

An Integrated Internet of Things and Prediction-based Optimization approach for real-time surface waste mining in Indian coal mining industry

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Abstract

INTRODUCTION: Surface waste mining (SWM) involves non-value-adding activities that affect operational efficiency in the mining industry. Improving fleet utilisation through real-time monitoring and coordinated dispatching can help address these challenges.

OBJECTIVES: This study develops an integrated framework combining Internet of Things (IoT)-based activity recognition with dynamic fleet dispatching to improve productivity and balance excavator utilisation and tipper waiting time.

METHODS: The framework comprises two phases. Phase I processes GPS and RFID telemetry to classify tipper activity states using machine learning. Phase II uses the recognised states to trigger a condition-based dispatching heuristic. A multi-objective model incorporating first-come, first-served queue recursion is evaluated through telemetry classification experiments and discrete-event simulations calibrated using operational data from an opencast coal mine in central India.

RESULTS: The gradient-boosting classifier achieves a macro-F1 score of 0.986. Increasing the fleet from 20 to 36 tippers reduces average excavator idle time from 2.78 to 0.70 hours per 8-hour shift. For the existing 30-tipper fleet, the proposed framework projects a 13.6% increase in productivity, from 4,100 to 4,659 tonnes per shift. Compared with fixed assignment, the dispatching heuristic increases production by 2.5% and reduces tipper waiting time by 66%. Under heterogeneous operating conditions, the heuristic maintains excavator output imbalance at a coefficient of variation of no more than 2.4%.

CONCLUSION: Integrating IoT-based activity recognition with condition-based dispatching provides a data-driven approach to improving fleet productivity and equipment utilisation in surface mining. The framework supports fleet-sizing and dispatching decisions while offering scope for extension to heterogeneous fleets and changing mine layouts.

Keywords: Surface waste mining; Internet of Things; Machine learning; Dynamic dispatching; Fleet management; Discrete-event simulation

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1. Introduction

With the rise in demand for coal since the Government of India launched "The Pradhan Mantri Sahaj Bijli Har Ghar Yojana (Saubhagya)" in 2017, as a primary source of electricity in India, coal mines must improve efficiency and mine-related activities to meet the excess demands. The

International Energy Agency (IEA) identified India as the world's fastest-growing coal consumer in absolute terms, projecting coal demand of 748 million tonnes (Mt) by 2024 against a domestic production of 537 Mt (IEA, 2019). Coal is presently one of the most significant power sources, and

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it will remain so until 2030 and beyond (Tongia and Gross, 2019).

Unlike most gifts of nature, coal comes with a wrapper: the soil and rock covering the seam. This overburden must be removed before extraction and ultimately becomes mine waste. Surface waste mining (SWM) operations are resource-intensive, involving the excavation and haulage of this overburden, along with low-grade stock heaps, tailings, and other waste. These procedures pose significant logistical challenges and impose heavy economic and environmental costs through high energy use, operational inefficiencies, and land degradation (Lumley and McKee, 2014). Globally, the growing volume of mine waste is recognised as a pressing environmental issue (Aznar-Sánchez et al., 2018; Valenta et al., 2023; Owen et al., 2024), prompting a parallel stream of research into how such waste can be recovered and valorised (Su et al., 2021; Cobîrzan et al., 2022; Helser et al., 2022; Konaté et al., 2022; Adesina, 2025). Within the mine, SWM requires the precise synchronisation of excavators, haul trucks (tippers), loaders, and support vehicles, making fleet management critical. However, conventional practices rely on static optimisation and human judgement, which cannot effectively respond to the real-time dynamics of mining operations (Liu and Kozan, 2016).

In this research, we examine the mining industry's haulage system, which accounts for 50-60% of total operating expenses (Ahangaran et al., 2012; Akbari et al., 2009). The proposed model aims to increase a mine's gross production by minimising the waiting time of tippers and the idle time of excavators. To achieve this, we propose a two-phase process. In the first phase, real-time Internet of Things (IoT) tracking devices (GPS sensors with an RFID-based communication link) record equipment activities, and a machine-learning classifier converts this data into an activity state for each tipper. In the second phase, a condition-based heuristic uses these states to dynamically dispatch tippers, allowing mine managers to monitor traffic and utilise the equipment more efficiently. The telemetry used to develop Phase I was recorded at a case mine, and the mine's operating parameters were used to simulate Phase II. The overall design is modular, ensuring the monitoring and dispatching components can be easily adapted to fleets of varying sizes.

1.1 Research Gap and Novel Contributions

Truck dispatching has been extensively studied, spanning single-stage heuristics (Hauck, 1973), multistage linear and mixed-integer programming formulations (White and Olson, 1986; Gurgur et al., 2011; Afrapoli et al., 2019), and reinforcement learning approaches (de Carvalho and Dimitrakopoulos, 2021; Huo et al., 2023). The adoption of IoT technologies and telematics has advanced the monitoring of mining equipment (Chaowasakoo et al., 2017; Yadav et al., 2021). Despite these developments, three limitations remain. First, existing dispatching models assume that truck locations and activity states are known

with certainty, whereas operational decisions in practice rely on noisy, irregularly sampled, and partially binary sensor data. Second, studies incorporating equipment data primarily focus on monitoring or predicting aggregate outcomes, such as production (Baek and Choi, 2020), without integrating the inferred equipment states directly into dispatching decisions. Third, queue-based dispatching models often estimate waiting and idle times using the number of trucks in a queue, overlooking the travel time of approaching trucks and potentially distorting these estimates, particularly in small fleets.

This study addresses these limitations through four contributions.

1. We develop a closed-loop, two-phase architecture that integrates activity-state classification with real-time truck dispatching. The classifier processes decoded GPS/RFID telemetry and triggers dispatching decisions at loading and unloading state transitions, linking equipment monitoring directly to operational control.
2. We formulate activity recognition as a seven-class classification problem, specify the sensor-level feature set, and establishes a transition-rule baseline. Classification performance is evaluated using temporally separated training and test datasets, with state-specific metrics and inference latency reported.
3. We develop a reproducible multi-objective dispatching model that computes waiting and idle times using a first-come-first-served Lindley recursion. The associated condition-based heuristic prioritises excavators experiencing flow-rate deficits and otherwise selects dispatch decisions that minimise expected waiting time, with computational requirements of only microseconds per decision.
4. The proposed approach is evaluated using data from an Indian opencast coal mine and a reimplemented discrete-event simulation. The analysis quantifies its operational, economic, and environmental implications and examines its robustness across mine sizes and fleet configurations.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature, Section 3 presents the problem formulation and mathematical model, and Section 4 describes the solution methodology. Section 5 details the experimental setup, and Section 6 presents the results. Section 7 discusses the managerial and theoretical implications, while Section 8 concludes with the study's limitations and directions for future research.

2. Literature Review

The literature review is structured around the three elements integrated in this study. Section 2.1 examines fleet management and truck dispatching in surface mining, Section 2.2 reviews IoT-based equipment monitoring and machine learning, and Section 2.3 discusses equipment

performance and sustainability before establishing the research gap.

2.1 Fleet Management Systems in Surface Mining

Fleet management systems (FMS) in surface mining have evolved from single-stage to multi-stage frameworks to improve operational efficiency and resource utilisation. Early approaches focused on determining the number of tippers required to transport material between excavators and destinations (Hauck, 1973; Alarie and Gamache, 2002). Multi-stage FMS typically address three sequential subproblems (Afrapoli et al., 2019): determining shortest paths using algorithms such as Dijkstra's algorithm (Dijkstra, 2022), optimising material flow along these paths using mathematical programming and queuing models, and dynamically allocating tippers to excavators to minimise idle time and improve fleet utilisation. Subsequent studies have examined energy-efficient scheduling (Patterson et al., 2017) and goal programming approaches (Mohtasham et al., 2021). Afrapoli and Askari-Nasab (2019) provide a comprehensive review of mining fleet management models and solution methods. Table 1 summarises representative contributions.

Table 1. Related literature concerning the solution for path optimization

Authors	N LP	Q T	L P	MI LP	Approach	Outcomes
White and Olson, 1986	x	x	✓	x	Computation	Meets desired production rate
Carmichael, 1987	x	✓	x	x	Integrated operation research, management and systems engineering	Meet target production rate
Soumis, Ethier, and Elbrond, 1989a	✓	x	x	x	Optimization	Optimize the number of tipper runs
Soumis, Ethier, and	✓	x	x	x	Optimization and Assignment	Maximize productivity

Elbrond, 1989b						ent problem
Kappas and Yegulalp, 1991	x	✓	x	x	Simulation	Optimize the number of tipper runs
White et al., 1993	x	x	✓	x	Computation	Improves Productivity
Ta et al., 2005	✓	x	x	x	Stochastic Optimization	Haulage in real-time
Ercelebi and Bascetin, 2009	x	✓	x	x	Optimization and Computation	Optimum truck numbers
Gurgur et al., 2011	x	x	✓	✓	Allocation Problem	Maximize productivity
Mena et al., 2013	x	x	✓	✓	Simulation and Optimization	Maximize productivity
Ta et al., 2013	x	x	✓	x	Approximation	Minimize the number of trucks
Upadhyay and Askari-Nasab, 2017	x	x	x	✓	Optimization for shovel allocation	Maximize productivity and maintain tonnage at the delivery point
Mohtasham et al., 2021	x	x	x	✓	Multi-Objective Goal Programming	Maximize Production rate
Das et al., 2024	x	x	x	✓	Meta Heuristic	Optimise pit-dump schedules with haulage selection.

NLP – Non-Linear Programming, QT- Queuing Theory, LP – Linear Programming, MILP – Mixed Integer Linear Programming

2.2 Machine Learning Approach for Fleet Management

Machine learning and IoT have expanded the capabilities of mining fleet management through equipment monitoring and predictive analytics. Lumley and McKee (2014) reported performance improvements through daily equipment data analysis while identifying data overload as a key challenge. Baek and Choi (2020) applied deep neural networks to predict ore production in truck-haulage systems. Chaowasakoo et al. (2017) examined how real-time equipment position and status information influence

truck dispatching, while Yadav et al. (2021) reviewed IoT–fog architectures for real-time monitoring in opencast mines. Reinforcement learning has also been applied to dispatching, including Q-learning for reducing greenhouse-gas emissions (Huo et al., 2023) and integrated production planning and truck dispatching under uncertainty (de Carvalho and Dimitrakopoulos, 2021). However, these approaches generally rely on predefined or simulated equipment states rather than recognising activity states directly from raw sensor data.

2.3 Equipment Performance, Sustainability, and Mine Waste

Improving equipment utilisation and reducing idle time can enhance both operational efficiency and environmental performance (Lumley and McKee, 2014). Existing studies have addressed real-time truck dispatching (Afrapoli et al., 2019), mining efficiency assessment using Data Envelopment Analysis (Wang et al., 2020), and transportation optimisation using mathematical programming and evolutionary algorithms (Pratap et al., 2016). Nevertheless, dispatching models generally assume known equipment states, whereas monitoring and machine-learning studies rarely integrate state recognition into dispatching decisions. This study addresses this gap by integrating sensor-based tipper activity-state recognition with event-triggered dispatching in a closed-loop framework. Table 2 positions the proposed approach against representative studies in terms of sensor data utilisation, activity-state recognition, dispatching optimisation, and closed-loop integration.

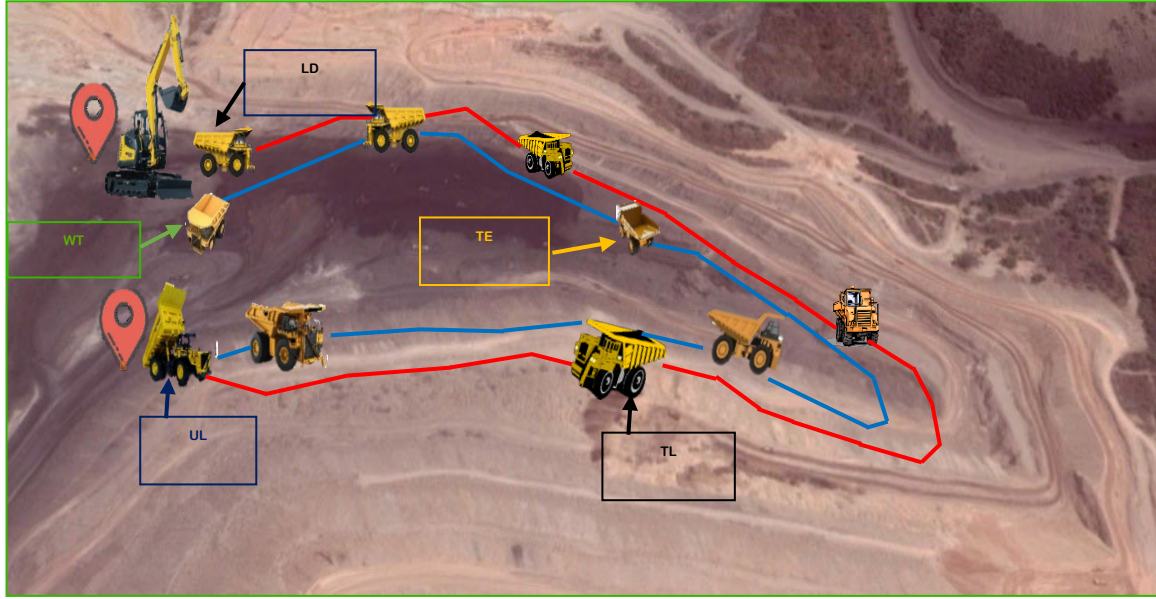
Table 2. Positioning of the present study against representative literature

Study	Operational/ sensor data	Activity -state recogn ition	Dispatc hing optimis ation	Close d-loop integra tion
Gurgur et al. (2011)	×	×	✓	×
Chaowasakoo et al. (2017)	✓	×	✓	×

Afrapoli et al. (2019)	×	×	✓	×
Baek and Choi (2020)	✓	×	×	×
Wang et al. (2020)	×	×	×	×
Yadav et al. (2021)	✓	×	×	×
Mohtasham et al. (2021)	×	×	✓	×
de Carvalho and Dimitrakopoulos (2021)	×	×	✓	×
Huo et al. (2023)	×	×	✓	×
This study	✓	✓	✓	✓

3. Problem Description

This section describes surface-mining logistics at an opencast coal mine in central India, referred to as XYZ for confidentiality. Overburden is removed using excavators and tippers operating along routes such as A-B-A (Fig. 1). At the loading face (A), an excavator loads waste material onto a tipper (loading, LD). The tipper transports the material to the dumping ground (B) (travelling loaded, TL), unloads it (unloading, UL), and returns empty to an excavator (travelling empty, TE). If the excavator is occupied, the tipper waits in its queue (waiting, WT) until service is available. A tipper may also remain stationary with its engine switched off, either empty (SE) or loaded (SL), for activities such as maintenance or breaks. These seven states collectively represent the tipper's activity at any given time. As mining progresses, the locations of loading faces and dumping grounds change. Although Fig. 1 illustrates one face and one dumping ground for clarity, the actual mine operates several of each. Dispatching follows a one-tipper-to-one-destination principle: at each decision epoch, a tipper is assigned a single destination, either an excavator after unloading or a dumping ground after loading. Each excavator serves one tipper at a time, following a first-come, first-served (FCFS) queue discipline.



UL- Unloading, WT- Waiting, Route of empty tipper from dumping ground to excavator; Route truck loaded with mine waste from excavator to dumping ground.
Location A = Source; Location B = Dumping Ground

Figure 1. Schematic representation of surface mine

The main challenge is to collect heterogeneous equipment data and convert them into actionable information for real-time monitoring and dispatching of tippers and excavators across the mine. To address this, each tipper is equipped with sensors that capture GPS position and speed, ignition, and hoist status, while an RFID-based communication system transmits the generated data to the mine control room. The data are then processed to recognise the activity state of each tipper (Section 5.1), and a mathematical model is formulated to minimise excavator idle time and tipper waiting time (Section 3.1).

3.1 Mathematical Model

The dispatching problem is defined over a shift of length H . Each tipper executes a sequence of cycles. In cycle c , a tipper travels empty from a dumping ground to an excavator, waits if the excavator is occupied, receives a load, hauls the material to a designated dumping ground, and unloads. The associated notation is detailed in Table 3.

Table 3. Notation of the dispatching model

Symbol	Description (unit)
Sets and indices	
I, i	Tipper
J, j	Excavators
K, k	Dumping grounds
C_i, c	Cycles performed by tipper i in the shift
Parameters	

H	Shift length (min)
L_{jk}	Haul distance between excavator j and dumping ground k (km)
v_i^L, v_i^E	Speed of tipper i when loaded and when empty (km/h)
s_j	Loading time at excavator j , including spotting (min)
u_k	Unloading time and dump-side delay at dumping ground k (min)
q_i, Q_i	Payload and nominal capacity of tipper i (t)
P_j	Material available at the face of excavator j in the shift (t)
F_j	Desired flow rate of excavator j (t/min)
Decision variables	
x_{ijc}	1 if tipper i is dispatched to excavator j in cycle c ; 0 otherwise
y_{ikc}	1 if tipper i is dispatched to dumping ground k in cycle c ; 0 otherwise
Auxiliary variables	
a_{ic}, b_{ic}, e_{ic}	Arrival at the excavator, start of loading, and end of loading for tipper i in cycle c (min)
r_{ic}	Time at which tipper i is released empty from the dumping ground in cycle c (min); r_{i0} is its release at the start of the shift
$p(i, c)$	Tipper-cycle served immediately before (i, c) at the same excavator
T_{ic}	Waiting time of tipper i at the excavator in cycle c (min)
W_{ic}	Idle time of the excavator immediately before it serves tipper i in cycle c (min)
f_j^-, f_j^+	Shortfall and excess of excavator j relative to its desired output (t)

The model minimises the total idle time of the excavators (1), the total waiting time of the tippers (2), and the aggregate shortfall from the desired flow rates (3). These objectives inherently conflict, as increasing the fleet size reduces excavator idle time while simultaneously extending tipper queues. The inclusion of maximum operators, binary variable products, and sequence-dependent terms $p(i, c)$ renders the formulation a non-linear mixed-integer programme. This complexity precludes exact solutions within the restricted computational window available following a state change. The problem is addressed using the condition-based heuristic detailed in Section 5.2. This heuristic evaluates the objectives lexicographically by prioritising the shortfall (Z_3), followed by the anticipated travel and waiting time of the dispatched tipper, a sequence that concurrently minimises the idle time of the destination excavator (Z_1, Z_2).

$$\min Z_1 = \sum_{i \in I} \sum_{c \in C_i} W_{ic} \quad (1)$$

$$\min Z_2 = \sum_{i \in I} \sum_{c \in C_i} T_{ic} \quad (2)$$

$$\min Z_3 = \sum_{j \in J} f_j^- \quad (3)$$

$$\text{s. t.} \quad \sum_{j \in J} x_{ijc} = 1, \quad \forall i \in I, c \in C_i \quad (4)$$

$$\sum_{k \in K} y_{ikc} = 1 \quad \forall i \in I, c \in C_i \quad (5)$$

$$a_{ic} = r_{i,c-1} + \sum_{j \in J} \sum_{k \in K} x_{ijc} y_{ik,c-1} \frac{60L_{jk}}{v_i^E} \quad \forall i, c \quad (6)$$

$$b_{ic} = \max\{a_{ic}, e_{p(i,c)}\} \quad \forall i, c \quad (7)$$

$$T_{ic} = \max\{0, e_{p(i,c)} - a_{ic}\} \quad \forall i, c \quad (8)$$

$$W_{ic} = \max\{0, a_{ic} - e_{p(i,c)}\} \quad \forall i, c \quad (9)$$

$$e_{ic} = b_{ic} + \sum_{j \in J} x_{ijc} s_j \quad \forall i, c \quad (10)$$

$$r_{ic} = e_{ic} + \sum_{j \in J} \sum_{k \in K} x_{ijc} y_{ikc} \left(\frac{60L_{jk}}{v_i^L} + u_k \right) \quad \forall i, c \quad (11)$$

Constraints (4) and (5) assign each tipper cycle to exactly one excavator and one dumping ground. Equation (6) calculates the arrival time at the excavator, where y_{ik0} represents the initial location of the tipper. Excavators

process tippers on a first-come, first-served basis; consequently, loading commences only when both the tipper and the excavator are available (7). The tipper waiting time and excavator idle time are derived from Equations (8) and (9), mirroring Lindley's (1952) recursion for a single-server queue. For any given tipper cycle, a maximum of one of these two variables will be strictly positive. Equations (10) and (11) determine the completion of loading and the subsequent release time from the dumping ground.

$$q_i \leq Q_i \quad \forall i \in I \quad (12)$$

$$\sum_{i \in I} \sum_{c \in C_i} q_i x_{ijc} \leq P_j \quad \forall j \in J \quad (13)$$

$$\sum_{i \in I} \sum_{c \in C_i: e_{ic} \leq H} q_i x_{ijc} + f_j^- - f_j^+ = F_j H \quad \forall j \in J \quad (14)$$

$$x_{ijc}, y_{ikc} \in \{0, 1\}; \quad f_j^-, f_j^+ \geq 0 \quad (15)$$

Constraint (12) restricts the payload of each tipper to its nominal capacity. Constraint (13) ensures that the material extracted by each excavator does not exceed the total available at its face. Once a face is depleted, the corresponding excavator requires relocation. Constraint (14) establishes a goal for the desired output $F_j H$ of each excavator, where $f_j^- > 0$ indicates an excavator operating in deficit and $f_j^+ > 0$ signifies an overperforming excavator. Finally, Constraint (15) specifies the variable domains.

$$\hat{a}_{ij} = t + \frac{60L_{jk}}{\bar{v}_i^E} \quad \forall j \in J' \quad (16)$$

$$\hat{T}_{ij} = \max\{0, R_j - \hat{a}_{ij}\}, \hat{W}_{ij} = \max\{0, \hat{a}_{ij} - R_j\} \quad (17)$$

$$\hat{f}_j^- = \max\{0, F_j \hat{a}_{ij} - M_j\}, \hat{f}_j^+ = \max\{0, M_j - F_j \hat{a}_{ij}\} \quad (18)$$

$$R_{j^*} \leftarrow \max\{R_{j^*}, \hat{a}_{ij^*}\} + \bar{s}_{j^*}, \quad M_{j^*} \leftarrow M_{j^*} + q_i \quad (19)$$

When tipper i finishes unloading at dumping ground k at time t , every candidate excavator $j \in J'$ is evaluated based on the expected tipper arrival time (Eq. 16), where the bar notation indicates the mean speed. The variable R_j represents the projected time when excavator j will become available after servicing all previously committed tippers, and M_j denotes the total material either loaded at or scheduled for excavator j . Equations (17) and (18) compute the expected waiting and idle times alongside the projected shortfall and excess, serving as the real-time equivalents of Equations (5), (6), and (11). Following the dispatch of a tipper to the selected excavator j^* , the parameters R_{j^*} and M_{j^*} are updated using Equation (19).

4. Proposed Solution Methodology

This section presents a suggested two-phase strategy for analyzing and solving the SFMS seen in Fig. 2. The decision to send the tippers from their respective locations is based on the input data acquired throughout both stages. In Phase I, sensors and RFID devices installed on tippers generate and transmit data, which are decoded, extracted, and tabulated (Section 5.1). Irrelevant fields are removed, and the remaining attributes are converted into Boolean features through one-hot encoding. The resulting activity states are defined by the transition conditions in Fig. 5. As

the activity state comprises seven categorical classes, Phase I is formulated as a multi-class classification problem and evaluated using classification metrics (Section 5.1.4).

Phase II uses the recognised activity states to dispatch tippers, minimising tipper waiting time and excavator idle time. The heuristic is triggered when a tipper enters the LD or UL state; otherwise, monitoring continues without a dispatching decision. Dispatching decisions consider excavator flow-rate deviations, expected travel time, and expected destination waiting time (Section 3.1.5). This two-phase framework integrates equipment monitoring and dispatching into a real-time operational loop.

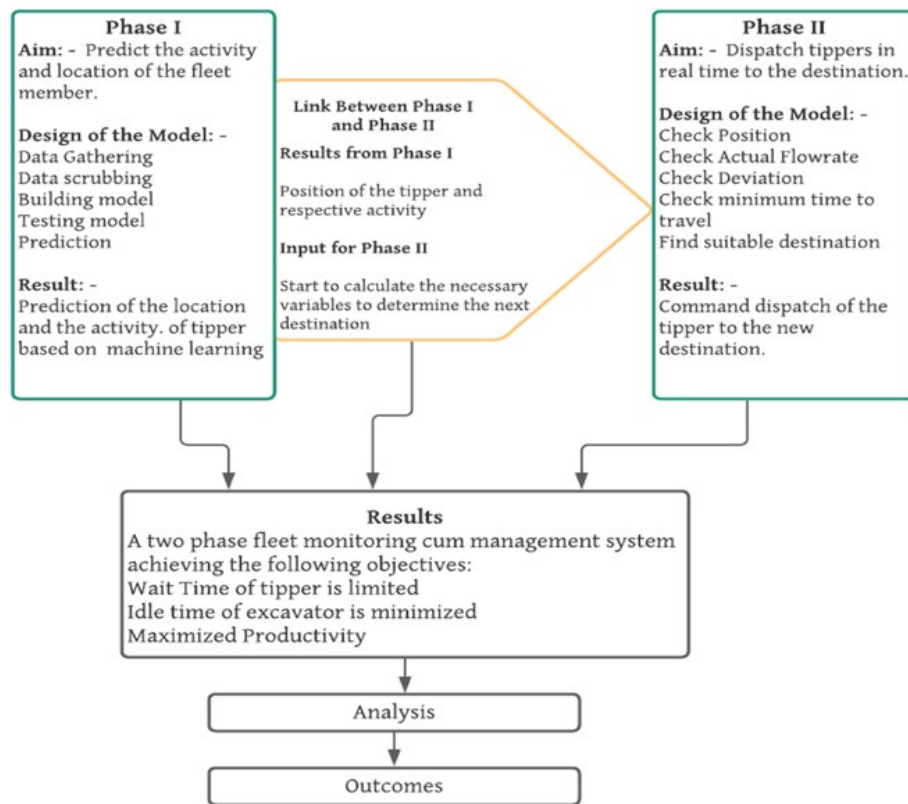


Figure 2. Framework of the proposed two-phase process for fleet monitoring system

5. Experimentation

This section evaluates the database generated by the RFID device mounted on the tipper, which pulls relevant data from raw data. Following processes, such as data generation, extraction, and scrubbing, remove any redundant information from the database. To prepare the database for correct output, the decision variables described above were cleaned using a one-hot coding method that solely represented the variables as Boolean datatypes. Here, a machine learning based technique has

been deployed to classify the data and presented it in the form of useful features. The next step in resolving the issue of reducing tipper wait time and excavator idle time. As stated in the problem description, the model provided in this work for resolving the tipper dispatching stage employs the 1-tipper-for-1-excavator concept. This section describes a step-by-step strategy to resolving the issue in both the monitoring and tipper dispatching stages.

5.1. Data and Data Processing for monitoring stage

This section explains the procedure to extract and process the huge volume of data to make the data viable to be

presented as important features. The whole process of converting the raw data into essentials features a series of operations is to be acted upon.

Step 1. Data generation and transmission

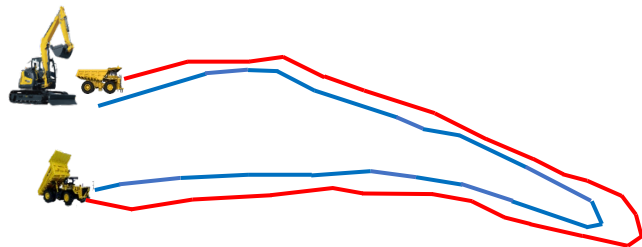


Figure 3. The route from excavator to dumping ground and back to excavator divided into several points

The route from the excavator to the dumping ground is divided into multiple nodes, as depicted in Fig. 3. Sensors installed in the mining equipment collect data on GPS location, speed, altitude, and other parameters, transmitting it via RFID to the mining manager. This data is compiled into a hexadecimal string, as shown in Fig. 4, and sent to the nearest control room.

Step 2. Data extraction

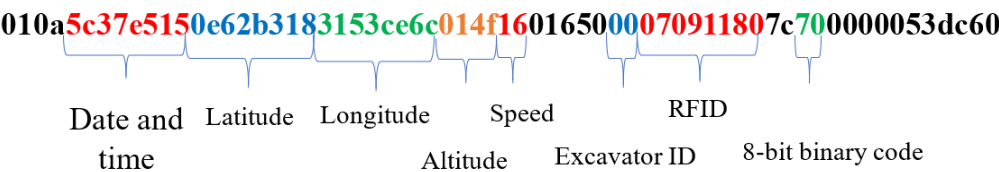


Figure 4. Raw data string and their meaning at different index positions

Once the RFID device receives the hexadecimal data string, the information is extracted from specific indexes, as illustrated in Fig. 4. These strings are generated and transmitted at various nodes along the path shown in Fig. 3. During mine operations, numerous data strings are received. In this section, we considered subset of the received strings to demonstrate the data extraction process, with the extracted information summarized in Table 4.

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Table 6. Notations used for solving the monitoring problem

Notation	Meaning
SE	Stop Empty
LD	Loading
TL	Travelling with Load
UL	Unloading
TE	Travelling Empty
WT	Waiting
SL	Stop with Load
S	Speed of tipper (km/h)
H	Hoist of tipper
I	Ignition of tipper

D	Distance between tipper and excavator (m), calculated as $D = 2R \arcsin(\sqrt{a})$, where $R = 6371$ km (haversine formula)
α	Difference in direction of the tipper
Δlat	Difference in latitude, $lat_2 - lat_1$ (rad)
Δlon	Difference in longitude, $lon_2 - lon_1$ (rad)
D_{30}	1 if $D < 30$ m; 0 otherwise
D_{50}	1 if $D < 50$ m; 0 otherwise
D_{150}	1 if $D < 150$ m; 0 otherwise
a	Haversine parameter: $a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1) \cos(lat_2) \sin^2\left(\frac{\Delta lon}{2}\right)$

To From	SE	TE	WT	LD	TL	UL	SL
SE	Default State	$I = 1$ $S > 5 \text{ kmph}$ $H = 1$					
TE	$I = 0$		$I = 1$, $S < 5 \text{ kmph}$ $H = 1$ $D < 150\text{m}$				
WT				$I = 1$ $S < 5 \text{ kmph}$ $H = 1$ $D < 30\text{m}$			
LD					$I = 1$ $S > 5 \text{ kmph}$ $H = 1$ $D > 50\text{m}$		
TL						$I = 1$ $S < 5 \text{ kmph}$ $H = 0$	$I = 0$
UL		$I = 1$ $H = 1$					
SL					$I = 1$		

Figure 5. Conditions for the features

The final dataset, containing only the features used for classification, is presented in Table 7. Ignition and Hoist correspond to the first two digits of the 8-bit IO code. Speed is encoded as 1 when the recorded speed exceeds 5 km/h and 0 otherwise. The Output column contains the numeric code of the activity state assigned using the conditions in Fig. 5, while Previous records the activity state at the

preceding observation, capturing the sequential dependence of tipper activities.

Table 7. Processed data ready to be fed in Machine learning model

D15 0	D5 0	D3 0	Igniti on	Hoi st	Spe ed	Previo us	Outp ut
1	1	1	1	0	0	TL	40
1	1	1	1	0	0	TL	40
1	1	1	1	0	0	TL	40
1	1	1	1	0	0	TL	40
1	1	1	1	1	0	UL	50
1	1	1	1	1	0	UL	50
1	1	1	1	1	0	UL	50
1	1	1	1	1	1	UL	50

Step 4: Activity-State Classification

Let $S = \{SE, TE, WT, LD, TL, UL, SL\}$ denote the set of activity states. For each tipper record t , the objective is to predict the current state $y_t \in S$ from a feature vector x_t . Two feature sets are evaluated. The first set, FS1, includes the Boolean indicators D_{150} , D_{50} , D_{30} , ignition, hoist, and speed, alongside the previous state. The second set, FS2, incorporates all FS1 features while adding the continuous distance to the excavator, vehicle speed, and the change in distance between consecutive records. During inference, the previous state is derived from the model's prediction for the preceding record.

A telemetry benchmark was generated using a kinematic model of the haul cycle, parameterised with data from the case mine (Table 10). Sensor noise was integrated into the observations. GPS position noise was modelled with a standard deviation of 2 m per axis, yielding an approximate 95% horizontal error radius of 4.9 m, consistent with typical open-sky GPS accuracy, multipath errors were modelled with a 2% probability and a standard deviation of 25 m, and speed noise was fixed at 1.5 km/h. Additional parameters account for queue creep, reversing during loading, engines remaining active during stops, and bit errors in the ignition and hoist signals. The resulting benchmark comprises 576,521 records from 30 tippers across six 8-hour shifts, featuring a mean sampling interval of 9.0 s. These benchmark settings are summarised in Table 8.

The first four shifts (384,383 records) were utilised for training, and the final two shifts (192,138 records) were reserved for testing. Hyperparameters were tuned through four-fold cross-validation on the training data, grouped by shift, utilising the macro-F1 score as the selection criterion. Four classifiers were evaluated: multinomial logistic regression (MLR), decision tree (DT), random forest (RF) (Breiman, 2001), and histogram-based gradient boosting (GBM) (Friedman, 2001). The transition rules depicted in Figure 5 were also assessed as a deterministic baseline. All classifiers were implemented using scikit-learn (Pedregosa et al., 2011). Performance was assessed using accuracy, macro-F1, Cohen's κ , per-state F1 scores, training time, and single-record inference latency.

Table 8. Settings of the telemetry benchmark

Item	Value
Tippers $\times$ shifts	30 $\times$ 6 (8 h each)

Haul distance;	6 to 8 km; 15 to 20 / 24 to 25
loaded/empty speed	km/h
Loading time,	15 to 20 min
including spotting	
Queue waiting time	Exponential, mean 2 min 20 s
Unloading time	1 to 3 min
Stops: empty (SE) /	10% / 5% of cycles; 5 to 30 / 5
loaded (SL)	to 20 min
Sampling interval	Uniform, 2 to 16 s
GPS noise	$\sigma = 2$ m per axis; 2% multipath outliers, $\sigma = 25$ m
Speed noise	$\sigma = 1.5$ km/h
Queue creep /	10% of WT records at 5 to 8
reversing into loading	km/h; first 60 to 120 s of LD at
spot	3 to 8 km/h
Engine left on during	30% of stops
stops	
Bit errors in ignition	1% of records
and hoist	
Class distribution (%)	SE 3.5, TE 27.2, WT 3.5, LD 26.9, TL 35.1, UL 2.9, SL 1.0
Training/test split	Shifts 1 to 4 / shifts 5 to 6

5.2 Proposed condition-based Heuristic

The dispatching model presented in Section 3.1 is solved using the condition-based heuristic detailed in Figure 6 and Algorithm 1. Based on the one-tipper-to-one-excavator concept, the heuristic assigns a single tipper to a destination immediately after Phase I detects that the equipment has transitioned into either the unloading (UL) or loading (LD) state. An unloaded tipper is directed to the excavator experiencing the most significant flow-rate shortfall, provided that at least one excavator is currently operating in deficit. If no deficit exists, the tipper is routed to the excavator offering the shortest combined expected travel and waiting time. A tipper currently undergoing loading is assigned to the dumping ground associated with the shortest expected turnaround time. Any destination whose capacity has been exhausted is systematically eliminated from the candidate set. Because each assignment requires a single evaluation of every available candidate, the computational complexity of the heuristic is $O(|J| + |K|)$.

Algorithm 1. Condition-based dispatching heuristic

Input: Tipper i , state σ_i recognised by Phase I, current time t , candidate sets $J' \subseteq J$ and $K' \subseteq K$, R_j , M_j , F_j

Output: Assigned destination for tipper i

- 1: **If** $\sigma_i = UL$ **then** (Tipper i is empty at dumping ground k)
- 2: **For each** $j \in J'$ compute $\hat{a}_{ij}$, $\hat{T}_{ij}$, and $\hat{f}_j^-$ using Eqs. (16) to (18)
- 3: **If** $\max_{j \in J'} \hat{f}_j^- > 0$ **then** $j^* \leftarrow \operatorname{argmax}_{j \in J'} \hat{f}_j^-$
- 4: **Else** $j^* \leftarrow \operatorname{argmin}_{j \in J'} \{\hat{a}_{ij} - t + \hat{T}_{ij}\}$
- 5: **If** the face of j^* is exhausted (Constraint 13) **then** $J' \leftarrow J' \setminus \{j^*\}$; return to Step 2
- 6: Dispatch i to j^* ; update R_{j^*} and M_{j^*} using Eq. (19)
- 7: **Else if** $\sigma_i = LD$ at excavator j **then**

```

8:  $k^* \leftarrow \operatorname{argmin}_{k \in K'} \left\{ \frac{60L_{jk}}{\bar{v}_t^L} + \hat{u}_k \right\}$ 
9: If dumping ground  $k^*$  is full then  $K' \leftarrow K' \setminus \{k^*\}$ ; return to Step 8
10: Dispatch  $i$  to  $k^*$  when loading concludes
11: Else continue monitoring tipper  $i$  (no decision required)

```

5.3 Simulation Model and Calibration

The proposed heuristic was initially evaluated in Python using case-mine parameters (Table 10), with results detailed in Section 6.2. A discrete-event simulation was then developed to incorporate the revised waiting-time formulation (Eqs. 7 to 9), facilitate policy comparisons, and conduct sensitivity analysis. This model features four excavators and two dumping grounds, supporting a 180 t/h production rate. Operational variables such as loading

times, haul distances, speeds, and payloads are sampled from the ranges specified in Table 10.

To accurately reflect empirical production values (Figure 9), the dump-side delay (u_k) was calibrated via a grid search that minimised the root-mean-square error. This established a delay of $u_k = 112$ min with a uniform variance of $\pm 20\%$. During execution, tippers are released at staggered intervals. Performance metrics are recorded over an 8-hour shift following a one-cycle warm-up. All configurations are replicated 30 times using independent random seeds, with results reported as means and 95% confidence intervals. The heuristic is compared against two baselines: a fixed assignment policy and a shortest-wait policy that routes tippers based solely on time, ignoring flow-rate deviations. The simulation closely matches historical data, reproducing reported production levels with a 6.3% mean absolute percentage error and excavator idle times with a 0.98 correlation. The underlying code is available upon request.

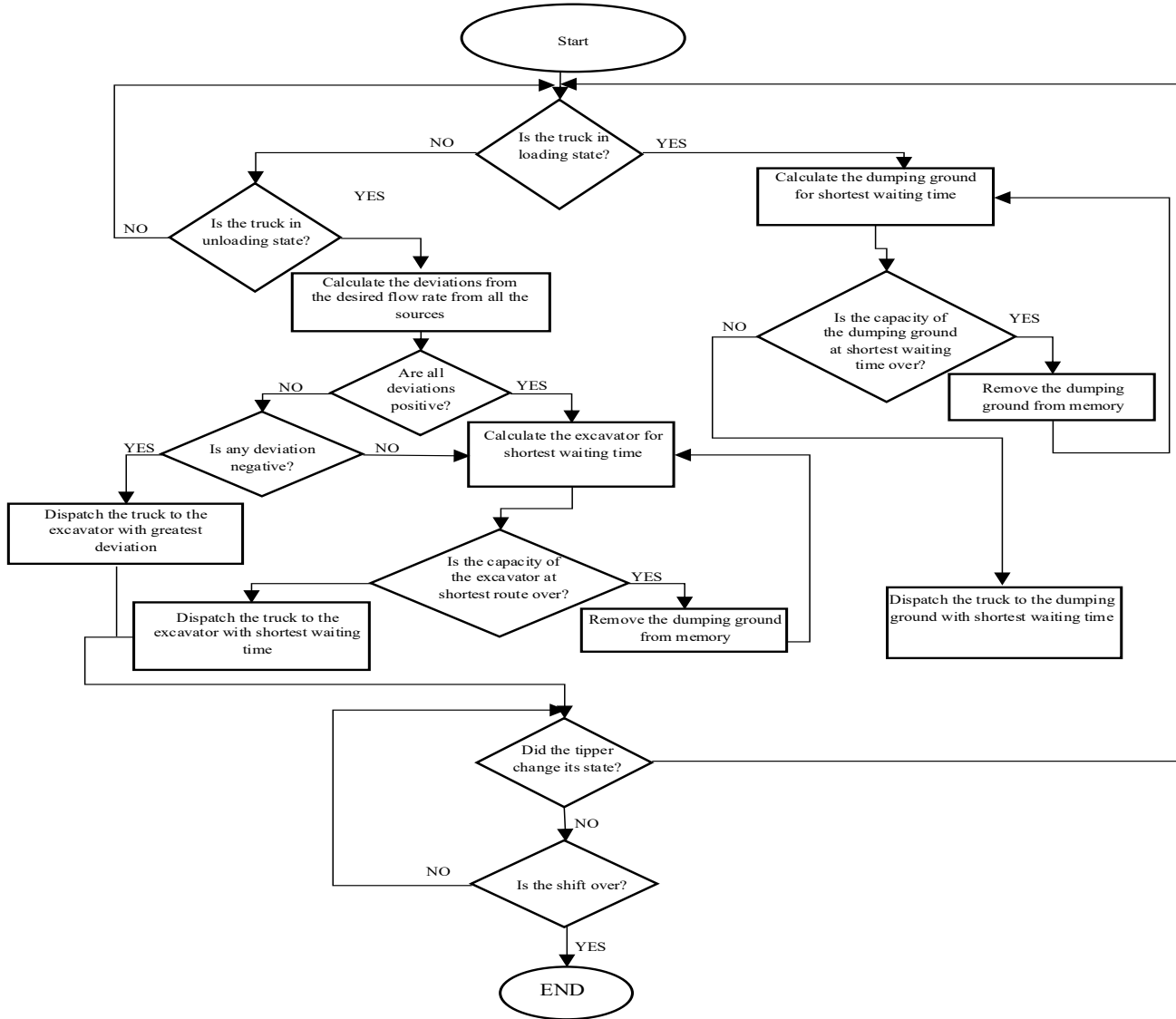


Figure 6. Flowchart of the working principle of the model

6. Results and Discussion

6.1 Activity-state classification

Table 9 presents the classifier performance on the test shifts. The transition rules (Fig. 5) achieve an accuracy of 0.964 but a macro-F1 score of only 0.881. While they effectively recognise frequent states (TE, LD, and TL), they struggle with rarer events. This failure occurs because single noisy readings, such as a multipath GPS error, an idling engine during a stop, or queue creeping, violate thresholds or trigger irreversible transitions. Furthermore, the rules do not account for all practical sequences, such as a stop immediately after unloading.

Incorporating the Boolean features (FS1) allows the trained classifiers to improve the macro-F1 score to a range of 0.957 to 0.972. The addition of continuous variables (FS2), specifically distance, speed, and distance change, further enhances recognition to between 0.966 and 0.986. The best-performing model, Gradient Boosting (GBM) with FS2, achieves an accuracy of 0.998, a macro-F1 of 0.986, and a Cohen's κ of 0.997. Critically, the loading (LD) and unloading (UL) states that trigger Phase II dispatching are recognised with exceptional F1 scores of 0.999 and 0.970, respectively. All machine-learning models process a single record in 1.8 to 24.6 ms (median time). This latency is significantly below the 2 to 16 s sampling interval, ensuring that the classifier does not bottleneck real-time operations. Although these benchmark results demonstrate that activity recognition is successfully framed as a classification task, eventual deployment will require validation on labelled field data.

Table 9. Classification performance on the test shifts

Model	Set	Acc.	Macro-F1	κ	F1 SE	F1 WT	F1 LD	F1 UL	F1 SL	Latency (ms)
Rules (Fig. 5)	FS1	0.964	0.881	0.951	0.762	0.941	0.980	0.880	0.650	N/A
MLR	FS1	0.990	0.957	0.986	0.899	0.992	0.997	0.928	0.892	1.8
DT	FS1	0.992	0.972	0.989	0.924	0.993	0.997	0.922	0.975	1.9
RF	FS1	0.969	0.961	0.958	0.924	0.977	0.956	0.924	0.986	23.9

GBM	FS1	0.991	0.970	0.988	0.924	0.987	0.997	0.924	0.963	5.9
MLR	FS2	0.993	0.966	0.991	0.922	0.991	0.999	0.917	0.933	2.8
DT	FS2	0.993	0.967	0.990	0.926	0.993	0.999	0.914	0.940	2.9
RF	FS2	0.994	0.969	0.991	0.926	0.990	0.999	0.917	0.950	24.6
GBM	FS2	0.998	0.986	0.997	0.975	0.995	0.999	0.970	0.960	5.2

Note: MLR = multinomial logistic regression; DT = decision tree; RF = random forest; GBM = gradient boosting. Acc. = accuracy. Set FS1 = Boolean features and previous state (Table 7); FS2 = FS1 plus distance, speed, and distance change. F1 scores for TE and TL are omitted as they exceed 0.956 for all learned models. Latency denotes the median time to classify one record. Selected hyperparameters (grids in brackets): MLR-FS1: $C = 1.0$; DT-FS1: max depth = 16; RF-FS1: max depth = 10, min samples leaf = 1; GBM-FS1: learning rate = 0.05, max leaf nodes = 15; MLR-FS2: $C = 0.1$; DT-FS2: max depth = 10; RF-FS2: max depth = 10, min samples leaf = 5; GBM-FS2: learning rate = 0.1, max leaf nodes = 15. [Grid search details: MLR: $C \in \{0.1, 1, 10\}$; DT: max depth $\in \{6, 10, 16\}$; RF: 100 trees, max depth $\in \{10, 20\}$, min leaf $\in \{1, 5\}$; GBM: learning rate $\in \{0.05, 0.1\}$, max leaf nodes $\in \{15, 31\}$].

To assess sensitivity to positioning accuracy, the benchmark was regenerated with GPS noise levels of $\sigma = 5$ m and 10 m per axis. The macro-F1 of the rule-based approach decreased marginally to 0.880 and 0.874, while the GBM (FS2) model maintained robust scores of 0.981 and 0.987, compared to 0.881 and 0.986 at $\sigma = 2$ m. This indicates that recognition is largely insensitive to positioning errors within this range, as the designated distance thresholds (30, 50, and 150 m) easily absorb the noise. Consequently, the primary advantage of the trained classifiers lies in their robustness against behavioural confounders and bit errors, rather than serving merely to compensate for GPS inaccuracies.

6.2 Dispatching Performance at the Case Mine

The real-time dispatching heuristic was evaluated using the case mine's operating data (Table 10). The key performance indicators are summarised in Table 11.

Table 10. Specification of XYZ coal mine

Sl No.	Parameter	Specification
1.	Excavator	Hitachi EX2500
2.	Tipper	Caterpillar 777G

3.	Nominal Tipper capacity	85 tons
4.	Average Load per tipper	55 – 60 tons
5.	Distance from Excavator to dumping ground.	6 to 8 km
6.	Loading time	15 to 20 mins
7.	Spotting time	5 to 10 mins
8.	Capacity of a spot	300 – 700 tons
9.	Mass flow rate	170 to 190 tons per hour
10.	Average loaded velocity	15-20 kmph
11.	Average Empty velocity	24-25 kmph
12.	Shift	8 hours

Table 11. Key Performance Indicator for the model

SI No.	Subject	KPI to evaluate
1.	Excavator	Loading time
2.	Source	Total Production
3.	Tipplers	Total Wait time.

The Python-implemented heuristic generated the results presented in Fig. 7, which shows excavator loading and idle times over an 8-h shift for fleet sizes ranging from 20 to 36 tippers. Loading time includes tipper spotting time, which XYZ confirmed to be uniformly distributed. The results illustrate how increasing fleet size shifts excavator time from idling to loading, informing fleet-sizing decisions.

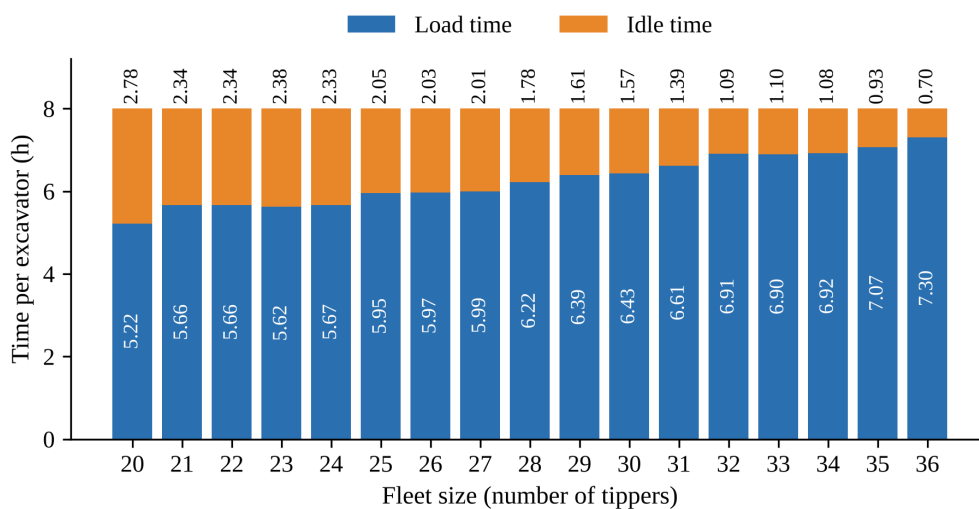


Figure 7. Load and idle times per excavator by fleet size

Fig. 8 shows that excavator idle time decreases as fleet size increases, from 2.78 h (166.8 min) per excavator with 20 tippers to 0.70 h (42 min) with 36 tippers, equivalent to

8.75% of an 8-h shift. The results were reviewed with mine management.

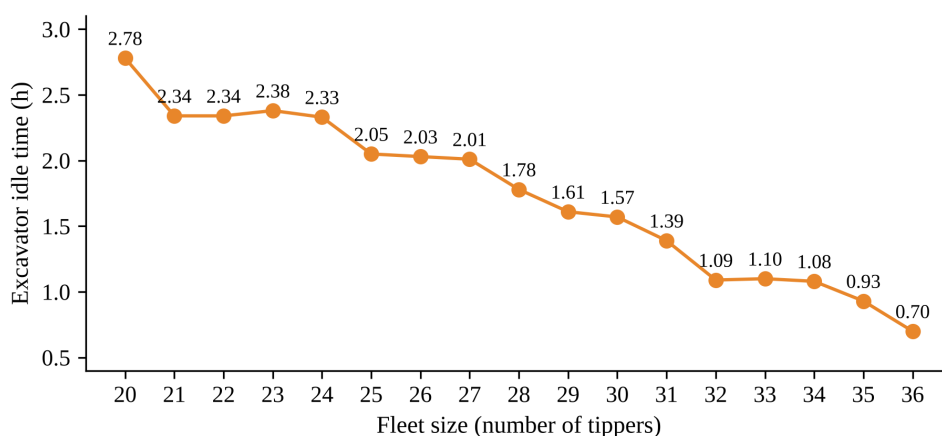


Figure 8. Behaviour of idle time with fleet size

Fig. 9 compares production under current mine operations and the proposed model. Production increases with fleet size under both approaches, while the proposed model consistently achieves higher output, increasing from 3,300 to 3,782 t with 20 tippers and from 4,500 to 5,293 t

with 36 tippers. For the existing fleet of 30 tippers, production increases from 4,100 to 4,659 t per shift, representing an improvement of 559 t (13.6%). The mine supervisor confirmed the operational feasibility of the model's dispatching decisions.

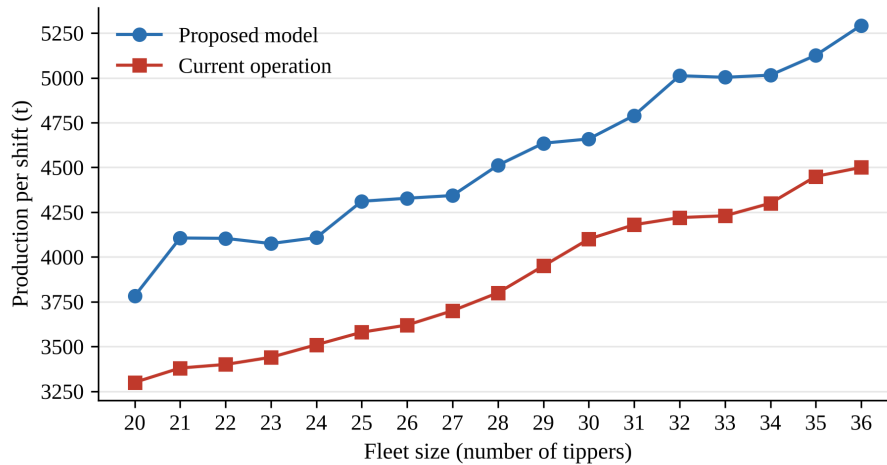


Figure 9. Production per shift

Fig. 10 presents the mean waiting time per tipper. Under the earlier queue-length formulation, waiting time increases from 6.16 min with 20 tippers to 8.76 min with 36 tippers. The corrected recursion in Eqs. (7)-(9), implemented in the re-implemented simulation, yields waiting times of 1.5 min and 12.7 min, respectively. The earlier formulation overestimates waiting for smaller fleets

and underestimates it for larger fleets, highlighting the importance of accounting for arrival times and queue dynamics. Larger fleets reduce excavator idle time but increase tipper waiting time, requiring a trade-off between the two effects and their associated costs when selecting fleet size (Section 6.5).

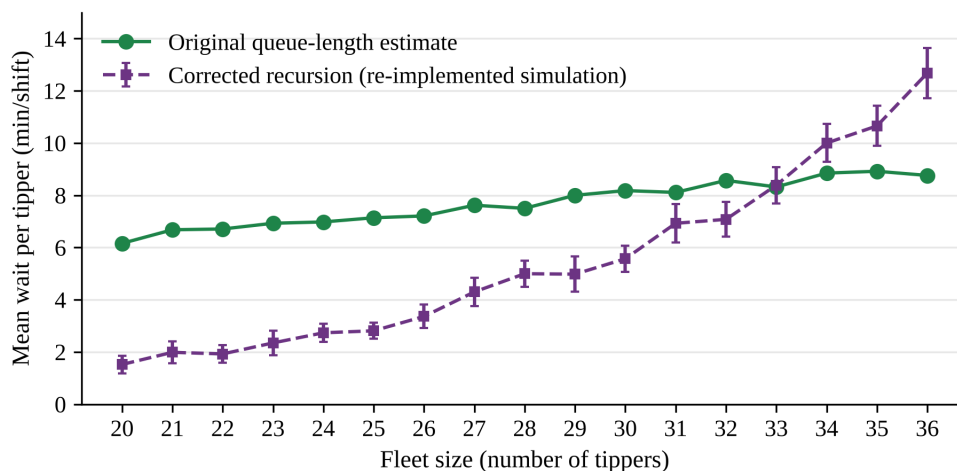


Figure 10. Mean waiting time per tipper

6.3 Comparison with Benchmark Policies

Table 12 compares the proposed heuristic with fixed-assignment and shortest-wait policies for the base case of

four excavators and 30 tippers. Relative to fixed assignment, the heuristic increases production by 2.5% (4,819 vs. 4,700 t per shift), reduces mean tipper waiting time by 66% (5.6 vs. 16.3 min), and decreases excavator

idle time from 2.03 to 1.88 h. The shortest-wait policy achieves slightly higher production (4,867 t) but results in greater excavator output imbalance, with a coefficient of variation (CV) of 13.0%, compared with 1.8% under the proposed heuristic. The heuristic therefore prioritises balanced production across excavators while maintaining competitive throughput, which is relevant when coordinated face advancement or material blending is required.

Table 12. Benchmark comparison and sensitivity analysis

Scenario	Production (t/shift) Proposed / Shortest-wait / Fixed	Waiting time (min) Proposed / Shortest-wait / Fixed	Excavator output imbalance, CV (%) Proposed / Shortest-wait / Fixed
Base case: 4 excavators, 30 tippers	4,819 / 4,867 / 4,700	5.6 / 5.3 / 16.3	1.8 / 13.0 / 8.4
3 excavators, 22 tippers	3,536 / 3,559 / 3,486	7.0 / 7.1 / 15.3	1.4 / 11.8 / 7.8
5 excavators, 38 tippers	6,131 / 6,145 / 5,983	5.0 / 5.3 / 16.5	1.8 / 15.1 / 8.5
6 excavators, 45 tippers	7,221 / 7,316 / 7,111	4.2 / 3.9 / 16.1	1.4 / 16.2 / 8.7
Haul distance × 0.75	5,100 / 5,109 / 4,975	8.5 / 7.5 / 20.2	1.9 / 9.2 / 7.6
Haul distance × 1.5	4,308 / 4,388 / 4,279	3.6 / 3.8 / 11.1	1.7 / 18.8 / 9.6

Tipper heterogeneity, CV = 0.3	4,618 / 4,712 / 4,551	13.1 / 8.6 / 22.1	2.4 / 12.0 / 10.3
Excavator heterogeneity, CV = 0.3	4,750 / 4,931 / 4,745	12.7 / 4.9 / 15.9	2.4 / 27.5 / 9.5
Route heterogeneity, ±3 km	4,919 / 4,992 / 4,906	7.4 / 12.7 / 18.7	1.6 / 21.4 / 10.1

Note: Results are means over 30 replications. The 95% confidence-interval half-widths for production are below 2.5% of the mean. CV denotes the coefficient of variation of excavator output within a shift.

6.4 Sensitivity Analysis: Mine Size and Fleet Heterogeneity

The heuristic was evaluated across different mine sizes, haul distances, and fleet heterogeneity levels using the re-implemented simulation (Fig. 11 and Table 12). Mine size varied from three to six excavators, maintaining a tipper-to-excavator ratio of 7.5, while haul distances ranged from 0.75 to 1.5 times the baseline of 6-8 km. Heterogeneity was introduced through tipper capacity and speed, excavator loading times (CV up to 0.3), and route distances (±3 km). Production per excavator remained between 1,179 and 1,226 t per shift across mine sizes. The heuristic maintained balanced excavator output, with a maximum CV of 2.4%, compared with 27.5% under the shortest-wait policy for heterogeneous excavator loading rates. However, this balance involved a throughput trade-off: under excavator heterogeneity, production was 3.7% lower than under the shortest-wait policy, and mean tipper waiting time increased to 12.7 min. For heterogeneous mines, target flow rates F_j can be adjusted in proportion to excavator capacity rather than set equally.

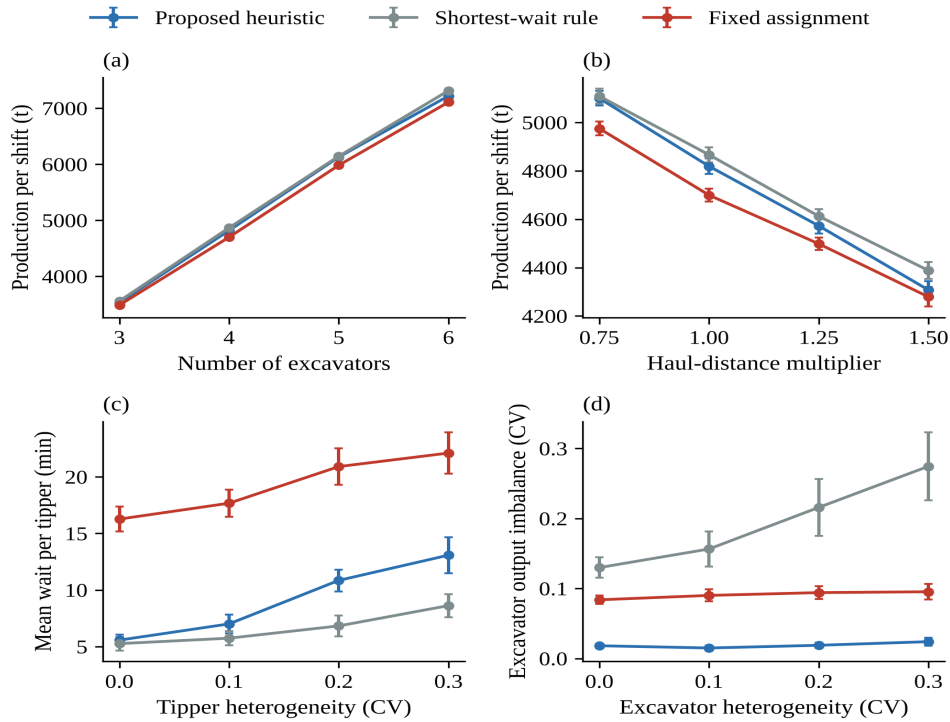


Figure 11. Sensitivity of dispatching policies to mine size and fleet heterogeneity

Note: Error bars represent 95% confidence intervals over 30 replications.

6.5 Economic and Environmental Benefits

The production gains in Fig. 9 were used to estimate fuel savings, operating costs, and emissions (Table 13). With 30 tippers operating for the same duration, the proposed model increases production by 13.6%, reducing fuel consumption per tonne by 12.0%. Alternatively, approximately 4,100 t per shift can be produced using 24 rather than 30 tippers. Releasing six Cat 777G tippers for an 8-h shift yields estimated diesel savings of 2,180–3,501 L, equivalent to 5.78–9.29 t of CO₂ and ₹2.08–3.33 lakh in fuel costs per shift. These estimates are based on simulated production and published fuel-consumption rates and require validation against mine fuel records.

Table 13. Economic and environmental estimates per 8-h shift

Indicator	Value	Basis
Production with 30 tippers: current/proposed	4,100/4,659 t (+13.6%)	Fig. 9
Fuel per tonne with 30 tippers	–12.0%	Same fleet operating hours

Fleet required for approximately 4,100 t/shift: current/proposed	30/24 tippers	Fig. 9
Cat 777G fuel rate (low/medium/high duty)	45.4/59.2/72.9 L/h	Caterpillar (2022)
Diesel saved (6 tippers × 8 h)	2,180/2,840/3,501 L	Calculated
Diesel CO ₂ emission factor	2.65 kg/L	IPCC (2006); CEN (2022)
CO ₂ avoided	5.78/7.53/9.29 t	Calculated
Diesel price	₹95.20/L	Delhi, 15 October 2026 (The Hans India, 2026)
Fuel cost saved	₹207,574/₹270,365/₹333,329	Calculated

Note: The emission factor is calculated as 74,100 kg CO₂/TJ × 43.0 TJ/Gg (IPCC, 2006) × 0.8325 kg/L, using the midpoint of the EN

590 diesel density range of 0.820–0.845 kg/L (CEN, 2022). Fuel rates were converted from US gallons per hour using 1 US gal = 3.785 L.

7. Managerial and Theoretical Implications

Mine managers worldwide must intensify operations and production to meet rising coal demands driven by industrial needs. The increasing energy demand necessitates continuous efficiency improvements. This paper's model addresses these challenges and provides actionable insights.

The case mine operates 30 Cat 777G tippers and produces 3,600–4,100 t per 8-h shift (Table 10). The proposed model increases production by 559 t (13.6%) per shift or achieves approximately the current output with 24 tippers, potentially saving 2,180–3,501 L of diesel and 5.8–9.3 t of CO₂ per shift (Figs. 9 and 10; Table 13). Fleet size selection should account for the trade-off between excavator utilisation and tipper waiting time. Where coordinated face advancement is required, the flow-rate-based heuristic maintains balanced excavator output with a modest reduction in throughput (Section 6.3).

The model emphasizes the prioritization of shovels in surface operations to achieve desired efficiency levels. Given the significant investments in mining equipment, idle operations signify inefficiency. Poor communication with tipper drivers exacerbates this issue. This paper highlights the importance of effective communication and monitoring systems for fleet management. A machine learning-based approach to daily data management is proposed to improve equipment performance. The model significantly reduces idle time for mining equipment, including unavoidable idle operations, allowing mine managers and planners to optimize operations empirically.

Academics can explore unconventional approaches to optimization problems. This paper highlights real-time decision-making and idle time reduction, offering a fresh perspective. The Fleet Management System (FMS) model is highly flexible, allowing operational adjustments to achieve objectives. However, equipment capacities and source-destination distances remain fixed due to existing costly assets. Had this model been implemented during the initial site setup, these parameters could have also been optimized.

For existing sites, the model helps improve equipment efficiency and performance. It gives mine managers an effective tool for monitoring and managing fleets, enhancing gross productivity and minimizing idle time. For academics, the model offers a platform for empirically exploring optimization strategies, focusing on reducing idle and wait times for maximum production.

8. Conclusion

The model for monitoring of fleet has been reliable with the prediction of an activity state. The reliable prediction

of the activity state of equipment provides us the liberty to run the model for determining the destination to reach on the actual time. Subsequently, the results of the monitoring model help in achieving better results in the dispatching model. This model also promises to reduce the system load while monitoring the fleet. Furthermore, the mine managers of XYZ preferred an effective fleet management system with machine learning-based data analysis as the model improved the equipment performance of the mine combines with the tipper dispatching model as discussed.

Although in simulation, the proposed model has potential with promising results in the field of surface meaning. With the current rate of production per shift with operation running with the present model, the fleet size is more compared to the proposed model. Had the aim been to produce the current gross production of XYZ, the proposed model would achieve the goal with a significantly lower fleet size. This model proposed in this paper is an unconventional optimization problem with an experimental approach to reduce the idle time of operation. The performance of this model is solely based on the scenario of XYZ, working based on homogenous mining operations.

The present model assumes a homogeneous fleet. Future research could extend it to heterogeneous fleets in which tippers transport both waste and coal to different destinations, irrespective of the receiving plant. Further work could also examine how dispatching decisions are communicated to drivers in real time to support effective implementation in operational mining environments.

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