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Discrete-event simulation of truck–excavator systems in surface mining using a finite-source closed-loop queuing model

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ABSTRACT

Truck-excavator interaction in surface mining is often modeled as finite-source, closed-loop queuing systems. An optimization-based approach is typically used, assuming deterministic and homogeneous fleet configurations. This paper aims to contribute to the current literature by implementing a simulation-based approach, discrete-event simulation (DES), to analyze a finite-source closed-loop queuing model in a surface mining operation. The case study used was coal overburden removal activities, which operate under a first-come, first-served discipline, and loop through four phases: loading, hauling, dumping, and returning. Under the current fleet configuration, the overburden removal activity is experiencing a 19,17% production shortfall and a match factor (MF) of 0.74. An MF below 1 indicates an under-truck system, where the excavator often idles while waiting for the trucks to arrive. Three scenarios were tested using the validated DES model: (1) the as-is scenario with four trucks and one excavator, (2) variations of truck quantity, and (3) a route improvement scenario to reduce travel time. Simulation results indicate that adding five trucks yields the highest productivity (533.86 BCM/hour), utilization (92.48%), and MF (0.91), while the route improvement scenario achieved nearly comparable performance (513.94 BCM/hour, 88.86% utilization, MF = 0.88) with lower resource. Although the current case study operates under a homogeneous fleet with a single excavator, this study also tests the DES model under heterogeneous fleet configurations and a multi-server setup involving two excavators. These findings highlight the DES capability in modeling and analyzing a queuing system under a finite-source closed-loop, both for homogeneous and heterogeneous fleet configurations.

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1. INTRODUCTION

Repetitive cycles, high work volumes, and the use of expensive heavy equipment can characterize surface mining operations. The mining sector is one of the most expensive and complex industries [1], but it plays a strategic role in generating value for other economic sectors in a country [2]. In terms of cost, loading and hauling activities are among the most cost-intensive components of surface mining, contributing over 50% to 60% of total operating costs [3], [4]. Furthermore, in surface mining, truck-excavator systems are widely used equipment combinations, where both performances are highly interdependent [5]. Depending on ore grade, trucks transport material from the pit to either a processing plant or a waste dump [3]. In practice, the success of this system depends on the coordinated work between the excavator that loads the material and the truck that transports it to its destination.

Several factors influence the performance of truck–shovel systems during loading. Manyele [6] found that loading location, excavator type, and truck–shovel pairing significantly impact loading productivity in open-pit mining operations. Researchers have given the truck-shovel problem significant attention due to its critical role in achieving efficient surface mining operations. Previous research has utilized an optimization and simulation approach to determine the optimum number of truck-excavator configurations. The optimization approach usually follows the queuing theory method under a single channel [4] or a multi-channel [3]. As an optimization approach, the studies assume deterministic parameter values and homogeneous fleet configurations. Furthermore, previous research has used simulation-based approaches, such as Monte Carlo and discrete-event simulation, to address gaps in deterministic assumptions and homogeneous equipment configurations. Sembakutti *et al* [7] used a Monte Carlo simulation to model uncertainty in truck availability and shovel performance. In addition, Baafi & Zeng [8] applied discrete-event simulation (DES) to evaluate surface mining performance under uncertain parameters and heterogeneous fleet configurations.

The trucks-shovel system can be classified as a finite-source closed-loop queuing model [9]. The number of customers and trucks remains constant (finite source), there are no entries or exits from outside the system (closed), and the trucks cycle through a defined stage (loop). Mathematically, Matsimbe [4] modelled this problem as M/M/1:FCFS/K/K, while Elijah *et al.* [3] modeled it as M/M/S:FCFS/K/K, depending on the assumption of the number of servers (excavators). Despite this, both models and all mathematical models assumed that the fleets, trucks, and excavators have deterministic and identical performance (homogeneous).

Relevant to the above background, this study aims to provide recommendations for the imbalance in the case study, an overburden activity in the coal mining industry. The case study currently utilises four trucks and one excavator system. Under this configuration, a 19.17% shortfall in overburden removal was observed in the last year of operation. Therefore, to determine the best configuration for the truck-excavator system, this study uses discrete-event simulation, which can account for not only the system's stochastic characteristics but also the heterogeneous performance of the truck-excavator.

To determine the best recommendation among the tested scenarios, this study uses general queue system performance metrics, such as waiting time and utilization rate, and a specific indicator widely used in the truck-excavator system, the match factor (MF). MF is introduced by Morgan & Peterson [10], and conceptually, it is the ratio between shovel productivity and truck productivity. MF ≈ 1.0 suggests an ideal match where neither the shovel nor the trucks are idle, waiting for the other. The MF in the case study under the current configuration is 0,74, indicating that the system is under-trucked, meaning that the excavator experiences idle time while waiting for trucks to return. Apart from providing recommendations for the current problem in the case study, the DES's capability to give recommendations under a heterogeneous fleet configuration was also tested in this study. Matsimbe [4] stated that future research should explore heterogeneous equipment configurations to enhance realism.

2. RELATED WORK

2.1. Optimization-based approach

MF is commonly used as an indicator in mining operations by comparing truck cycle time and excavator service time. Taufik *et al*. [11] used MF to evaluate system efficiency that incorporates trucks and excavators. Furthermore, to enhance planning accuracy, researchers have also integrated MF into optimization-based models. Isnafitri *et al.* [12] developed a Mixed Integer Linear Programming (MILP) model to determine optimal truck–excavator allocation while minimizing investment and transportation costs. Fikri & Gusman [13] utilized MF and a queuing model to evaluate production shortages in overburden removal and found that imbalanced fleet sizing (truck-excavator) is the main issue. In this paper, MF was used to validate the balance of mining equipment. In addition, Elijah *et al.* [3] applied a multichannel queuing model (M/M/S: FCFS/K/K) to determine ideal fleet size and minimize idle time. Similarly, Matsimbe [4] applied an optimization-based queuing model using the M/M/1:FCFS/K/K structure, where the shovel is modeled as a single server and K denotes the total truck population. Moreover, Palayukan *et al*. [14] applied an optimization model under a single-channel system and MF to identify the optimal number of trucks. The study demonstrated that adding one truck increases MF from 0.79 to 0.99, indicating better synchronization of fleet configuration.

Previous researchers have also employed advanced modeling approaches. Kappas & Yegulalp [9] used a Markovian queuing network to analyze the truck-excavator system in a pit mining operation. Furthermore, Permana *et al*. [15] performed a comparative analysis of three different approaches in the study of truck-excavator configurations: MF, optimization, and linear programming.

Although the queuing problem is typically analyzed using a classical optimization model, a heuristic approach may be employed, especially as complexity increases due to the heterogeneity of the configuration. Rokbani *et al.* [16] analyze the implementation of bi-heuristics in a combinatorial context, such as the traveling salesman problem. In addition, Khalaf *et al*. [17] employed a particle swarm optimization (PSO) to estimate the cost and duration of

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Table 1. Previous research on the truck-excavator system

Author	Year	Method	Channel	Source Type
Fikri & Gusman [13]	2024	Optimization	Single	Homogeneous
Taufiq *et al*. [11]	2024	Optimization	Single	Homogeneous
Isnafitri *et al*. [12]	2021	Optimization	Single	Homogeneous
Elijah *et al*. [3]	2021	Optimization	Multi	Homogeneous
Matsimbe [4]	2020	Optimization	Single	Heterogeneous
Sembakutti *et al*. [7]	2017	Simulation	Single	Homogeneous
Baafi & Zeng [8]	2019	Simulation	Multi	Homogeneous
Ozdemir & Kumral [5]	2019	Simulation + Optimization	Multi	Heterogeneus
Kappas & Yegulalp [9]	1991	Optimization	Single	Homogeneous
Ghaziania *et al*. [18]	2021	Simulation	Single	Homogeneous
Permana *et al*. [15]	2020	Optimization	Single	Homogeneous
Palayukan *et al*. [14]	2019	Optimization	Single	Homogeneous
Setiawan *et al*.	-	Simulation	Single, Multi	Homogeneous, heterogeneous

a construction project. This study suggests the potential to integrate a heuristic into the queuing problem, particularly as complexity increases.

2.2. Simulation-based approaches

The optimization-based model is suitable under specific assumptions, including a particular arrival-service distribution, deterministic assumptions about activities, and homogeneous fleet parameters. Simulation techniques have become increasingly relevant for overcoming the limitations of optimization-based models. Sembakutti *et al.* [7] demonstrated that a deterministic approach may not account for operational uncertainty and recommended a Monte Carlo simulation to model variability in truck availability, queuing, and shovel performance.

In addition, for wider applications of simulation in a similar context, Turan *et al.* [19] utilized a risk-based simulation model for maintenance and spare parts inventory simulation. Similarly, Asa [20] applied a Monte Carlo simulation to evaluate cost variability and investment risk in open-pit equipment planning, emphasizing that equipment selection should refer to quantitative analysis rather than intuition.

Among simulation techniques, discrete-event simulation (DES) is widely used for analyzing mining systems. Baafi & Zeng [8] developed a DES to assess truck–shovel performance using a wide range of indicators, including waiting time, cycle time, utilization, production output, and MF. Torkamani & Nasab [21] also employed discrete-event simulation to model mining operations but incorporated heterogeneous truck and shovel types. Odzemir & Mustafa [5] applied a simulation-based optimization approach that combines discrete-event simulation (DES) with linear programming (LP). Both studies, although using different modelling approaches, utilise MF as one of the primary instruments for evaluating performance. Table 1 provides an overview of previous research on analyzing the truck-excavator system. Most research focuses on single-channel and homogeneous fleet performance, with minor research, such as Ozdemir & Mustafa [5], evaluating multi-channel and heterogeneous fleet performance. Therefore, in this study, both analyses – homogeneous and heterogeneous, as well as single-channel and multi-channel - will be evaluated using a simulation technique. Furthermore, this study also considers SimPy modeling, whereas previous studies have predominantly focused on commercial simulation software packages.

3. RESEARCH METHODS

This paper presents a case study of the truck-excavator system in open-pit mining. The queuing model is categorized as a finite-source closed-loop queuing structure, where a fixed population of trucks repeatedly cycles through the system [9]. The DES is modelled using the SimPy library in Python, which provides a process-oriented simulation environment for modeling entities, event handling, and resource contention.

3.1. Queue system structure

Most papers divide the queuing system in open-pit mining into four activities: loading, traveling with the load, dumping, and returning empty [22], with only one paper adding one more activity: repair/maintenance [9]. In this study, four main activities were considered in the truck-excavator system in surface mining. Fig. 1 depicts the closed-loop queuing system structure comprising three facilities: the overburden area (excavator point), the haul road, and the dumping site

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(disposal). Truck flow is depicted as a solid line moving from the overburden area to the dumping site and back to the overburden area. In addition, the material flow is shown in a dashed line, from the overburden area to the dumping site.

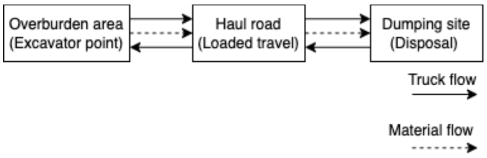

Fig. 1. Operating structure of truck-excavator system

3.2. Queue system modelling

The DES model is developed using SimPy, a Python-based process-based DES library. SimPy enables detailed modeling of time, resources, and process logic. Zinoviev [23] provides a step-by-step guide to DES modeling using SimPy. Fig. 2 illustrates the pseudocode of DES SimPy used in this paper. The pseudocode illustrates a single-server queueing system with a homogeneous fleet configuration, where excavators serve as servers and trucks as customers. Each truck is modeled as a SimPy process, while the excavator is depicted as a shared SimPy resource with limited capacity. Each truck cycles through operational phases using yield statements that pause the process for the required activity time. The simulation runs from time 0 to a predefined duration.

The time spent on activities, including waiting, loading, travel, dumping, and return, was calculated through direct observation and historical data. Table 2 contains information on the data collection of loading time. After the data was collected, a distribution test was conducted and used as input in SimPy.

Table 2. Collected data for Loading Time

No	Digging	Swing Load	Passing	EmptyS wing	Total Time
1	19,77	18,58	7,23	14,7	60,28
2	19,51	18,46	6,45	15,61	60,03
3	20,26	17,54	7,56	16,29	61,65
…	…	…	…	…	…
49	19,89	17,05	6,52	16,27	59,73
50	19,95	18,07	7,19	16,03	61,24

Furthermore, the output of the simulation was calculated using the following formula:

a. Truck cycle time

Truck cycle time (T_{cycle}) is calculated by summing the total time of truck operation in one loop. The durations of each operation are derived from field historical data.

$$T_{cycle} = T_1 + T_2 + T_3 + T_4 \quad (1)$$

where T_1: loading time at the excavator (including queueing, if any); T_2: travel time from loading area to dumping site; T_3: dumping time; and T_4: return time from the dumping site to the loading area.

```
Input:
  N = Number of trucks
  sim_duration = Total simulation time
  excavator = SimPy Resource (capacity = 1, representing a single-server queue)
For each truck i in 1 to N do:
  Start Process TruckCycle(i)
Process TruckCycle(truck_id):
  # Repeat until the simulation clock reaches the simulation duration
  While simulation clock < sim_duration do:
    cycle_start ← current simulation time
    # Request access to excavator
    Request excavator
    Wait until excavator is available
    Record waiting_time
    # Loading phase
    Determine loading_time
    Wait for loading_time
    Release excavator
    # Travel loaded
    Determine travel_time
    Wait for travel_time
    # Dumping phase
    Determine dumping_time
    Wait for dumping_time
    # Return empty
    Determine return_time
    Wait for return_time
    cycle_end ← current simulation time
    Record cycle_time ← cycle_end − cycle_start
End Process
Output:
  - Total number of completed cycles
  - Average truck waiting time
  - Average cycle time
  - Excavator utilization
  - Productivity
  - Match Factor (MF)
```

Fig. 2. Pseudocode for single channel – homogeneous fleet

b. Excavator utilization

Excavator utilization (U_e) is calculated as the ratio of cumulative excavator utilization to simulation time. Higher utilization indicates better synchronization, while a lower utilization indicates idle periods due to insufficient truck capacity.

$$U_e = \frac{T_{active}}{T_{sim}} \quad (2)$$

where U_e: excavator utilization (expressed as a proportion or %); T_{active}: cumulative time the excavator is actively loading trucks; and T_{sim}: total simulation time.

c. Productivity Rate

The productivity (P) is calculated as the ratio between the total volume moved during the simulation and the total simulation time.

$$P = \frac{N \times V}{T_{sim}} \quad (3)$$

where P: productivity rate (in BCM/hour); N: total number of truck cycles completed during the simulation; V: volume moved per truck per cycle

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(BCM); and T_{sim}: the simulation time in hours (hours)

d. Match Factor (MF)

MF represents the balance between loading and hauling capacities and is commonly used to determine the optimal number of trucks that a single shovel can efficiently serve. Conceptually, MF is calculated as the ratio between shovel productivity and truck productivity. MF ≈ 1.0 suggests an ideal match where neither the shovel nor the trucks are idle, waiting for the other. The MF formula is divided into homogeneous and heterogeneous fleets. For homogeneous fleets, where all trucks and shovels are identical in capacity and performance, the MF formula was introduced by Sembakutti *et al.* [7] and is expressed as:

$$MF = \frac{(number\ of\ trucks) \times (loading\ time)}{(number\ of\ loaders) \times (cycle\ time)} \tag{4}$$

Furthermore, in heterogeneous fleets, where truck or shovel types vary, Burt & Caccetta [24] proposed a more generalized formulation that accounts for differing cycle and service times across fleet elements:

$$MF = \frac{(number\ of\ trucks)}{\left(\sum_j \frac{(number\ of\ loaders)}{loading\ time_j}\right) \times \left(\sum_i (trucks_1 \times cycle\ time_i\right)} \tag{5}$$

4. RESULTS AND DISCUSSION

4.1. Case study of the truck-excavator system

The case study was obtained from coal mining in Kalimantan. Table 3 depicts the existing system configuration of trucks and excavators in surface mining. The simulation results in this study were validated using two approaches: structural validation and data comparison. The structural validation was conducted to ensure that the conceptual model, as shown in Fig. 3, Fig. 4, and Fig. 5, accurately represents the real world.

Table 3. Existing System Configuration

Parameter	Value
Bucket loaded capacity	3.2 m^3
Bucket fill factor	0.83
Dump truck capacity	900 m
Average speed of a loaded truck	170 m / minute
Average speed of an empty truck	220 m / minute
Dumping and standby time	4.5 minutes
Waiting time to start loading	3.2 minutes
Bucket per truck	12

4.2. Scenario overview

4.2.1. *As-is scenario*

In the *as-is* scenario, DES was run using a configuration of 4 trucks and one excavator. Fig. 3 illustrates the *as-is* queueing structure, while Table 4 presents the performance of the *as-is* simulation. The truck waiting time was 0.31 minutes, while the excavator utilization reached 75.12%. The average cycle time was 17.39 minutes, representing the total time required for a truck to complete one full cycle – loading, hauling, dumping, and returning. The MF of the *as-is* was 0.74, indicating a moderate match between truck cycle time and excavator loading time. Under the *as-is* condition, the excavator idles while waiting for the truck to return, or the system does not fully utilize the excavator's capacity. To address the system's sub-optimality, improvements can be made by either adding trucks or reducing travel time.

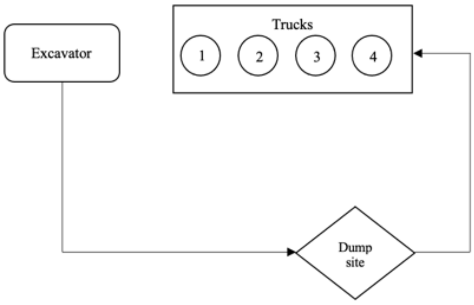

Fig.3. As-Is scenario and scenario 2. Route optimization

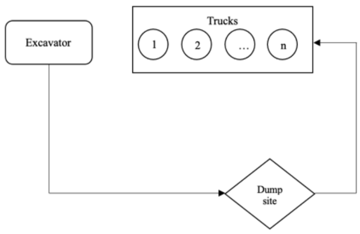

Fig. 4. Scenario 1. Different number of trucks – one excavator

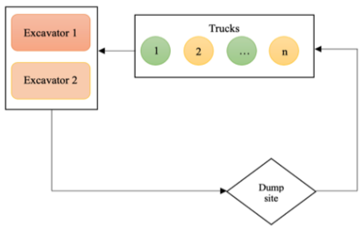

Fig. 5. Scenario 2. Heterogeneous trucks and excavator configuration

Table 4. Comparison of as-is and scenario 2

Performance Indicator (1)	Base Scenario (2)	Scenario 2: Optimizing Route (3)
Average truck wait time	0.31 min	0.33 min
Average truck cycle time	17.39 min	14.60 min
Total cycle completed	108 (≈ 27 per truck)	129 (≈ 32 per truck)
Excavator utilization	75.12%	88.94%
Productivity rate	430.27 BCM/hour	513.94 BCM/hour
Match factor	0.74 (74%)	0.88 (88%)

Table 5. Comparison of different numbers of trucks in Scenario 1

No of Truck	Avg. Wait Time (min)	Avg. Cycle Time (min)	Total Cycle	Excavator Utilization (%)	Total BCM Moved	Productivity (BCM/hour)	Match Factor
3	0.158381	17.250654	82	56.833333	2613.504	326.688	0.556501
4	0.314914	17.387557	108	75.125000	3442.176	430.272	0.736159
5	0.504377	17.572765	134	92.479167	4270.848	533.856	0.910500
6	2.325584	19.441618	145	100.000000	4621.440	577.680	0.987572

4.2.2. Scenario 1: n trucks - 1 excavator

Scenario 1 aims to test the system's performance under different fleet configurations. Fig. 3 depicts the queue structure of Scenario 1, while Table 5 presents a comparison of the simulation under *n*-truck configurations.

Under the 3-truck configuration, the productivity, excavator utilization, and MF were 326.69 BCM/hour, 56.83%, and 0.56, respectively. The 3-truck configuration indicates under-truck performance, with excavators idling for 44% of the operation time. Furthermore, the 4-truck configuration, which also represents the *as-is* state, has a productivity of 430.27 BCM/hour, 75.13% excavator utilization, and 0.74 MF. This result suggests that the company should focus on reducing the number of active trucks, particularly in response to planned or unplanned conditions.

The performance of the 5-truck configuration increased significantly compared to 3 or 4-truck scenarios. The productivity rate was 533.86 BCM/hour, the excavator utilization was 92.48%, and the MF was 0.91. This result indicates a balance between truck cycle time and excavator loading time, as evidenced by MF being almost equal to 1. Furthermore, in the 6-truck configuration, the system is shown as under-excavator as the truck's waiting time has increased significantly from 0.50 minutes (for five trucks) to 2.33 minutes (for six trucks). Adding a sixth truck maximizes excavator utilization but creates inefficiencies due to increased truck queuing.

4.3. Scenario 2: route improvement

Scenario 2 aims to test the effect of improving road conditions on the system performance. The road improvement was indicated by a 30% reduction in truck travel time. The simulation was run under the same configuration as the *as-is*, as depicted in Fig. 4. Scenario 2 yields a significant improvement in system performance, as shown in Table 5.

The productivity rate, excavator utilization, and the MF were 513.94 BCM/hour, 88.94%, and 0.88, respectively. This finding suggests that improving road conditions can be an alternative strategy. However, further analysis is needed to determine the best solution across both technical and economic aspects, which are beyond the scope of this paper. Therefore, a future evaluation is necessary to determine the optimal solution, accounting for both technical and economic factors.

4.4. Discussion and interpretation

A performance comparison was conducted to evaluate three scenarios: as-is, adding one truck (5 trucks), and route improvement. Five truck configurations were selected from Scenario 2 based on MF values, and road improvements reduced travel and return times by 30%. Table 6 presents the results of the comparison among the three scenarios.

The three scenarios have distinct performance as indicated by the MF. The MF for Scenarios 1, 2, and 3 is 0.74, 0.91, and 0.88, respectively. An MF close to 1 indicates a well-balanced system of truck and excavator. The simulation reveals that improving the *as-is* can be achieved by adding a truck or improving road conditions. Friswell & Williamson [25] emphasized that a low balance between the truck and the excavator in mining operations not only reduces productivity but also contributes to driver fatigue.

Relevant to this study, Kulula & Akande [26] found that road quality significantly influences mining operation productivity. This research highlights the importance of paying attention to road conditions and conducting evaluations to reduce travel time. Prasetyo *et al.* [27] also stated that improving workflow was crucial in increasing the productivity of mining equipment. Prasetyo *et al.* [27] found that workflow improvements affect cycle time and directly enhance productivity.

Furthermore, future research should consider the

Table 6. Comparison of scenarios

Scenario	Avg. wait time (min)	Avg. cycle time (min)	Total cycle	Excavator utilization (%)	Total BCM moved	Productivity (BCM/hour)	Match Factor
4 trucks	0.314914	17.387557	108	75.125000	3442.176	430.272	0.736159
5 trucks	0.504377	17.572765	134	92.479167	4270.848	533.856	0.910500
4 trucks + route improvement	0.329528	14.598873	129	88.937500	4111.488	513.936	0.876780

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Table 7. Heterogeneous fleet configuration – one excavator

Performance	Truck Type A	Truck Type B
Loading time (T1)	3.2 mins	2.8 mins
Loaded travel time (T2)	5.29 mins	6.2 mins
Dumping time (T3)	4.5 mins	4.6 mins
Empty return time (T4)	4.09 mins	4.3 mins
Truck capacity	31.87 BCM	36.00 BCM
Excavator Performance	Excavator Type A	Excavator Type B
Efficiency factor	1	1.2

impact of heterogeneous truck and excavator types on the system's performance. As noted by Matsimbe [4], fleet heterogeneity can introduce additional complexity into the queuing model; therefore, advanced simulation models are required to capture variability across equipment. This study further aims to analyse the modelling of heterogeneous truck and excavator configurations. Based on the dataset of excavators and trucks (Table 7), this study further evaluated DES SimPy performance in analyzing heterogeneous fleet configurations.

DES SimPy handles fleet heterogeneity by treating each entity as an independent, persistent process with its own parameters and internal logic. Mathematical models often assume equipment homogeneity to simplify calculations, whereas GUI-based DES may restrict customization of entities. However, SimPy offers flexibility by allowing a unique set of attributes for each process using dictionaries. Under a heterogeneous fleet model, each truck has distinct characteristics, including loading time, travel speed, and capacity. The individual characteristics are stored in the parameter dictionary and remain attached to the truck throughout the loop.

The queue structure for the heterogeneous fleet scenario is depicted in Fig. 5, and the simulation results are shown in Table 8. To determine the best combination of truck and excavator, the decision should align with the objective of the decision-makers. Production target and MF can be prioritized as primary criteria, as previous research used MF because it can capture both sides of trucks and excavators. For example, suppose the target is at least 10,000 BCM per day. In that case, the company should consider a configuration of 12 trucks and 2 excavators, given 1.96 MF, excavator utilization over 80%, and an average waiting time of 1.09 minutes.

Moreover, standard operating procedures (SOPs) for loading and hauling are necessary to maintain operational performance. Litvin & Litvin [28] highlighted that the excavator's rotation angle significantly affects mining productivity. Moreover, Suhendar *et al*. [29] found that bucket fill factor, swell factor, and cycle time affect the productivity of mining equipment. Additionally, technologies can be installed to monitor system performance. Šopić *et al*. [30], developed a video analysis system using machine learning to monitor and gather real-time data on excavator operations.

To conclude the discussion, this paper reveals the effectiveness of DES SimPy in modelling a heterogeneous fleet. However, this study does not incorporate investment and operational costs into the decision-making process. As mentioned in the previous chapter, there are two promising alternatives: adding more trucks or improving road conditions. The decision should be made by considering both technical and economic analyses, which are outside the scope of this

Table 8. Simulation result of multi-server and heterogeneous fleet configuration

Truck Count	Total Cycles	Total BCM Moved	Productivity (BCM/hr)	Avg Truck Cycle Time (min)	Avg Truck Wait Time (min)	Excavator 1 Utilization (%)	Excavator 2 Utilization (%)	Match Factor
4	109	3692,72	461,59	17,38	0,08	43,61	21,43	0,69
5	136	4557,34	569,67	17,35	0,16	52,57	30,44	0,88
6	162	5489,21	686,15	17,46	0,16	63,61	33,68	1,03
7	185	6218,09	777,26	17,67	0,46	69,35	43,29	1,20
8	213	7221,96	902,75	17,64	0,35	77,85	50,80	1,36
9	239	8046,45	1005,81	17,71	0,47	85,20	59,52	1,54
10	262	8886,84	1110,86	17,93	0,64	89,13	67,81	1,67
11	286	9647,59	1205,95	18,12	0,87	96,34	73,99	1,83
12	308	10447,85	1305,98	18,35	1,09	98,14	83,10	1,96
13	324	10924,73	1365,59	18,85	1,65	99,29	91,81	2,08
14	338	11461,77	1432,72	19,47	2,23	99,75	98,75	2,16

research. Therefore, future research should consider the cost element in the analysis, as conducted by Al-Masri [31], which evaluated both technical and financial parameters in a heterogeneous truck-excavator system using DES. In addition, Kulula & Akande [26] stated that operational disturbances, such as random breakdowns and routine maintenance, can significantly reduce productivity. Therefore, integrating such stochastic events into future simulations will better reflect real-world uncertainties. Zankoul *et al*. [32] compared DES and ABM in mining operations and found that both methods yield similar system performance. However, Zankoul *et al*. [32] highlighted that ABM offers distinct advantages when the researcher aims to model a truck, an excavator, and a road segment as an individual autonomous agent. For example, in ABM, a truck can be modelled to decide on a route, wait in a queue, load, and dump.

Furthermore, research integrating simulation and optimization has increased in recent decades. Khajvandsany *et al*. [33] integrate a multi-objective optimization algorithm with a simulation algorithm. Method integration yields a near-optimal solution, as evidenced by reduced transportation costs and increased productivity. In addition, to monitor performance efficiently and effectively, information technology can be integrated into the mining activity. Fisonga & Mutambo [34] developed an application based on the NET platform to determine the optimum number of truck-excavator combinations, using waiting time and MF as performance indicators.

4.5. Research implications

The findings of this research offer several managerial and theoretical implications. From a managerial perspective, this study provides an additional approach for mining companies to determine the optimal configuration of a truck-excavator. The mathematics-based approach, such as optimization (MILP [12], queuing model [3], [4], [14]) and MF [11], [13], [14], is suitable for homogeneous fleets and one excavator configurations. However, under heterogeneous and stochastic configurations, a simulation-based approach, as in this paper, is necessary to analyze the system. Additionally, this research confirms that the company should prioritize maintaining the truck-excavator's optimal configuration. The imbalance will lead to a decrease not only in productivity but also contribute to driver fatigue [25].

Furthermore, the simulation-based alternative can also be viewed as a theoretical contribution of the paper. Additionally, SimPy, as demonstrated in this study, can serve as an alternative tool for simulating DES. Publish material that is available to illustrate the step-by-step process of SimPy, as in a paper [23]. In this study, SimPy can effectively capture the complexity of a finite-source closed-loop queuing model in heterogeneous fleets. To conclude, this research builds on previous studies that have primarily focused on deterministic, homogeneous assumptions.

5. CONCLUSION

This study used a simulation-based approach, DES, to analyze the best configuration of a truck-excavator in a surface mining operation. The system can be categorized as a finite-source closed-loop queuing model. The simulation was developed using SimPy. After the model was validated, three scenarios were evaluated to understand the effects of fleet configuration and road improvement on queuing system performance.

The simulation indicates that the current configuration, four trucks and one excavator, yields an MF of 0.74 and contributes to a 19.17% shortfall in overburden removal. For under 0.74 MF, the system indicates the excavator is underutilized. Furthermore, the performance under five trucks and one excavator is 92.48% excavator utilization, 533.86 BCM/hour productivity, and an MF of 0.91. In addition, the route-improvement scenario that reduced travel and return times without increasing fleet size yielded nearly equivalent results (88.86% utilization, 513.94 BCM/hour, MF = 0.88). The simulation reveals that an alternative to improve the as-is is either adding one more truck or improving road conditions.

Furthermore, this study tested DES performance under heterogeneous truck and excavator configurations and a multi-server (two-excavator) system, in addition to the homogeneous fleet configuration. The results indicate that SimPy effectively captures entity-level variability and queue interactions. However, this study is still limited to specific fleet configurations and does not consider cost aspects or external field factors. Future research can be conducted by incorporating cost modeling across different fleet configurations and testing the DES's performance in selecting the optimal configuration under heterogeneous performance conditions. These results also highlight the importance of maintaining the optimal number of truck-excavator configurations to avoid productivity losses. Therefore, future research can also be conducted by incorporating stochastic breakdowns to simulate disruptions accurately.

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