Integrating Discrete Event Simulation and Game Theory in Mining Operations

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ABSTRACT

Mining operations are a group of complex systems characterized by dynamic interactions among multiple equipment types, human operators, and other stochastic events. There are various traditional approaches, but they often overlook the behavioral and strategic decisions made by operational agents, such as shovel and truck operators, whose actions can significantly influence productivity and efficiency. This study is a review of the integration of discrete event simulation and gaming theory in the decision-making process on the operational level in mining. This review paper will discuss how discrete event simulation captures the cyclical and stochastic characteristics of the mine at an operational level. This includes cycle times, queuing, breakdowns, and other dispatching strategies, while with game theory discusses the strategic interactions among operational players, including shovel operators, truck operators, and the maintenance and dispatch team, and how their decisions interact and make better decisions. We will review and discuss how, with game theory, we can use operational players to make strategic decisions using trade-offs from these players and also combine the use of scenario testing from Discrete Event Simulation using these trade-offs to make optimal decisions regarding mining operations.

1. Introduction

Modern mining has come a long way, evolving from the industrial age into Industry 4.0, where digital technologies like the Internet of Things (IoT), artificial intelligence (AI), and big data are increasingly integrated into mining operations. These innovations have enabled real-time monitoring, predictive maintenance, and improved safety and productivity. However, experts are now pointing toward the emergence of Industry 5.0, which focuses on more advanced technologies and closer collaboration between humans and machines to create more sustainable and adaptive systems [6].. As these technologies mature, mining processes and systems will become more complex, pushing companies to prioritize digital strategies, restructure their business models, and develop new organizational frameworks to remain competitive [12, 38] . These shifts will enhance strategic planning, operational resilience, and sustainable resource management.

Modern mining operations are complex, and it involves systems that bring together a wide range of interacting components. Haul trucks, shovels, crushers, stockpiles, maintenance teams, and human operators all work within a network that changes from moment to moment. Conditions in the field are stochastic: haul distances vary, roads degrade, equipment fails unexpectedly, and operator performance shifts with experience and fatigue. In large open-pit mines, truck and shovel systems form the core of production, yet their efficiency depends on how well these diverse elements are coordinated in real time [34, 35]. The timing of maintenance, the flow of material, and the ability to respond to changing circumstances all shape the mine's overall productivity [35].

ISBN: 978-1-55195-548-3

Adding to this technical complexity are the human and contractual factors that influence everyday operations. Individual operators and contractors often pursue their own performance targets, which do not always align with the broader objectives of the mine. These conflicting priorities, combined with the inherent variability of mining environments, make straightforward analytical optimization extremely challenging. For this reason, researchers and engineers increasingly rely on simulation and behavioural modeling approaches that can account for both operational uncertainty and human decision-making [20, 27]. Such methods offer a more realistic understanding of how large-scale mining systems function under real-world conditions.

Discrete Event Simulation (DES) has been extensively applied in the mining industry to represent and analyse key operational processes such as loading, hauling, dumping, queuing, and equipment downtime [30, 33]. It provides a detailed, time-dependent depiction of system performance, allowing practitioners to conduct "what-if" analyses under uncertain and variable conditions. Nevertheless, conventional DES models often rely on deterministic or rule-based decision logic, which tends to overlook the strategic and adaptive behaviours exhibited by human operators and organisational units in real operations.

In contrast, Game Theory (GT) offers a rigorous mathematical framework for examining strategic interactions among multiple decision-makers, exploring how their cooperative or competitive choices influence collective outcomes [4, 18]. Current decision-support systems in mine planning often struggle to reflect the complexity of human behavior and the changing nature of operational processes. Traditional Discrete Event Simulation (DES) models are good at showing time-based system flows. However, they do not effectively model strategic decision-making and flexible behaviors. On the other hand, Game Theory (GT) is useful for examining strategic interactions among agents, but it overlooks operational constraints over time. This gap reduces the realism and usefulness of mine planning tools. To solve this problem, a hybrid modeling approach is proposed that combines GT and DES. This approach aims to improve the analytical depth and operational relevance of decision-support systems by capturing strategic behavior along with its practical operational outcomes.

Discrete Event Simulation (DES) in Mining Operations

Discrete Event Simulation (DES) is a commonly used modeling technique that represents complex systems as sequences of discrete, time-stamped events. Each event indicates a specific change in the state of the system, while the system stays the same between events. This method offers a practical and flexible way to show how processes develop and interact over time, especially in dynamic and interdependent settings like mining [14]. In a DES model, entities such as trucks, shovels, or production orders move through different operational stages. Resources like haul roads, maintenance crews, and equipment function under limits of availability and capacity. Events like loading, hauling, breakdowns, repairs, and dispatching are modeled to reflect real-world processes. Unlike continuous simulations, DES moves forward using a next-event time progression. This allows for precise modeling of time-dependent behaviors and random variability in mining operations [34].

1.1. Truck–Shovel Modelling and Fleet Optimization

A primary use of DES in mining is to model truck and shovel cycles and to optimize fleet size. In these models, trucks go through operational states like loading, hauling, dumping, and returning. Shovels and haul roads act as limited resources that restrict throughput. When these resources are in use, queues form. This results in delays and lower system efficiency. DES enables the simulation of random equipment breakdowns, repair times, and dispatch strategies. This helps engineers examine how different setups, like fleet size, travel time, and loading policies, affect overall productivity and cost. Notably, studies by Moradi Afrapoli et al. [22]and Fahl and Askari-Nasab [30] showed how DES can effectively model these interactions and support better decision-making in fleet planning, dispatching logic, and equipment use.

1.2. Haul Road Modelling and Network Analysis

DES is also used to simulate how haul road networks behave in mining operations. Trucks move through complex road systems that differ in grade, width, traffic density, and congestion levels. By modeling these interactions, DES helps analysts spot problem areas and evaluate solutions like adding road lanes, changing routes, or adjusting speed limits. These models offer insights into how haul road design and routing strategies impact travel times, queuing, and overall efficiency. Such simulations are crucial in large open-pit mines, where haul distances are long and traffic volumes are high [11]. Improvements to road networks based on simulation results can greatly reduce delays, cut fuel costs, and boost productivity.

1.3. Maintenance Scheduling and Equipment Downtime

Another important area where DES provides value is in maintenance scheduling and downtime analysis. Equipment failures and routine servicing are treated as separate events that temporarily take machinery out of service. This lets mining planners test different maintenance strategies, like preventive and reactive, and evaluate their effect on equipment availability and production continuity. By including data on failure rates, repair times, and service intervals, DES models can show the operational and financial effects of different maintenance policies. Torkamani and Askari-Nasab [34] Click or tap here to enter text.and Karikari and Askari-Nasab [14] have demonstrated how DES can optimize maintenance schedules to reduce disruption, balance resource use, and maintain production levels in various operational scenarios.

1.4. Advantages and Limitations of DES in Mining

DES offers several advantages in modeling mining operations. It captures the inherent variability and randomness of processes like cycle times, equipment breakdowns, and task durations. Its ability to show the dynamic interdependencies among system components, such as how queuing at one location affects utilization at another, enables detailed scenario analysis and optimization. Engineers can use DES to test different configurations before making changes, which helps reduce the risks and costs linked to physical modifications. The method also provides detailed performance metrics, like waiting times, bottleneck frequencies, and resource usage, which support strategic decision-making [30].

However, DES also has its challenges. Effective simulation depends on high-quality input data, such as equipment performance statistics, failure distributions, and travel durations. Developing, validating, and maintaining these models takes significant skill and time. Smaller operations may find it hard to justify the costs and effort involved. Additionally, DES models, like all models, depend on simplifications and assumptions. If not managed carefully, these can introduce errors or lower accuracy [11]. Despite these drawbacks, DES remains a powerful tool in modern mining, providing strong support for operational planning, production optimization, and decision-making.

Game Theory (GT) in Mining

Game Theory (GT) is a branch of applied mathematics and economics that studies how decision-makers interact when the outcome for each participant depends on the choices of others. It provides a framework for analysing competition, cooperation, and negotiation among rational agents in strategic settings [4, 8].

Key elements of Game Theory include:

- Players: These are the groups involved in the game. In mining, players may include mining companies competing for mineral rights, government regulators enforcing environmental rules, local communities seeking social benefits, or internal departments, like production and maintenance teams, with conflicting resource needs. For example, two mining companies working in nearby areas might compete in a strategic land acquisition game.

- Strategies: The possible actions or policies available to each player. Examples include producing high or low output, choosing whether to comply with regulations, or deciding when to invest in decarbonisation initiatives [21]. These are the actions or decisions that each player can take. In mining, strategies could include selecting a production schedule, choosing a processing method, negotiating royalty payments, or investing in community infrastructure. For example, a mining firm might decide between aggressive extraction to boost short-term profits or sustainable mining to keep long-term stakeholder support.
- Payoffs: The outcomes or utilities each player receives based on the combination of strategies chosen. Payoffs can represent profit, environmental impact, social welfare, regulatory penalties, or reputation effects [5]. These are the results or benefits that come from a mix of strategies chosen by the players. In mining, payoffs can be measured by profit, resource recovery, environmental compliance, or social permission to operate. For instance, a company that accepts stricter environmental standards may incur higher costs but can gain long-term access to high-quality ore deposits due to better community relations.
- Equilibrium: A condition in which no player can improve their outcome by changing strategy while others remain constant. Common forms include Nash equilibrium, Stackelberg (leader–follower) equilibrium, and cooperative versus non-cooperative structures [10, 17]. This is the point at which no player wants to change their strategy, based on what others are doing. This situation is commonly called Nash Equilibrium. In mining, equilibrium can happen when several companies agree on production limits. This helps prevent flooding the market with too much supply and keeps prices favorable for everyone involved.
- Game Structure: The characteristics that define how the game is played, such as whether it is one-time or repeated, simultaneous or sequential, involves complete or incomplete information, or allows players to cooperate and form coalitions [9]. This refers to what each player knows when making decisions. In mining games, information asymmetry often exists. For example, a junior exploration company might have private geological data when negotiating with a larger operator. Limited or imperfect information affects the risk and uncertainty connected to each strategy.

In the mining and resource extraction context, Game Theory is especially valuable because it reflects the strategic nature of interactions among multiple stakeholders. Mining firms compete in production and pricing decisions, governments impose and adjust regulations, and local communities negotiate social and environmental benefits [4]. By modelling these interactions, Game Theory helps to explain and predict how competing objectives and strategic behaviour shape overall outcomes in the sector.

1.5. Benefits and Limitations of Game Theory in Mining

Game Theory (GT) offers a useful way to examine strategic interactions in the mining sector. These interactions often involve internal and external stakeholders who influence operational decisions. In modern mining, stakeholders can include production planners, maintenance teams, regulatory bodies, contractors, and community members. Each group has its own goals but operates under common limitations. Unlike traditional optimization models that assume a single authority makes decisions, GT acknowledges that each decision-maker act on their own, which can lead to competitive behavior, conflicting incentives, or the necessity for negotiation and coordination [4, 18]. From an operational perspective, GT is helpful for understanding conflicts and collaboration within the mine. For instance, the maintenance and production departments often compete for limited equipment. One department might want to maximize uptime, while the other pushes for regular servicing to prevent future breakdowns. GT can analyze these trade-offs using non-cooperative or Stackelberg game models to find equilibrium strategies and propose aligned policies. In multi-firm operations, such as those involving shared haul roads or processing plants, GT models how different operators might compete or cooperate for shared resources, impacting congestion, delays, and productivity. Traditional scheduling models often overlook these dynamics, yet they are crucial for overall performance.

Furthermore, GT helps us understand how outside pressures such as regulatory changes or community requests impact operational choices. For example, new emissions laws or transport limits may force companies to change their dispatch strategies, redirect traffic, or adjust fleet resources. GT allows planners to forecast these adjustments as strategic responses to external factors, helping them anticipate unintended effects and design better compliance strategies [5, 9]. Nonetheless, GT models tend to be abstract and lack the time-related and random details necessary for simulating actual mine operations. They do not factor in time delays, queues, equipment failures, or resource interdependencies, which are vital in mining. This is where Discrete Event Simulation (DES) becomes important. While GT captures the basic interactions and motivations of stakeholders, DES translates these choices into time-based operational results. For instance, GT might suggest that two teams should share equipment access in a maintenance bay. A DES model can then show how this agreement affects equipment downtime, task durations, and production output across shifts.

This combination of methodologies is especially valuable in optimizing fleet dispatch. Strategic decision rules, such as competitive or cooperative dispatch, can be modeled with GT, while DES measures their effects on production cycles, wait times, and idle rates. In haulage systems where, different players use limited resources, GT aids in mapping route choices, and DES quantifies the repercussions in delays, fuel use, and systemic bottlenecks [14]. In the end, mining operations gain from this combined approach because it links strategic thinking with operational realities. GT sheds light on how individuals act when pursuing their interests or negotiating under constraints, while DES connects these actions to the actual performance of mining systems. This two-layer modeling framework improves the realism and effectiveness of decision-support tools in mine planning, fleet management, scheduling, and resource coordination.

Research Gap

Limitations of DES in Mining Operations

While Discrete Event Simulation (DES) has become a key tool in mining for modeling time-dependent operations like haulage, fleet scheduling, and maintenance, its traditional uses depend heavily on static decision rules. These rules, often based on operational guidelines like “dispatch truck when shovel is idle,” work well in predictable situations but lack flexibility when conditions are dynamic or uncertain [34]. This limits DES's ability to show adaptive decision-making, especially when human behavior or organizational strategies change due to unexpected issues like equipment failures or production delays [14]. Additionally, DES models usually view decision-makers as passive elements in the system rather than active agents. As a consequence, operational models fail to capture competition between departments, behavioral changes due to regulations, or negotiation over shared resources. These elements are common in real mining settings. This limitation reduces the model’s usefulness in complex, multi-agent scenarios that involve coordination among stakeholders, trade-offs in risk, or meeting regulatory requirements [30].

1.6. The Case for Strategic, Adaptive Agents

The lack of strategic agents, which are entities that can learn, anticipate, and adjust, is a major issue in traditional DES frameworks. In mining, these agents could be departments, contractors, or even autonomous systems that change their actions based on changing conditions and the actions of others. Unlike rule-based entities, strategic agents consider not only immediate results but also long-term effects. This allows for the simulation of negotiation, conflict, and cooperation [18]. Game Theory (GT) offers a great basis for incorporating this behavior. GT models how agents with opposing or cooperative interests make decisions that depend on each other. It shows strategic feedback loops, incentive structures, and equilibrium behavior. This enables a more detailed simulation of how operational actors respond to regulations, market signals, or resource limits. In mining, this could involve modeling how two departments compete for shared equipment or how companies react to emission pricing mechanisms [4, 21].

1.7. Integration of DES and GT: A Hybrid Modelling Opportunity

Combining DES with GT addresses the limitations of each method. DES is strong at showing time-based operational performance, including queues, downtimes, scheduling, and throughput. In contrast, GT focuses on strategic reasoning, adaptation, and decision interdependence. A hybrid DES-GT model allows researchers to simulate how strategic behavior influences, and is influenced by, the dynamics of the mining system [5, 34].

For instance, a hybrid model could simulate how departments decide between using limited equipment aggressively or conservatively. It could analyze the operational results, such as longer queue times, maintenance backlogs, or decreased throughput. The model could also study compliance behavior by showing how firms adjust operations in response to environmental regulations and how those choices impact production reliability or community relations [25].

These integrated models enable:

- Endogenous decision-making based on equilibrium analysis.
- Strategic resource competition within operational constraints.
- Policy compliance modeling that reflects both behavioral and process-level effects.
- Risk-sensitive planning, where agents adapt to system shocks or disruptions.

Ultimately, hybrid DES-GT frameworks mark an important step toward more realistic, multi-agent simulation tools in mining. They help decision-makers understand how strategy and operations evolve together, providing deeper insights into system behavior, operational trade-offs, and long-term planning.

Table 1. Summary of modelling approaches.

Modelling Approach	**Focus Area**	**Strengths**	**Limitations (with authors & years)**	**Mining Use Cases (with sources)**
Discrete Event Simulation (DES)	Operational processes (haulage, maintenance, queuing)	Models time-dependent dynamics; effective under uncertainty	Fixed rules; lacks adaptive behaviour *[14]*	Fleet dispatch, shovel–truck cycles, congestion *[34]*

Game Theory (GT)	Strategic interactions (compliance, negotiation, competition)	Captures incentive-driven, interdependent agent decisions	Ignores process-level constraints like queues, delays *[21]*	Environmental compliance, permit negotiation *4; [9]*
Hybrid DES–GT	Integrated operational + strategic decision-making	Links strategic behaviour with operational outcomes; supports adaptive agents	Requires complex integration + high-quality data *[25]*	Strategic equipment uses under constraints *5; [18]*

Integrated Framework Diagram: Linking GT and DES

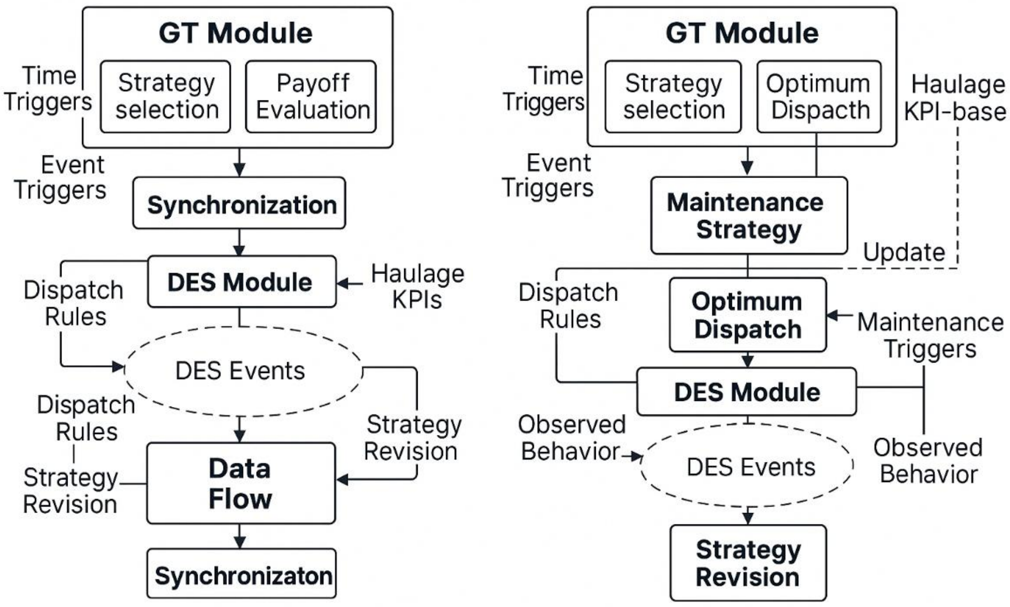

Figure 1. Integrated framework diagram: linking GT and DES for haulage and maintenance.

The two diagrams illustrate distinct levels of integration between strategic decision-making and operational simulation, making each suitable for different classes of mining problems. The first diagram represents a dispatch-focused GT–DES framework, in which game theory is applied primarily to evaluate and update dispatch strategies based on haulage-related key performance indicators (KPIs), including cycle times, shovel idle percentages, queue lengths, and truck utilization. This structure is most appropriate for operational contexts where variability arises primarily from fleet interactions such as traffic congestion, shovel assignments, or haul-road bottlenecks rather than from equipment reliability. It is typically used in short-term optimisation tasks, real-time dispatch support, fleet sizing analyses, or the assessment of alternative routing heuristics. Because maintenance is not explicitly modelled within the strategic layer, this framework is well suited to situations where equipment availability is relatively stable or where maintenance activities are governed externally, for instance by original equipment manufacturer (OEM) schedules or centralized planning protocols.

In contrast, the second diagram depicts a fully integrated production and maintenance GT–DES framework, where strategic behavior influences and is influenced by both dispatching operations and equipment health dynamics. In this configuration, the game-theoretic module governs not only operational decisions but also maintenance strategies, including the timing of preventive maintenance, inspection schedules, and condition-based triggers. This approach is more suitable for environments where equipment downtime, failure rates, and maintenance planning have a direct impact on haulage productivity and strategic interaction such as cases involving mixed ownership fleets or competition for limited maintenance resources. The discrete event simulation component explicitly models breakdowns, repair delays, and reliability-driven constraints, creating a feedback loop through which maintenance decisions affect operational KPIs and ultimately reshape equilibrium strategies. This makes the second framework particularly relevant for long-term planning, reliability-centered scheduling, life-cycle asset management, and studies examining incentive alignment between production units and maintenance teams. In summary, the first model is ideal when the primary research focus is on dispatch responsiveness, while the second is essential when addressing questions that require a joint representation of production performance and equipment reliability within a unified strategic-operational system.

1.8. Conceptual Overview

The integration begins with game theory, which defines a set of agents, their available strategies, and the payoffs associated with different decisions. These strategies reflect real-world operational decisions, such as how trucks choose loading points or how maintenance crews schedule interventions. Once defined, these strategies are implemented in a DES model that simulates the system's stochastic and time-based behaviours [37].

Simulation outcomes are analysed to determine whether the current strategies lead to system inefficiencies (e.g., idle assets, long queues). If suboptimal patterns emerge, the incentive layer adjusts the rules or payoffs, guiding the system toward better equilibria a process rooted in mechanism design [16]. This creates a feedback loop: GT → DES → Incentive Design → GT, evolving the system iteratively.

1.9. Layers of Integration

Agents consisting of trucks, shovels, maintenance, and management are modelled as players in a game. Each is assigned a strategy space that defines their decision options [24]. For example, trucks may select between queues, and maintenance teams may choose between preventive or reactive tasks.

1.9.1. Payoff Modeling

Each agent is assigned a payoff function based on operational goals:
A payoff function combines key operational KPIs that matter to each agent.
It converts simulation outputs (from DES) into a numerical utility value reflecting how well a strategy performs.

This is the general structure used to build payoff functions in a GT–DES mining framework.

$$(\quad)$$

Where:

Ui = Payoff (utility) of agent is the numerical score showing how good the agent's chosen strategy is; the higher the value, the better the outcome for that agent.

`∑w·Performance KPIs:` This is the reward part of the payoff.

1. w = weight

- A weight between 0 and 1

- Determines how important a given KPI is to the agent
- Example: trucks may care more about tonnage than fuel cost, so tonnage has a higher w

2. Performance KPIs

These come from the DES simulation and represent positive outcomes, for example:

- T: hauled tonnage
- Us: shovel utilization
- R: reliability
- P: production / throughput

The agent receives reward for good KPIs.

$\sum\lambda\cdot$ **Penalties:** This is the penalty part of the payoff.

3. Λ = Penalty weights

- Indicate how strongly an agent dislikes a negative outcome
- Example: a maintenance agent may place a high penalty on breakdowns

4. Penalties

Negative indicators from DES, such as:

- Q: queue time
- I: idle time
- BD: breakdown duration
- C: cost
- E: emissions

This formula can be applied to these:

a) Trucks: Maximize tonnage while minimizing idle/queue time, etc.

$$U_{Truck} = w_1 \frac{T}{T_{max}} - \lambda_1 \frac{Q}{Q_{max}} - \lambda_2 \frac{I}{I_{max}} - \lambda_2 \frac{C_f}{C_{f\,max}} - \lambda_4 \frac{B}{B_{max}} \tag{2}$$

Where:

Typical DES outputs needed:

- T = total hauled tonnage
- Q = average queue time
- I = idle time
- C_f = fuel consumption or cost
- B = breakdown count or duration

Shovels: Maximize utilization, reduce wait time, etc.

$$U_{Shovel} = w_1 U_s - \lambda_1 \frac{W}{W_{max}} - \lambda_2 \frac{D_s}{D_{s_{max}}} - \lambda_3 \frac{\mathrm{L}}{L_{max}} \tag{3}$$

Where:

- Us = shovel utilization

- W = truck waiting time at the shovel
- Ds = shovel downtime
- L = loading cycle deviations

Maintenance: Minimize downtime, optimize intervention timing, etc.

$$U_{maint} = w_1 R - \lambda_1 \frac{BD}{BD_{max}} - \lambda_2 F_r - \left(\lambda_3 \middle| F_p\right) - F_{pout} (4)$$

Where

- BD = breakdown duration
- Fp = preventive maintenance frequency
- Fr= reactive maintenance events
- R = reliability index (0–1)

b) Management: Balance throughput and cost. These payoff models influence strategy selection and are foundational to mechanism design [26].

$$U_{mgmt} = w_1 \frac{P}{P_{target}} - \lambda_1 \frac{C}{C_{max}} - \lambda_2 \frac{E}{E_{limit}} + w_2 R + w_3 \theta (5)$$

Where:

- P = production/throughput
- C = operating cost
- E = emissions or regulatory violations
- R = system reliability
- θ = strategy compliance level

1.9.2. Simulation Embedding

Strategies from GT are translated into behaviour rules embedded in DES. The simulation then reproduces real-time operations, resource allocation, queues, and breakdowns, generating data on throughput, delays, and utilization [3, 37]. These operational outcomes map directly to agent payoffs.

1.10. Incentive/Mechanism-Design Layer

Using feedback from simulation results, this layer adjusts the game environment modifying payoffs, adding penalties, or incentivizing behaviors [16]. This ensures local agent decisions lead to system-optimal equilibria. The updated rules are then reintroduced into the GT model for a new simulation cycle, refining the outcome iteratively [16].

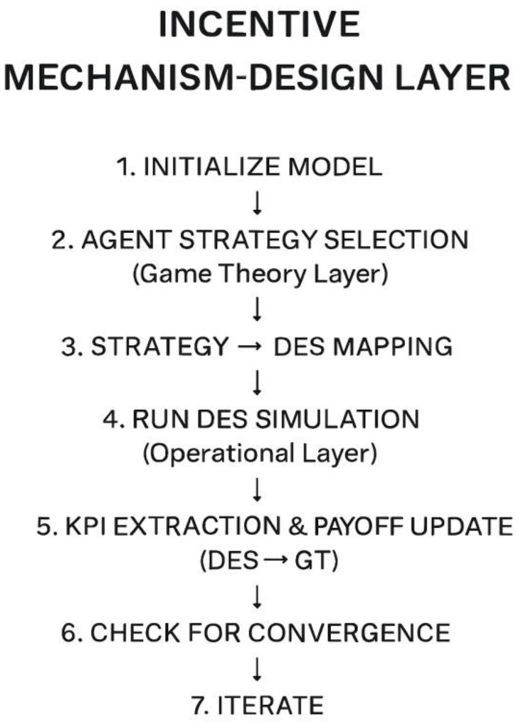

Figure 5.2. Incentive mechanism design layer.

1.10.1. Practical Considerations

To implement this framework, several practical elements must be addressed:

- Input Data: Accurate operational logs and time-motion data are necessary for both payoff modelling and simulation calibration. To implement this framework, several practical elements must be addressed: High-quality operational data is fundamental to the effective application of the GT–DES framework in mining, as both payoff modelling and simulation calibration rely on realistic representations of site-specific behavior. Mining operations routinely generate detailed datasets, including haul cycle logs, time-motion studies, equipment health records, breakdown histories, and maintenance schedules, which serve as the foundation for parameterizing the discrete event simulation (DES) model. Calibration follows a structured, data-driven approach in which operational parameters such as truck travel times, shovel loading durations, dumping times, congestion delays, and equipment failure distributions are statistically fitted to historical data.
- Calibration & Validation: DES parameters must be tuned to reflect reality and validated against historical performance. These parameters are progressively refined through iterative comparisons between simulated outputs and observed key performance indicators (KPIs), including cycle times, equipment utilisation, queue lengths, and shift production. The validation phase then assesses whether the calibrated model can reliably reproduce system behaviour under independent operational conditions. This is achieved through expert evaluation by dispatchers, fleet controllers, and maintenance personnel, as well as statistical validation using metrics such as root mean square error (RMSE), mean absolute percentage error (MAPE), or confidence-interval analysis, to ensure close alignment between simulated and historical KPIs [3].

- Computational Cost: Iterative loops with complex strategy spaces can become resource-intensive, requiring optimization for scalability Beyond calibration and validation, two additional factors affect the robustness of GT–DES integration in mining applications. The first is computational cost, which can become substantial due to the iterative nature of strategy evaluation, particularly when exploring large decision spaces involving dispatch policies, maintenance scheduling, or equipment allocation. High-fidelity simulations incorporating detailed haul road layouts and complex interactions between loading and hauling units may require advanced methods such as surrogate modelling, optimisation algorithms, or parallel computing to maintain feasibility. The second consideration is the framework's transferability.
- Generalizability: While specifically designed for mining operations, the layered structure that combines strategic decision-making with stochastic operational dynamics is also applicable to other resource-intensive industries. Systems such as mineral processing facilities, bulk material logistics networks, and energy infrastructure reliant on equipment reliability and material flows could benefit from similar integration principles. Nevertheless, the core advantage of the framework lies in its ability to capture the intricate relationship between strategic decisions and operational variability in mining, where fleet interactions, resource competition, and dynamic system conditions critically shape production outcomes.By bridging strategic reasoning (GT) and operational execution (DES), this framework allows for data-driven mechanism design in complex, agent-driven systems. It provides a structured path from modelling agent strategies to simulating and optimizing system-wide performance through iterative incentive refinement [24].

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2. Case Domains & Illustrative Examples

The integration of Game Theory (GT) and Discrete Event Simulation (DES) can be illustrated across several key operational domains. Each example demonstrates how DES captures system dynamics, while GT introduces strategic agent behavior. Together, they form a powerful modeling framework for decision-making in complex, multi-agent environments.

2.1. Truck-Shovel System

The truck-shovel system is a cornerstone of surface mining operations, governing the flow of material from extraction to dumping points.

- DES Role: DES is traditionally used to model truck cycle times, shovel loading durations, queue lengths, and system throughput. It captures operational variability such as travel delays, equipment failures, and dispatch logic [28].
  GT Layer: Game Theory adds a behavioural layer by representing trucks and shovels as rational agents. Trucks compete for shovel access, while shovels may prioritize certain trucks to maximize utilization. This interaction can be modeled as a non-cooperative queue selection game, where each truck selects the shortest expected queue to minimize waiting time [3].
- Integration Value: Integrating GT with DES allows simulation of decentralized decision-making and coordination dynamics, providing insights into how dispatch rules or incentive

structures affect equilibrium behaviour and productivity. It enables exploration of cooperative versus competitive equilibria and the effect of information sharing on operational efficiency [24]. The DES simulation returns key performance indicators such as cycle time, utilisation, queue length, downtime, and production, which are then fed back into agent payoff functions. These KPIs enable each agent to evaluate how alternative strategies, dispatch rules, or incentive structures influence operational outcomes and equilibrium behaviour. Through this iterative loop, the integration reveals how decentralized decision-making and coordination mechanisms shape productivity, stability, and system-wide efficiency in mining operations.

2.2. Maintenance Scheduling and Fleet Availability

In mining and industrial fleet management, maintenance scheduling must balance equipment reliability with continuous production needs.

- DES Role: DES simulates breakdown events, repair queue lengths, maintenance resource allocation, and their impacts on system availability and output [2]. It enables testing of different maintenance policies under stochastic operational conditions.
- GT Layer: GT captures the strategic trade-off between maintenance teams (who seek preventive interventions) and production managers (who aim for maximal uptime). These actors can be modelled as players in a dynamic game where short-term production gain competes with long-term reliability [37].
- Integration Value: A GT–DES approach enables incentive-compatible maintenance planning by allowing simulations to explore how various payoff structures, such as reliability bonuses, downtime penalties, or rewards for priority-based interventions, influence agent behaviour and encourage more cooperative equilibria. By embedding these incentives directly into the agents' payoff functions and assessing their effects through discrete event simulation (DES), the framework ensures that maintenance decisions are aligned with production objectives rather than operating in conflict with them. This integration helps reveal mechanisms that harmonise departmental goals, reduce strategic opportunism, and limit disruptions across the system. As a result, the approach facilitates the joint optimisation of short-term productivity and long-term equipment reliability within a decision environment driven by equilibrium dynamics [16].

2.3. Haul Road Network and Assignment

Haul road network efficiency critically influences fuel use, travel times, and cycle consistency in open-pit and large-scale logistics operations.

- DES Role: DES models simulate truck movement, road congestion, queuing at intersections, and dynamic travel times under different loading and dispatching scenarios [37]. Such simulations identify bottlenecks, test infrastructure layouts, and assess network capacity.
- GT Layer: GT can be applied to model route choice and resource allocation as congestion or coordination games. Each truck acts strategically, selecting routes that minimize expected travel time while anticipating other agents' choices [13, 16].
- Integration Value: The integrated GT–DES model offers a robust platform for evaluating decentralized routing incentives, including congestion pricing, priority access schemes, and

adaptive route-switching policies, aimed at guiding agents toward traffic patterns that enhance overall network performance. By connecting individual routing choices to network-level outcomes derived from discrete event simulation (DES), the framework supports system-wide planning that aligns local decision-making with global objectives. This alignment ensures that agent-level optimizations contribute to improved haulage efficiency and production stability across the mining operation [3].

Challenges, Methodological Issues & Best Practices

The integration of Game Theory (GT) and Discrete Event Simulation (DES) offers a rigorous framework for capturing the interplay between strategic decision-making and stochastic operational processes in mining systems. While this approach enhances the ability to model complex, interdependent behaviours, it also introduces several analytical challenges. These challenges primarily concern the accuracy of behavioural representations, the precision of operational modelling, and the conditions required for system-level convergence. The following subsections examine the key technical factors that affect the reliability and practical relevance of GT–DES models, and they identify the conditions under which such integration yields valid and operationally meaningful insights.

2.4. Data Requirements

The success of a GT-DES framework depends fundamentally on the quality and completeness of data for both components.

- The effectiveness of a GT–DES framework depends not only on the availability of data but also on the alignment between behavioural and operational datasets, as any inconsistency can lead to biased equilibrium outcomes. Discrete event simulation (DES) requires accurate inputs such as cycle time distributions, queue dynamics, failure rates, and maintenance records to replicate realistic haulage and loading behaviour [2, 28].

- Game theory, on the other hand, relies on empirically derived representations of agent objectives, strategy spaces, and decision sensitivities, often informed by field data or expert judgement [16]. When behavioural parameters such as cost sensitivity, risk aversion, or perceived waiting penalties are mis-specified, the resulting equilibrium strategies may be mathematically consistent but behaviourally unrealistic. This creates a risk of model divergence, where strategic predictions are optimal for a DES environment that is not properly calibrated. Such misalignment disrupts the necessary coherence between strategic and operational layers, undermining the reliability and interpretability of the equilibrium outcomes.

A lack of consistent or integrated data can lead to model divergence between the behavioural (GT) and operational (DES) layers.

2.5. Verification and Validation

Ensuring that both the simulation model and the game-theoretic assumptions are credible is essential.

- Validation in a GT–DES system presents significant analytical complexity, as it involves confirming not only that the discrete event simulation (DES) accurately reproduces historical operational behaviour but also that game-theoretic (GT) equilibria remain valid when implemented within the DES environment. Traditional DES validation typically involves comparing simulated key performance indicators (KPIs) such as idle time, queue lengths, and throughput with historical data to ensure the model reflects operational realities [31].

- Verification ensures that the model is implemented correctly and that GT assumptions such as rational behaviour or payoff consistency are logically coherent and computationally accurate [16].
- Cross-validation between GT-predicted equilibria and DES outcomes enhances credibility, helping confirm that theoretical equilibria correspond to practical system performance. A key requirement is cross-validation, where the equilibrium strategies derived from the GT model are executed within the DES framework to assess whether they produce stable, realistic outcomes. This step ensures that the strategic solutions do not introduce unintended operational consequences such as congestion, instability, or degraded performance. Ultimately, an equilibrium is only meaningful if it is both theoretically sound and operationally viable.

2.6. Computational and Modelling Complexity

- The integration of Game Theory (GT) and Discrete Event Simulation (DES) introduces nonlinear feedback loops, where strategies selected within the GT layer influence DES outcomes, which in turn affect payoff structures and trigger subsequent strategy updates. This iterative feedback architecture increases both the computational demands of the system and the risk of non-convergence. The presence of high-dimensional strategy spaces, stochastic variability in DES outputs, and repeated game dynamics can result in oscillatory or chaotic behaviour, where equilibrium either takes an extended time to emerge or fails to stabilize entirely [24].

From an analytical standpoint, this complexity undermines the reliability of best-response dynamics. When DES outputs exhibit high variance, payoff gradients become noisy and imprecise, leading to unstable strategy adjustments or convergence to suboptimal solutions. As a result, simplification techniques such as surrogate modelling, reduced-state abstractions, and modular decomposition are not merely computational aids but essential components for ensuring tractability and preserving equilibrium stability within the integrated GT–DES framework

2.7. Behavioural Realism

A central analytical challenge in applying classical game theory (GT) to mining operations stems from GT's reliance on assumptions of perfect rationality, complete information, and stable preferences conditions that rarely hold in real operational environments. Mining departments and equipment operators typically exhibit bounded rationality, make decisions using heuristics shaped by experience, and adapt their behaviour incrementally in response to local constraints such as congestion, delays, or shifting production pressures [32]. When GT-based models ignore these behavioural characteristics, the resulting equilibria may be mathematically consistent yet behaviourally invalid, leading to predictions that diverge from actual operator responses under uncertainty.

To mitigate this gap, integrating behavioural modelling approaches such as evolutionary game dynamics, reinforcement learning, or agent-based decision rules provides a more realistic representation of how strategies evolve through adaptation rather than strict optimization ([3]. Within such a framework, discrete event simulation (DES) serves as an operational testbed where the impacts of adaptive or heuristic-driven decision-making can be evaluated in terms of system stability, queue formation, equipment coordination, and overall production flow. The analytical insight is that behavioural misalignment, rather than mathematical formulation errors, is often the dominant factor limiting the accuracy and practical relevance of equilibrium predictions in

2.8. Expert Buy-In and Organizational Implementation

- A GT–DES system may be technically sound yet fail in practical application if its mechanisms conflict with existing institutional norms or operational constraints. Incentive structures developed through mathematical optimization, such as strict penalties for equipment downtime or highly dynamic routing protocols may prove unworkable in environments governed by union agreements, safety standards, or managerial discretion [37]. This creates an analytical risk of implementation infeasibility, where a theoretically optimal equilibrium cannot be applied in practice.

To mitigate this risk, it is essential to involve domain experts in the modelling process to ensure that payoff structures, behavioural assumptions, and operational constraints align with real-world practices and organizational priorities [2]. In addition, clear reporting and visualisation of causal relationships between strategies and outcomes enhance interpretability, making it more likely that decision-makers will adopt model recommendations. Ultimately, the practical validity of a GT–DES model depends not only on its analytical robustness but also on its compatibility with the institutional and operational context in which it is deployed.

2.9. Best Practices for GT-DES Integration

1. Best practices function as analytical safeguards that help prevent structural failure modes within GT–DES frameworks. One critical practice is incremental integration, which involves validating the game-theoretic and simulation components independently before combining them, thereby reducing the risk of feedback instability. Grounding both layers in empirical data through careful calibration helps minimise divergence between predicted and observed behaviour, improving model accuracy and operational relevance [28]. Sensitivity analysis plays a key role in identifying parameters that exert a disproportionate influence on equilibrium outcomes, thereby informing model refinement and enhancing robustness [2]. Robustness checking further ensures that equilibrium strategies remain stable under varying conditions and uncertainties, avoiding overdependence on fragile or overly specific solutions [31]. Additionally, transparent reporting of model assumptions and causal mechanisms supports auditability, reinforces credibility, and enhances reproducibility. Together, these best practices strengthen model reliability, increase strategic relevance, and improve the likelihood that GT–DES insights will inform actionable and sustainable decisions in mining operations.

3. Conclusions

The integration of Game Theory (GT) and Discrete Event Simulation (DES) presents promising avenues for advancing both methodological development and operational decision-making in mining systems. While prior studies have explored these methods independently, the research gap lies in establishing a unified framework capable of linking strategic behaviour with stochastic operational processes at the equipment-interaction level. The framework proposed in this study addresses this gap by formalizing, the mathematical structure of agent payoffs, the data-exchange cycle between GT and DES, and an operational-level integration methodology where dispatching, routing, and maintenance strategies are iteratively evaluated through simulation. This contribution goes beyond reviewing prior work by offering a structured architecture and decision loop that can be implemented, calibrated, and validated in real mining environments.

Future research should expand this foundation by operationalizing payoff calibration using empirical behavioural data, incorporating adaptive learning mechanisms into agent strategy updates, and formalizing equilibrium conditions under stochastic variability. Methodological extensions may include hybrid GT–DES–agent-based models, real-time digital twins with embedded strategic layers, and evolutionary game formulations to capture long-term adaptation among mining fleets. Such developments will enable more rigorous characterization of strategic interactions and support the transition toward autonomy and decentralized coordination.

Application-wise, the proposed framework opens the door for quantitative evaluation of incentive-compatible dispatching policies, cooperative versus competitive fleet interactions, and owner–contractor negotiation structures. It also provides a foundation for designing mechanisms that align production targets with sustainability objectives such as energy efficiency, equipment health, and emission reduction. By moving beyond a descriptive comparison of DES and GT, the current work establishes an implementable modelling architecture that links behavioural strategy selection with operational performance. In doing so, it provides a research-ready platform for developing actionable, mathematically grounded decision-support tools suited to the increasing complexity and digitization of modern mining operations.

4. References

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