

# Advancing Mine Haulage Modeling Through AnyLogic: From Simulation Design to Future Research Pathways

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## ABSTRACT

*This study presents the development and implementation of a high-level hybrid simulation framework for truck–shovel operations in open-pit mining using AnyLogic. The model integrates agent-based and discrete-event paradigms to simulate haulage dynamics under varying road grades, truck loading strategies, and speed configurations derived from rimpull–retard curves. By linking geometric, operational, and behavioral components, the model serves as a flexible experimentation environment for mine operations research and digital twin integration. The initial outcomes validate the feasibility of using AnyLogic for large-scale mining logistics, while the proposed future research directions emphasize reinforcement learning, data-driven optimization, and predictive digital twins.*

## 1. Introduction

Haulage systems form the operational backbone of surface mining, governing the flow of material between loading points and processing destinations such as crushers, stockpiles, and waste dumps. Their performance directly influences overall mine productivity, unit cost, and energy efficiency. In large, decentralized operations such as those in oil sands, gold, and base-metal open pits, hundreds of haul trucks interact with multiple shovels and crushers across vast, dynamically changing road networks. Under these conditions, small inefficiencies in dispatching, routing, or road-grade management can propagate into significant production losses.

Traditional approaches to mine-haulage analysis have relied on deterministic cycle-time models or spreadsheet-based calculations that assume fixed routes, constant speeds, and stable operating conditions. While simple to implement, these methods fail to capture systemic variability caused by fluctuating payloads, road degradation, congestion, weather effects, and unplanned equipment downtime. To address these limitations, simulation-based methods particularly discrete-event and agent-based simulations have become foundational in modern mine-planning research and industrial practice. They provide a controlled environment for evaluating operational policies, validating data-driven predictions, and exploring “what-if” scenarios before implementing changes in the field.

Although several commercial haulage simulators exist such as Haulsim, Arena, and SimMine, most operate as “black boxes” with limited integration capability. They typically rely on static process flowcharts, making it difficult to tightly couple them with external data sources or optimization algorithms. For contemporary mining operations seeking digital-twin capabilities—where simulation, prediction, and optimization interact in real time—this rigidity presents a significant barrier.

The motivation for adopting AnyLogic stems from its ability to combine discrete-event and agent-based modeling within a single environment while offering full access to Java extensibility. This enables the definition of custom behaviors, ingestion of external data sources (e.g., road networks, rimpull-retard curves), and integration with machine-learning or optimization engines through Python, Gurobi, or ONNX Runtime. The result is a high-fidelity, flexible simulation framework capable of representing both microscopic haulage dynamics and macroscopic operational KPIs.

The present study contributes to the development of a hybrid AnyLogic simulation targeted at medium- to large-scale open-pit mining operations. The model focuses on:

- a) Capturing physical realism; modeling road grade effects, loaded vs. empty speed factors, queueing, and shovel loading policies.
- b) Creating a modular architecture; allowing each component (truck, shovel, road segment, crusher) to function as an independent agent for scenario testing and reinforcement learning integration.
- c) Establishing data connectivity; reading road and performance data directly from site CSVs or databases to ensure that simulation parameters remain synchronized with real operations.
- d) Providing validation and comparing environment in later stages; Serving as a benchmark against commercial tools such as Haulsim for calibration and structural verification.
- e) Laying the groundwork for advanced decision systems; Preparing the simulation to host reinforcement-learning dispatchers, stochastic optimization routines, and predictive digital-twin functionalities.

## 2. Literature Review

### 2.1. Discrete Event Simulation (DES)

One of the foundational contributions is the hierarchical mine production scheduling framework of Ben-Awuah, Kalantari, Pourrahimian and Askari-Nasab [5]. They developed a discrete-event simulation (DES) model to link long-term mine plans with short-term production schedules under uncertainty, using SLAM to represent drilling, blasting, loading, and hauling operations. The simulation evaluated the robustness of strategic schedules when exposed to stochastic operational conditions and demonstrated that DES can bridge different planning horizons more realistically than purely deterministic MILP models. Building on this line of work, Torkamani and Askari-Nasab [20] proposed a linkage between truck–shovel operations and short-term mine plans using DES. Their model explicitly represented truck queues, shovel loading times, and road travel as discrete events, enabling planners to test whether a short-term mining schedule was operationally feasible given haulage dynamics. The key insight was that a schedule that looks feasible in a static plan can fail operationally when truck queues, stochastic cycle times, and haul distances are accounted for; DES thus becomes a necessary complement to short-term planning models. At the micro-level, Upadhyay and Askari-Nasab [21] introduced micro-simulation of mine haulage systems, where trucks travel along segmented haul roads with speeds governed by rimpull-based equations and speed-reduction factors. Their work showed how grade, rolling resistance, and segment length can be translated into segment-level travel times using truck performance curves, providing a physics-informed basis for haulage simulation that goes beyond simple average speeds.

The recent research has produced several works that explicitly discuss the benefits and best practices of DES in mining. Fahl and Askari-Nasab [6] present a concise review and position paper on the “Benefits of Discrete Event Simulation in Modeling Mining Processes,” contrasting DES with deterministic spreadsheet analysis. They emphasize DES’s ability to represent discrete, dynamic, and

stochastic systems, perform “what-if” analyses, and capture interactions between equipment pieces (e.g., shovel–truck–crusher) that are difficult to handle analytically. Their case study on equipment selection shows that simulation can uncover bottlenecks and variability effects that deterministic models systematically overlook. Karikari and Askari-Nasab [12] broaden this perspective in “Enhancing Mining Operations and Productivity through Discrete Event Simulation: A Comprehensive Literature Review.” They systematize DES applications across drilling, blasting, haulage, processing, and maintenance, and argue that DES is particularly well suited to mining systems because it handles event-driven logistics, resource constraints, and variability in cycle times. The review also compares DES to agent-based simulation, continuous simulation, and Monte Carlo methods, concluding that DES remains the most pragmatic simulation paradigm for operational mining problems, while also highlighting the need for more integrated simulation–optimization and digital-twin frameworks.

A parallel stream focuses on HaulSim-based haulage models as practical digital twins of operating mines. Karikari and Askari-Nasab [10] developed an oil sands operation simulation using HaulSim, providing a practical guide to building and calibrating truck–shovel–crusher networks in a commercial DES environment. Their work demonstrates how production data, road geometry, and equipment specifications can be integrated to validate a HaulSim model against oil sands operations, and how scenario testing can support operational decision-making. More recently, Karikari and Askari-Nasab [11] extended this line into a comprehensive simulation model for mining operations, again using HaulSim, with an emphasis on model development, implementation, and validation against real production data. These HaulSim studies show that DES can serve effectively as a practical digital twin, but they inherit the limitations of commercial, relatively “closed” software: restricted access to internal logic, limited integration with external machine-learning models, and constraints on building custom agent behaviors.

Research has also extensively explored the intersection of simulation and mathematical optimization. Anaraki, Rabbani, Ghaffarimoradi, and Afrapoli [4] proposed a simulation-based optimization framework for truck allocation in open-pit mines, where candidate truck allocation policies are evaluated using DES and then improved via heuristic or metaheuristic search. Their model captures stochastic travel times, queuing, and loading variability, and demonstrates that simulation-based optimization can outperform static analytical allocation rules, particularly when cycle time variability and shovel idle probabilities are significant. Earlier, Ben-Awuah et al. [5] had already linked strategic scheduling to DES, and use simulation to evaluate multi-objective optimization outputs and to study trade-offs between production, cost, and other performance measures [2]. Extending this simulation–optimization paradigm to environmental and technology-transition questions. For example, Zamani et al. [25] evaluate truck–shovel versus in-pit crushing and conveying (IPCC) configurations using DES, quantifying throughput, cost, and greenhouse-gas implications of alternative material-handling systems. Pasha and Afrapoli [19] propose an integrated stochastic discrete–continuous simulation-based optimization framework for GHG mitigation in mining operations, coupling discrete events (equipment dispatch, loading, hauling) with continuous emission processes within a simulation–optimization loop.

Simulation situates as an interaction environment for AI algorithms, especially deep reinforcement learning (DRL). Noriega & Pourrahimian [15] developed an AI-based truck fleet dispatcher trained in a discrete-event simulation model of an open-pit operation, where stochasticity is modeled at every stage of the truck and shovel operating cycle. The DRL agent learns dispatch decisions (which truck should go to which shovel or dump) by interacting with the DES environment, improving throughput and reducing queuing without the need for hand-tuned rules. This work feeds into a more recent work by Noriega, Pourrahimian, and Askari-Nasab [16] who propose a Deep Reinforcement Learning-based real-time open-pit truck dispatching system. In that study, a Double Deep Q-Learning algorithm is trained on a DES model of the truck–shovel system to learn a stochastic control policy

that accounts for uncertain cycle times, varying fleet sizes, and operational disruptions. Simulation here is explicitly used as a training ground for intelligent dispatchers, not just as an evaluation tool. Related contributions, such as AI-enhanced fleet-assignment models [24] and systematic reviews of DRL applications in mining [3], further underscore the growing importance of flexible, high-fidelity simulation platforms for training and evaluating advanced learning algorithms.

## 2.2. AnyLogic Related Research

AnyLogic, a multi-method simulation platform, has been widely adopted in academic studies for this purpose because it supports discrete event simulation (DES), agent-based modeling (ABM), and system dynamics (SD) within one environment [7]. This flexibility enables users to model complex mining scenarios that involve both the stochastic, process-driven events of haulage cycles and the dynamic interactions of autonomous agents or continuous material flows.

### 2.2.1. AnyLogic in Discrete Event Simulation (DES) in Mine Haulage Models

Discrete-event simulation has been widely adopted as a primary methodology for modeling haulage operations due to its natural alignment with the sequential processes of loading, traveling, queuing, and dumping. Several studies have developed detailed DES models in AnyLogic to analyze and improve mine haulage performance. For instance, Jung, Baek, and Choi [9] constructed a DES model of a limestone quarry's truck-loader cycle, integrating field-surveyed service-time distributions and leveraging AnyLogic's real-time visualization to continuously monitor cycle times, queue lengths, and equipment utilization. Their model replicated actual production patterns and revealed operational bottlenecks, demonstrating the dual value of DES for rigorous analysis and intuitive visual validation. Similarly, Lee and Kim [13] used AnyLogic to evaluate optimal truck and excavator fleet sizes in a South Korean quarry, incorporating heterogeneous truck capacities, rock types, and loading conditions. Through simulation-based optimization with OptQuest, they identified cost-minimizing fleet configurations and highlighted how excessive truck counts can induce congestion and elevate operating costs. Together, these studies illustrate the ability of DES in AnyLogic to represent detailed operational processes, capture complex equipment interactions, and provide actionable insights for improving haulage system productivity.

A parallel line of research has used AnyLogic to model more integrated or hybrid mining systems, particularly where haulage interacts with other operational processes. Parakh and Russell [17] developed a high-level DES model of an underground gold-platinum mine that linked ore production, surface transport, milling, and backfilling within a unified digital-twin framework. Their model combined discrete events (such as truck dispatching and shift changes) with continuous material-flow dynamics supported by AnyLogic's fluid-flow library, enabling engineers to test alternative scheduling scenarios and assess system-wide bottlenecks. Other hybrid approaches include the work of Park, Jung, and Choi [18], who introduced a machine-learning-enhanced DES model for predicting truck cycle times and ore production. Their PSO-optimized SVM model achieved strong predictive accuracy and was embedded directly into a DES environment to evaluate production outcomes at truck- and section-level detail. Complementarily, Liu, Sun, Liu, & Wang [14] demonstrated that a routing-optimization model implemented in AnyLogic can substantially improve equipment utilization and reduce transportation costs under slope-stability constraints. Collectively, these studies show that AnyLogic supports the development of hybrid, multi-domain mining simulations that integrate haulage, production, and auxiliary processes for deeper operational insight.

Across these studies, the advantages of using AnyLogic's Process Modeling Library for mining DES applications are consistently emphasized. Authors highlight the platform's ability to incorporate realistic operational features including haul-road geometries, shift schedules, loading and dumping

delays, and heterogeneous equipment fleets while generating detailed performance statistics for validation and decision-making. The visual and interactive modeling environment is repeatedly cited as a strength, as it facilitates verification of model logic and enhances communication of results through 2D and 3D animations [9]. Furthermore, AnyLogic's native support for optimization e.g., OptQuest in Lee and Kim's work [13] and integration of geospatial data enhances the robustness and realism of haulage simulations. Although these benefits depend heavily on the quality of input data and careful model calibration, the reviewed literature demonstrates that DES models developed in AnyLogic can reliably identify bottlenecks, determine optimal fleet configurations, support "what-if" scenario analysis, and validate the feasibility of haulage system designs before operational implementation.

### 2.2.2. AnyLogic in Agent-Based Modeling (ABM) for Haulage Systems

Agent-based modeling (ABM) has proven effective for capturing decentralized interactions in mine haulage systems, especially when simulating autonomous equipment or complex traffic behavior. A representative example is Goli et al. [7], who modeled each haul truck as an autonomous agent in AnyLogic with behavior rules for movement, collision avoidance, and intersection priority, thereby quantifying collision risk across mixed autonomous and human-driven fleets. Their findings indicated that a fully autonomous fleet reduced collision probability by approximately 91%, with intersections representing the highest-risk zones. Similar agent-centric modeling principles appear in hybrid simulation studies [1, 22], where truck and shovel agents make localized decisions within an integrated ABM–DES haulage environment. Together, these studies demonstrate the usefulness of ABM for representing behavioral variability, emergent traffic patterns, and the safety impacts of autonomy in mine haulage operations.

Beyond safety and collision-risk assessment, ABM has been explored as a means of modeling decentralized routing, queue selection, and adaptive behavior in mining systems. Although pure ABM haulage studies are relatively rare in the academic literature, works such as Acheampong et al. and Vasquez-Coronado et al. [1, 22] they illustrated how agent-based decision rules can be embedded within hybrid DES–ABM frameworks to model dynamic fleet interactions, haul-route adjustments, and supervisory control. These studies show that agents can respond autonomously to congestion, shovel availability, or operational delays—capabilities that are difficult to represent in traditional process-based DES. Industry-oriented AnyLogic traffic-management models further reinforce this perspective by using multi-agent structures to simulate decentralized vehicle navigation and congestion avoidance. Collectively, these examples highlight that ABM provides a flexible modeling paradigm for mining applications where adaptive, rule-based, or decentralized behavior is operationally relevant.

A growing stream of research integrates ABM with discrete-event simulation (DES) and reinforcement learning (RL) to support intelligent haulage management and real-time decision-making. Acheampong et al. [1] developed a hybrid ABM–DES framework in which truck and shovel agents learn improved dispatching and coordination strategies through Deep Q-Networks, enabling adaptive responses to operational variability. Complementing this approach, Vasquez-Coronado et al. [22] introduced a supervisory control agent that dynamically adjusts operational policies based on KPIs such as throughput, grade distribution, and shovel utilization, forming an early digital-twin prototype. Together with findings from Goli et al. [7] on autonomous-agent behavior, these studies demonstrate that AnyLogic's multi-paradigm simulation environment is well suited for embedding learning agents, modeling adaptive fleet behavior, and supporting the development of autonomous and smart-mining systems under uncertainty.

### 2.2.3. Summary of Findings and AnyLogic's Role

Table 1 provides an overview of the key studies reviewed, highlighting their modeling approach and main findings. A clear theme is that multi-method modeling often yields the best representation of mine haulage systems. Many authors chose AnyLogic specifically for this reason – it allowed them to build models that were not restricted to one paradigm. For example, an open-pit model might primarily be DES but include an ABM sub-model for truck interactions, or a predominantly ABM model might still use event logic for processes like loading queues. The ability to incorporate GIS data (mine layouts, road networks) and visualize the model in 3D was also cited as an advantage in communicating results and verifying behavior [7, 9].

In terms of key insights for mining engineering, the studies consistently demonstrate how simulation with AnyLogic can uncover improvements in haulage efficiency and safety. Optimal fleet sizing (avoiding under- or over-trucking) was identified to minimize costs [13]. Bottleneck analysis showed where infrastructure upgrades (e.g. additional conveyors or larger shafts) would pay off in increased throughput [23]. When it comes to technological change like automation, simulation quantified a dramatic potential reduction in accidents with autonomous trucks [7], supporting business cases for Autonomous Haulage Systems. These findings inform both operational decisions (dispatching strategies, shift planning) and strategic investments (fleet procurement, road design, autonomy adoption).

According to the reviewed literature, the benefits of using AnyLogic for modeling haulage systems include : (1) Flexibility and multi-method integration – enabling a more comprehensive model of the mining system than single-method tools [7]; (2) Visual validation and real-time visualization – improving model credibility and stakeholder buy-in [9]; (3) Built-in experimentation and optimization tools – allowing users to find optimal scenarios (as seen with OptQuest for equipment allocation) [13]; and (4) Extensibility – support for custom logic (e.g. Petri nets, algorithms) and integration of external data (GIS coordinates, production databases) to closely mirror reality [7].

On the other hand, a few limitations were noted. Building high-fidelity models can be data-intensive – requiring time studies or detailed mine data – and the accuracy of outputs is only as good as the inputs and assumptions. Some models had to simplify certain aspects (e.g. assume unlimited resources or neglect minor delays) to keep the scope manageable [13]. Another practical limitation is runtime and complexity: agent-based models with dozens of trucks and complex logic can become computationally heavy, though none of the papers reported insurmountable performance issues. It's also worth noting that AnyLogic, as a general simulator, may require more effort to set up a mining model compared to niche mining simulation software; however, its flexibility often yields a more insightful model in the end.

In summary, AnyLogic has proven to be a powerful tool in the mining engineering domain for haulage system analysis, offering a blend of modeling methods that can capture the intricacies of these systems. The academic studies reviewed demonstrate tangible benefits – from cost savings and throughput gains to safety improvements – obtained by simulating haulage operations. As mines continue to evolve with automation and greater data availability, the use of multi-method simulation platforms like AnyLogic is likely to expand, enabling engineers to experiment virtually and optimize haulage systems in ways that were previously impractical or too risky to test in the field. The literature of the past decade provides a strong foundation, showing that AnyLogic-based simulations can yield significant operational insights and guide better-informed, safer, and more efficient haulage system management in the mining industry.

Table 1. Recent Academic Studies Using AnyLogic for Mining Haulage Systems.

Study (Year)	Modeling Approach	Scope and Key Insights	Notable Benefits / Limitations of AnyLogic
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(9)	<b>DES (process modeling)</b>	Open-pit truck–loader haulage (limestone mine). Simulated loading, travel, dumping with field-calibrated times. Key findings: Real-time simulation outputs matched production; identified truck queue delays. Overcame prior lack of real-time KPI monitoring by visualizing truck movement and throughput live.	AnyLogic allowed real-time 3D visualization of the haul cycle and easy capturing of KPIs during runs. Enabled verifying model accuracy against mine data. Limited by need for detailed time studies as input.
(13)	<b>DES + Optimization</b>	Quarry haulage optimization with two truck sizes and two excavator sizes. Simulation experiments (with OptQuest) to find cost-minimal fleet size. Key findings: Determined optimal number of trucks per excavator – too few or too many trucks raise cost. Optimal configuration cut operating cost by ~20–77% across different scenarios. Highlighted diminishing returns beyond a fleet size sweet-spot.	Multi-scenario experimentation was facilitated by AnyLogic’s built-in optimizer. The tool handled complex interactions (open-pit + underground haul) in one model. Assumptions like unlimited blasting were used to isolate haulage factors (a modeling choice, not tool limitation).
(17)	<b>Hybrid DES + continuous</b>	Underground mining & backfilling (gold/PGM mine). Annual planning model linking ore extraction, hoisting, milling, and tailings backfill (used AnyLogic process + fluid libraries). Key insights: Exposed bottleneck shifting between mining and backfill: at times backfill plant throughput constrained mining, elsewhere shaft capacity was the limit. Provided guidance on where to add capacity (e.g. backfill infrastructure) to boost production.	Integrated discrete and continuous processes in one model (a digital twin of mine operations). AnyLogic’s libraries allowed modeling the continuous flow of tailings alongside discrete haulage events. Benefit: easy scenario testing (e.g. varying tailings supply) for planners. The model’s breadth required simplifying some details (e.g. aggregated daily rates).
(7)	<b>ABM + DES (hybrid)</b>	Open-pit haul trucks – autonomous vs manual. Agent-based trucks interacting on haul roads with collision logic; integrated with DES loading/unloading events. Key findings: Autonomous haulage systems (AHS) can reduce truck collision frequency by ~90% greatly improving safety. Also identified mine intersection hotspots where collisions tend to occur under manned operations. Supports safety and productivity benefits of AHS adoption.	AnyLogic provided an agent framework for trucks with custom behaviors (proximity detection, yielding). The platform’s flexibility enabled combining process flow (queuing at shovel) with agent interactions (road navigation) seamlessly. Visualization of moving trucks aided analysis. A challenge was ensuring credible agent rules – needed to calibrate truck speeds and sensor ranges to real data.
(Wang et al., 2022)	<b>DES (Petri net logic) + SD elements</b>	Coal mining-separation-backfilling system (underground). Used GSPN-based model in AnyLogic to simulate the linked chain of coal face production, on-site processing, and waste backfilling. Key findings: Verified that mining and processing capacities were balanced, but backfill capacity was slightly lagging demand, creating a potential bottleneck.	Demonstrated AnyLogic’s ability to model complex process dependencies and resource-sharing. The Petri net approach was implemented through state logic in AnyLogic, showing its extensibility. Benefit: Detailed bottleneck analysis in a unified model. Limitation: The model assumed certain resources (manpower, explosives) were unconstrained to

focus on logistics, meaning those aspects would need separate consideration.

#### 2.2.4. AnyLogic Capabilities

Key features leveraged in this study include:

- Hybrid simulation: Combining agent-based and discrete-event paradigms for operational realism, ensuring high and middle level of abstraction with different targeted details. Figure 1 shows classifying simulation methodologies.

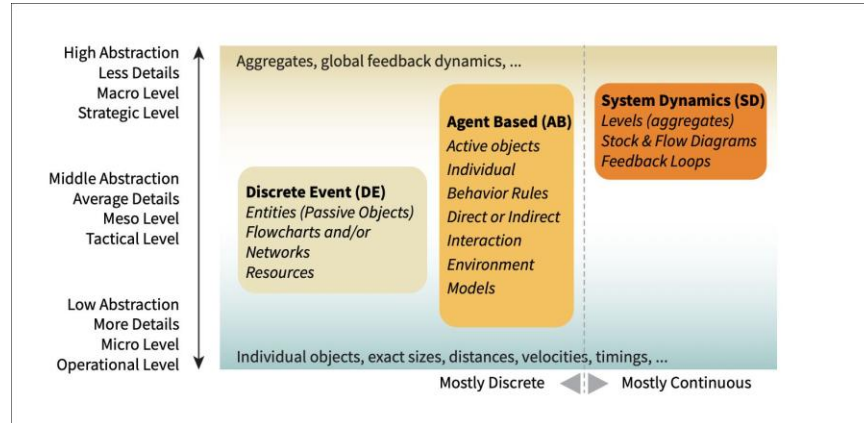


Figure 1. Simulation classification levels [8].

- Java extensibility: Integration with custom classes for data ingestion, road geometry parsing, and diagnostic tracing.
- Data integration: Support for CSV-based network imports and dynamic configuration from operational databases.
- Experimentation flexibility: Support for parameter sweeps, Monte Carlo simulation, and RL experiments (Alpyne RL).
- 3D visualization and GIS: Realistic spatial visualization of mine topography and equipment movement for validation and stakeholder communication.

#### 2.3. Research Gap and motivation

Across the reviewed DES, HaulSim, and AnyLogic-based haulage models, there is still no openly extensible, hybrid DES–ABM simulation framework that (i) represents segment-level, grade-dependent truck physics using rimpull–retard curves, (ii) exposes its internal logic and data interfaces for tight coupling with reinforcement learning, ONNX-based predictive models, and MILP optimization, and (iii) is designed explicitly as a reusable testbed for digital-twin style experimentation rather than as a closed, case-specific model. This absence of an integrated, physics-informed, and AI/optimization-ready AnyLogic environment for open-pit haulage constitutes the main research gap that motivates the present study.

### 3. Methodology

The proposed methodology integrates data ingestion, model architecture design and behavioral logic to develop a hybrid simulation of mine haulage operations in AnyLogic. It follows three major stages:

(1) data preparation and input processing, (2) agent and event modeling, and (3) scenario definition and experimentation.

### 3.1. Data Preparation and Inputs

Data were collected and processed from site operational and design datasets to ensure that simulation parameters reflect real mine conditions, as summarised in Table 2.

Table 2. AnyLogic model configuration.

Input Type	Description	Source	Integration Format
Road Geometry	3D polylines with X, Y, Z coordinates defining haul routes and elevation profiles	Deswik / CSV export	Imported via custom Java parser
Speed-Grade Factors	Rimpull-retard curve-derived functions mapping grade (%) to loaded/empty speed (km/h)	OEM CAT 797F data	CSV table read during initialization
Truck-Shovel Parameters	Payload capacity, bucket size, loading rate, and position coordinates	OEM specs and site logs	Parameterized via AnyLogic variable blocks
Operational Data	Distribution inputs (cycle times, payloads, ..)	Fleet Management System (FMS)	AnyLogic input
Simulation Controls	Experiment duration, fleet size, and scenario configuration	User-defined	AnyLogic experiment panel

Each data component is automatically validated for consistency (e.g., matching coordinate systems, non-negative lengths, payload balance) before initialization.

### 3.2. Model Architecture

The model employs a hybrid simulation approach that combines the following two parts:

1. Discrete-event simulation (DES): Governing process flow events such as “Truck Arrives,” “Shovel Loads,” and “Dump Completed.”
2. Agent-based simulation (ABS): Representing individual trucks, shovels, and road segments as autonomous agents with behavioral logic.

#### Simulation Model Key Components

- Truck Agent:
  - a) Attributes: payload, state (loaded/empty), route ID, location, travel time.
  - b) Behaviors: `traverse()`, `loadAtShovel()`, `dumpAtCrusher()`.
  - c) Decision rules: governed by loading strategies.
  - d) Interaction: communicates with Shovel agents to request and release loading queues.
- Shovel Agent:
  - a) Manages loading sequences, bucket passes, and idle times.
  - b) Supports stochastic loading durations with configurable variance.
- Road Network Module:
  - a) Reads CSV-based road data to construct a polyline network.
  - b) Each segment stores horizontal length, elevation change, and grade percentage.

- c) A `travelTimeOnString()` function dynamically computes traversal time using grade-dependent speed factors.
- **Crusher / Dump Agent:**  
Serves as terminal node; tracks cumulative throughput and queue length.
- **Controller Logic:**  
Global event scheduler managing truck release intervals, queuing discipline (FIFO), and experiment time horizon.

### 3.3. Simulation Logic and Behavioral Flow

The dynamic behavior of the system is governed by discrete events and agent interactions, as implemented in Figure 2:

1. **Dispatch Phase:** A truck requests assignment and selects route.
2. **Loading Phase:** Truck enters queue; shovel loads based on a loading strategy logic.
3. **Haul Phase:** Loaded truck traverses the road network, using per-segment grade-based speeds.
4. **Dump Phase:** Truck unloads at crusher; empty return trip initiated.
5. **Cycle Recording:** Travel time, queue time, and payload logged.

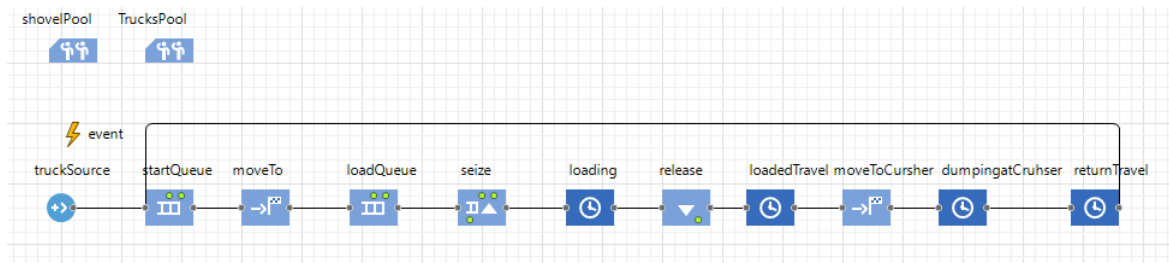


Figure 2. Truck-shovel simulation logic flowchart.

### 3.4. Scenario Design

Two main experiment sets were implemented:

1. **Experiment 1 – Loading Strategies**
  - Objective: Assess throughput and payload variability differences between different loading strategy.
  - Independent variable: loading strategy.
  - Dependent variables: average cycle time, payload variance, queue time.
  - Run time: 24 hours
2. **Experiment 2 – Speed–Grade Configuration**
  - Objective: Quantify the effect of grade-dependent speed mapping on travel time realism.
  - Independent variable: speed factor model (constant vs. rimpull-based).
  - Dependent variables: segment travel time deviation, total cycle time.
  - Run time: 72 hours

## 4. Case Study

The case study aimed to validate the hybrid AnyLogic model against realistic operational conditions and examine how loading policies and grade-dependent travel speeds influence overall system performance.

### 4.1. Model Configuration

The model key parameters for both experiments are shown in Table 3 to represent a medium open pit operation:

Table 3. Simulation model parameters.

Parameter	Value / Range	Source
Truck payload capacity	336 t	CAT 797F specs
Shovel bucket size	61 t	OEM data
Road gradient range	-12% to +12%	Mine road
Simulation time	24 & 72 hours	Scenario input
Time step	1 s	Model parameter

### 4.2. Experiment 1: Different loading strategies Comparison

24-h AnyLogic runs were executed with identical road, fleet, and shovel settings. The sole factor varied was the Last-Pass Threshold—the minimum fraction of a full bucket required to perform the final pass:

- Using 100% last pass (LP) percent loading strategy: Loading continues until truck reaches payload threshold (allow arbitrary small top-ups).
- Using 100% last pass percent loading strategy: (final pass must be a full bucket).

Table 4. Experiment 1 results summary.

Metric	LP-0 (0%)	LP-100 (100%)	$\Delta$ (100% – 0%)
Total moved (t)	44,936	39,419	-5,518 (-12%)
Elapsed time (h)	23.86	23.94	0.84%
Loads completed (count)	114	112	-2 (-1.8%)
Avg throughput (t/h)	1,884	1,646	-237 (-12.6%)
Avg mass per load (t)	394	352	-42 (-10%)
Mass variability (CV)	42%	33%	-9%
Avg passes per load	$\approx$ 4.93	$\approx$ 3.7	-1.2 passes
Total shovel passes (est.)	$\approx$ 570	$\approx$ 414	-27%

Referring to Table 4, LP-0 yields higher tonnage and tph but at the cost of markedly higher variability and more passes per cycle. LP-100 trades some output for tighter control (lower CV) and fewer passes, which is operationally attractive (less shovel wear, shorter loading time, smoother crusher feed). LP-100 (full last pass required) reduces variability and shovel effort (-27% passes) while sacrificing ~12% throughput compared to LP-0. With hard payload caps, LP-100 provides a more realistic and equipment-friendly policy; LP-0 is suitable for stress-testing but should not be used without caps due to overfill artifacts.

The boxplot of mass per load in Figure 3 illustrates a substantial improvement in payload consistency under the LP-100 policy. LP-0 exhibited a wide distribution, with a coefficient of variation (CV) near 0.28, suggesting uneven truck fills and frequent under- or over-loading. In contrast, LP-100 achieved a lower CV of approximately 0.15, indicating that most payloads clustered tightly around the target truck capacity (~350–400 t). The reduction in spread confirms that the automated last-pass control significantly stabilizes loading accuracy.

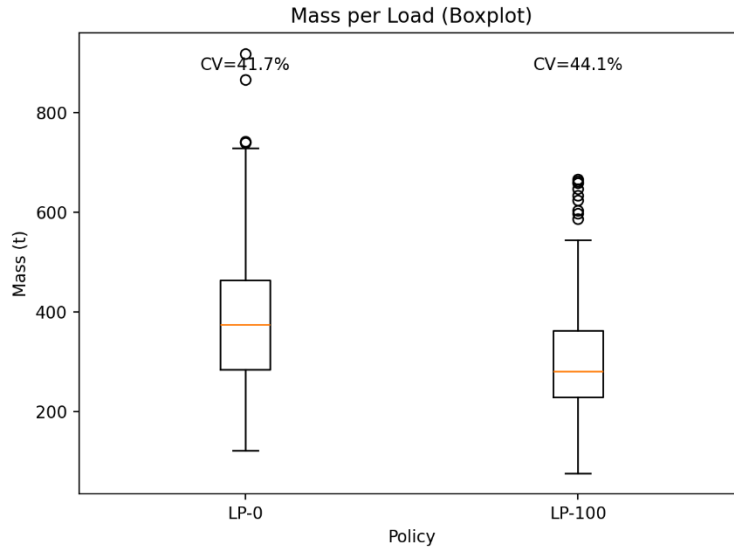


Figure 3. Payload variability and consistency.

The histogram of passes per truck in Figure 4 reveals a marked reduction in variability. Under LP-0, pass counts ranged broadly from 3 to 9, reflecting inconsistency in operator behavior and load judgment. LP-100 demonstrated a condensed range, predominantly 4–5 passes per truck, consistent with a more standardized shovel loading cycle. This tighter distribution correlates with shorter and more predictable cycle times, improving fleet coordination and dispatch rhythm.

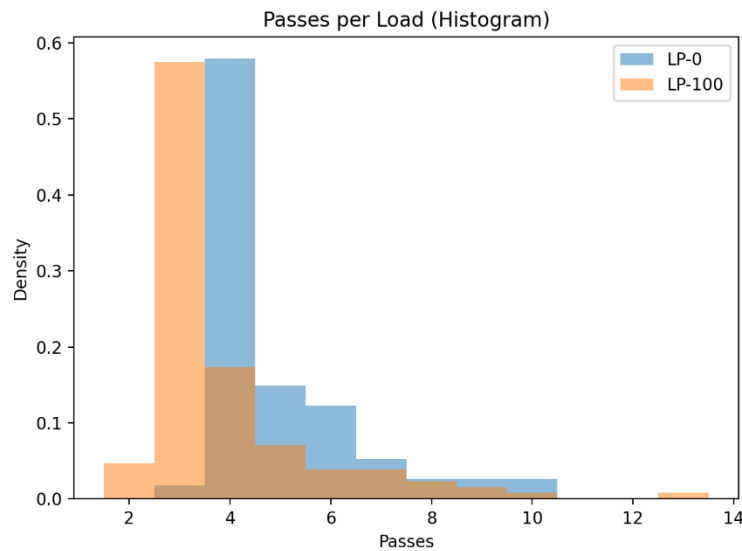


Figure 4. Pass distribution behavior.

The hour-by-hour throughput (tons per hour, TPH) comparison in Figure 5 shows LP-100 delivering a notably steadier feed profile to the crusher. The LP-0 time series fluctuated heavily, with hourly

deviations exceeding 20 % of the mean TPH. In contrast, LP-100 maintained throughput within  $\pm 10$  % of the average, producing a flatter and more stable curve. This stability is critical for minimizing surge bin oscillations, sustaining consistent crusher utilization, and improving downstream processing efficiency.

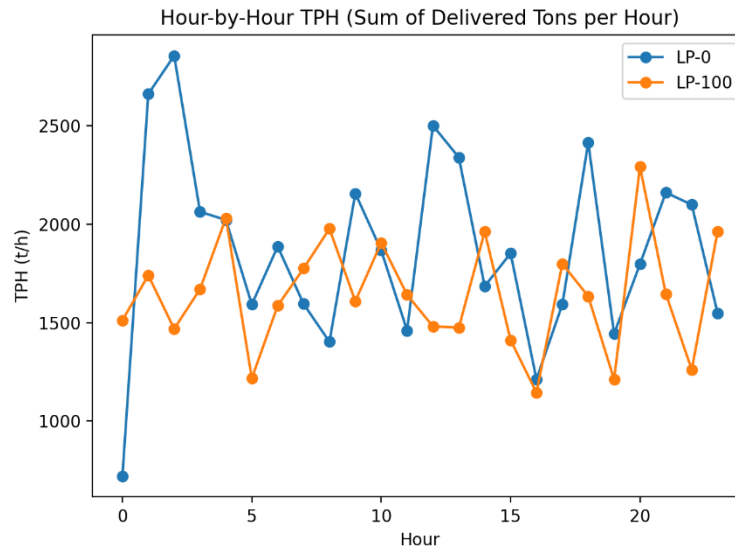


Figure 5. Hourly throughput stability.

### 4.3. Experiment 2 Road Grade and Speed Configuration

This experiment evaluated the influence of road grade and speed–grade factors on haulage performance. All trucks followed an identical two-way route, traveling outbound (loaded) via Road 1 → Road 3 and returning (empty) via Road 3 → Road 1.

Over a 72-hour simulation, the system hauled a total of 145,791 t, corresponding to an average throughput of approximately 2,025 t/h. Each full cycle (outbound + return) required  $\approx 21.5$  min, comprising a loaded travel time of 740.1 s (12.3 min) at 11.86 m/s (42.7 km/h) and an empty travel time of 550.0 s (9.2 min) at 15.96 m/s (57.5 km/h). The deterministic configuration produced a nearly linear cumulative tonnage profile, indicating stable fleet utilization with minimal fluctuations in hourly throughput.

Segment lengths along Road 1 varied between 0.5 m and 319 m, with grade values from  $-10.97$  % to  $+3.29$  %. Critical segments included:

- Seg 101: 284.5 m,  $-0.39$  % (long gentle downhill)
- Seg 103: 319.1 m,  $-0.03$  % (extended flat)
- Seg 104: 101.3 m,  $-10.97$  % (steep downhill; primary braking zone)

Speed-grade correction factors were applied in simulation experiment as in Table 5

Table 5. Grade and load factors.

Grade (%)	Loaded Factor	Empty Factor	Interpretation
-12	0.287	0.667	Steep downhill: loaded trucks 71 % slower
-7	0.533	1.000	Moderate downhill: loaded 47 % slower
0	1.000	1.000	Flat: no difference
+4	0.650	0.958	Gentle uphill: loaded 35 % slower

+8	0.325	0.675	Steep uphill: loaded 68 % slower
+12	0.208	0.483	Very steep: loaded 79 % slower

The steepest observed grade (−10.97 %) substantially reduced downhill velocity for loaded trucks and serves as a bottleneck for braking and retarder calibration. The road-grade and speed-factor configuration produced a consistent average haulage rate of  $\approx 2,025$  t/h under deterministic conditions. Performance sensitivity was primarily driven by grade severity, dispatch timing, and route congestion rather than by speed calibration errors.

## 5. Future Research Directions

The current AnyLogic model provides a high-level robust platform for operational simulation, yet several promising research extensions can significantly enhance its predictive and prescriptive capabilities through:

### 5.1. Reinforcement Learning and Policy Optimization

Integrating reinforcement learning (RL) to enable autonomous decision-making in truck–shovel assignments. Using frameworks such as Alpyne RL and ONNX runtime, trucks can learn adaptive policies that:

- Minimize queueing and idle times.
- Select optimal routes based on stochastic travel times and dynamic conditions.
- Learn cost- or carbon-aware dispatching behavior.

### 5.2. ONNX-Integrated Predictive Models

Embedding pre-trained ONNX models for predicting:

- Haul speeds under variable terrain and weather conditions.
- Payload deviations based on density uncertainty.
- Shovel productivity under fatigue and shift variations. This integration will allow AnyLogic to function as a “live digital twin” interacting with ML inference in real-time.

### 5.3. FMS Database Integration and Data Validation

Connecting the simulation with FMS Mine’s operational database to enable:

- Real-time calibration of speed–grade curves.
- Validation against Fleet Management System (FMS) logs.
- Comparison of predicted vs. actual dispatch and tonnage profiles.

### 5.4. Multi-Objective Optimization Coupling

Combining the simulation with Gurobi-based MILP or stochastic optimization models to explore:

- Trade-offs between productivity, cost, and equipment utilization.
- Optimal shovel–truck–region assignments under uncertainty.
- Integration with Sequential Learning or SPO+ optimization pipelines.

### 5.5. Reinforcement-Learning-Driven Simulation Experiments

Designing experiments where trucks learn to respond dynamically to:

- Road degradation and variable speed factors.
- Changing crusher availability.
- Priority adjustments based on blend targets or ore grade constraints.

### 5.6. Integration with Contextual Stochastic Optimization

Building on ongoing SPO+ and Sequential Learning research by linking predictive uncertainty estimates (from simulation outputs) with decision-rule optimization, enabling end-to-end stochastic decision pipelines.

## 6. Conclusion

The developed AnyLogic simulation serves as a flexible, high-fidelity framework for studying mine haulage dynamics and testing data-driven operational strategies. Positioned within the broader literature, it responds directly to two recurring themes: (i) the demonstrated value of discrete-event simulation (and increasingly hybrid DES–ABM models) for capturing variability, queuing, and equipment interactions in mining systems, and (ii) the growing need for open, extensible platforms that can be tightly coupled with optimization, AI, and digital-twin infrastructures, beyond the “black-box” nature of many commercial simulators. By adopting AnyLogic’s multi-method environment, this work builds prior DES-based haulage models, HaulSim case studies, and recent AI-enhanced dispatching frameworks, while explicitly targeting an architecture that can host reinforcement learning, ONNX-based prediction, and MILP/SPO+ decision engines in a unified workflow.

Methodologically, the study establishes a structured pipeline that begins with validated data ingestion (road geometries, rimpull–retard speed–grade factors, OEM specs, and FMS-style distributions), proceeds through a hybrid DES–ABM architecture (truck, shovel, road, and crusher agents coordinated by process logic), and culminates in controlled scenario experiments. The two proof of concept experiments illustrate how this architecture can be used as an experimentation testbed: Experiment 1 shows that alternative loading strategies (e.g., last-pass policies) can be evaluated in terms of throughput, shovel effort, and payload variability, while Experiment 2 demonstrates how grade-dependent speed factors map into segment-level travel times and overall cycle-time realism. The early results confirm that the model reproduces plausible tonnage rates, cycle-time breakdowns, and variability patterns, and that it is sensitive to operational policies and geometric attributes in ways consistent with the physics of haulage and findings reported in prior DES studies.

At the same time, these initial experiments underscore several important research gaps that define the next stages of this work. First, the current dispatch logic remains rule-based; there is a clear opportunity to embed reinforcement-learning agents that learn shovel–truck assignment and routing policies directly from interaction with the simulation, closing the loop between the hybrid model and AI controllers. Second, the speed–grade and productivity relationships are still driven by calibrated look-up tables and deterministic factors; integrating ONNX-based predictive models would allow the system to capture environment-dependent behavior (e.g., weather, road degradation, density uncertainty) in a more data-driven way. Third, validation is presently based on stylized case-study conditions rather than live FMS feeds and fully instrumented production data, so a key future step is systematic calibration and back testing of the model against real haulage logs and, where applicable. Finally, the model has not yet been tightly coupled to multi-objective optimization frameworks (e.g., Gurobi-based MILP and stochastic programming) that can exploit its outputs as a fast evaluation oracle for trade-off analysis across productivity, cost, carbon intensity, and grade-control objectives.

In summary, this work demonstrates that AnyLogic's hybrid DES–ABM capabilities provide a robust foundation for an open, extensible haulage simulation environment that is suitable for digital-twin and intelligent dispatch research. The literature review highlights a clear trajectory from standalone DES models, through simulation–optimization and early DRL frameworks, toward fully integrated, data-driven digital twins. The methodology and early results presented here position the proposed model as a steppingstone along that trajectory: already capable of capturing key operational dynamics and policy effects, yet intentionally designed to be extended with reinforcement learning, ONNX-integrated prediction, FMS connectivity, and contextual stochastic optimization. Addressing these research gaps will be the focus of future work, with the ultimate goal of enabling autonomous, resilient, and explainable decision systems for open-pit haulage planning and real-time control.

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