs, reinforcing the need for integrated analysis. These insights demonstrate the importance of jointly managing variability, capacity, and buffering when designing and operating complex production systems.

CONCLUSIONS

This study investigated the variability propagation at the mine–plant interface and evaluated productivity under alternative operational scenarios. As discussed, such interfaces typically introduce additional complexity due to the interaction between discrete and continuous processes, making system behavior difficult to analyze using a single modelling approach. To address this challenge, this study proposed a hybrid modelling framework to represent the stochastic dynamics of the mining stage with DES and an analytical queueing model to evaluate the behavior of the downstream continuous crushing system.

The results demonstrate strong practical applicability with scenarios showing that productivity improvements can be achieved through different operational strategies, including fleet expansion, reduction of micro-stoppages, and increased buffer capacity. Among them, reducing micro-stoppages provides the best cost–benefit balance, as many of these events are associated with control and operational issues and can be mitigated with limited investment.

Beyond its immediate application to mining systems, the proposed hybrid modelling framework contributes to the broader field of production systems engineering by offering a scalable approach to analyze discrete, continuous interactions. The ability to decompose complex systems while preserving key interaction dynamics represents a relevant methodological advance, particularly for large-scale industrial applications.

Future research could extend this approach by integrating optimization techniques for automated decision support, incorporating economic evaluation of scenarios, and expanding the framework to cover entire supply chains, including rail and port operations. Additionally, the explicit modelling of uncertainty propagation across multiple interfaces remains a promising avenue for further investigation.

Use of AI-Assisted Technologies

Artificial intelligence tools were used for bibliographic semantic search and organization, and to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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