Optimizing Green Truck Dispatch in an Open Pit Mine through a Multi-Objective Simulation and Optimization Framework with Fuel Consumption Consideration

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ABSTRACT

In open pit mining, trucks play a vital role in transporting materials. By optimizing truck dispatching strategies, both productivity and sustainability principles can be effectively enhanced. This research focuses on developing a new framework for green truck dispatching, aiming to accomplish four specific objectives: minimizing the deviations from target production rates set by strategic plans, reducing shovel idle time, minimizing truck wait time, and minimizing truck fuel consumption. The significant contribution of this study lies in the inclusion of Greenhouse Gas (GHG) mitigation by considering fuel consumption reduction as an objective, which brings direct economic and environmental benefits. To account for uncertainty in open-pit mining operations, a discrete event simulation using Arena software is employed. Different scenarios are examined based on objective weights. The case study conducted at Gol-E-Gohar mines in Iran, an iron ore mine, demonstrates that the developed framework successfully reduced fuel consumption by 4.88% per ton of production. In absolute terms, this equates to a total reduction of over 12,000 liters of fuel. By prioritizing fuel consumption, a potential reduction of up to 6% in fuel consumption per tonne of production is attainable, potentially leading to a significant overall decrease of up to 20,000 liters in fuel consumption.

Keywords: *Truck dispatching, Open-pit mine, Discrete Event Simulation, Real-Time Decision Making, Fuel Consumption, Multi-objective optimization*

1. Introduction

The mining industry, vital for the global economy and population growth, faces challenges due to its energy consumption and emissions. Approximately 8% of global greenhouse gas emissions stem from the mining industry (Rahnema et al., 2023). Energy efficiency improvement is crucial for environmental sustainability, but research in this area, especially related to energy-intensive activities like haulage in open-pit mines, is lacking. Both the industry and academia recognize the challenge of inadequate energy efficiency in mining, underscoring the importance of advancing environmental sustainability (Patterson et al., 2017). Certain mining projects, such as iron, bauxite, and coal ventures, attribute 41% to 66% of energy consumption and 37% to 54% of greenhouse gas emissions to mineral loading and hauling activities (Feng et al., 2022). Apart from the substantial

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environmental impact, the mining haulage system entails noticeable operational costs. Haulage expenses constitute a significant portion of mining operational costs, around 50-60% (Alarie and Gamache, 2002; Moradi-Afrapoli et al., 2021; Moradi Afrapoli et al., 2019; Moradi Afrapoli and Askari-Nasab, 2017; Upadhyay and Askari-Nasab, 2019).

The truck fleet transports materials from shovels to plants or waste dumps depending on the type of the material. The process of dynamically assigning a truck first to a shovel and then to an unloading point is referred to as truck dispatching. Efficient truck dispatching is vital for optimizing productivity, profitability, and sustainability. This research addresses truck dispatching in open-pit mining, proposing an innovative approach that considers factors like truck capacity, distances, extraction rates, and plant capacity. The goal is a solution that meets operational needs, enhances productivity, reduces costs, and contributes to sustainability by reducing greenhouse gas emissions. This study examines truck dispatching in open-pit mines, where trucks aren't locked to specific areas. Instead, they're assigned based on real-time factors such as shovel availability and production rates. To achieve this, a multi-objective stochastic simulation and optimization framework is developed, utilizing mathematical models and simulations to optimize truck dispatching, with a primary focus on minimizing fuel consumption and carbon emissions. In summary, effective truck dispatching enhances open-pit mining success by improving productivity, cost-efficiency, and environmental impact. This research develops a framework considering the dynamic nature of mining, aiming to provide practical, optimized solutions that adapt to operational changes.

In the subsequent sections, after a brief literature review, the benchmark methods for dispatching trucks will be introduced, and then the new framework applied in this research will be presented. This will be followed by a detailed explanation of the case study, including key performance indicators (KPIs) and different operational scenarios. Moving on to the results, the paper will analyze how well the framework performed in the case study, comparing it to the benchmark methods. Finally, in the last section, the paper will have a thorough discussion of the results, drawing conclusions, and suggesting areas for future research.

2. **Literature Review**

Truck dispatching in open-pit mines is a critical aspect of mining operations. It involves determining the optimal allocation and routing of trucks to transport materials from mining sites to dump sites for further processing. Truck dispatching decisions have direct impact on production rate, operational cost, fuel consumption, and subsequently GHG emissions. Efficient truck dispatching strategies can lead to satisfy the target production requirement, as well as reducing the operational cost, and GHG emissions. Therefore, well-coordinated truck dispatching plays a crucial role in balancing production needs with environmental considerations. Cost-efficient dispatching methods are a priority for industrial companies, while sustainable dispatching methods align with the preferences of governments and communities. Past research has employed three distinct approaches including, operations research, queuing theory, and simulation techniques to optimize decision-making in this context (Upadhyay, 2013). In the upcoming sections, a range of studies focusing on truck dispatching, routing, and allocation problems are reviewed and categorized based on their methodologies and underlying objectives. These perspectives are organized into two primary viewpoints: the economical perspective and the environmental perspective.

2.1. Economical Perspective

Ataeepour and Baafi (1999) applied a simulation model using Arena simulation software to examine the impact of truck dispatching on mine productivity by ensuring optimal utilization of available trucks and shovels, with the trucks being identical in their scenario. Topal and Ramazan (2010) introduced mixed integer programming model to meet production targets and optimize the truck schedule considering the truck maintenance cost in an open-pit mine. Souza et al. (2010) introduced a hybrid algorithm combining greedy randomized adaptive search procedure (GRASP) and general variable neighborhood search (GVNS) metaheuristics for dynamic truck allocation in an open-pit mine. Their approach aimed to minimize truck usage while meeting production and quality goals. Zhang and Xia (2015) employed integer programming to optimize open-pit mine truck dispatching, resulting in cost reduction and production objectives satisfaction. Matamoros and Dimitrakopoulos (2016) presented a new method to optimize truck fleet allocation. Their method handled input parameter uncertainties and improved allocation efficiency resulting in cost savings in a multi-element iron mine case study. Fadin and Moeis (2017) applied a "look-ahead algorithm" approach (Jang et al., 2001) to solve open-pit mine truck dispatching. Combining simulation and optimization models with real data, the approach aimed to optimize truck routes and schedules, boosting production, and reducing operational costs. Utilizing discrete event simulation, the research tested multiple dispatching scenarios. Shishvan and Benndorf (2019) investigated optimizing material dispatch in coal mines, particularly focusing on safe placement of diverse overburden types. Their approach considered equipment factors like capacity, performance, and availability to make dispatch decisions. Alexandre et al. (2019) developed two Multi-objective Genetic Algorithms (MOGAs) to efficiently and dynamically allocate trucks in an open-pit mine. The goals were to maximize production and minimize costs within operational constraints. Wang et al. (2023) addressed real-time truck dispatching challenges in open-pit mines, optimizing full and empty truck stages. Unlike prior methods, the model splits into full and empty truck dispatching, aiming to minimize waiting times, path flow deviations, and transportation costs with adjustable weights. To gain a deeper understanding of truck dispatching, it would be beneficial to explore two comprehensive review studies on the subject. Newman et al. (2010) reviewed mine planning operations, including open-pit truck dispatching, categorizing strategies and analyzing their mathematical basis. Moradi Afrapoli and Askari-Nasab (2017) conducted a comprehensive assessment of fleet management methods, addressing path determination, production optimization, and real-time dispatching. They examined various allocation techniques like queuing theory, linear programming, goal programming, and stochastic programming.

2.2. Environmental Perspective

As global warming concerns grow, most of the large organizations are investing more resources and effort into reducing energy consumption and emissions of pollutants (Ganji et al., 2020). In spite of efforts to reduce energy consumption, numerous mines find it difficult to reduce their energy consumption (Awuah-Offei, 2016). The literature extensively covers green vehicle routing problems in various industries, emphasizing sustainability and environmental factors. However, the mining sector's exploration of green vehicle routing is comparatively limited. Awuah-Offei (2016) reviewed previous studies regarding energy efficiency in loading and hauling activities within the mining industry. Yu et al. (2016) used mixed integer programming to optimize shovel production plans and truck allocations, reducing costs, fuel consumption, and emissions. They also considered equipment failure uncertainties with a multi-scenario approach. Gonzalez et al. (2017) presented a simulation-based approach to determine the optimal balance between carbon emissions and operational costs in underground mining projects. Mohtasham et al. (2021) used mixed integer linear programming to optimize truck scheduling in open-pit mines, aiming to maximize production, minimize deviations in head grade, and tonnage, and minimize fuel consumption. In a follow-up study, Mohtasham et al. (2022) addressed fleet cycle time uncertainty using a multi-stage approach involving simulation-based optimization and a novel heuristic algorithm for real-time truck scheduling decision-making in open-pit mines, targeting production loss and fuel consumption reduction. Mirzaei-Nasirabad et al. (2023) presented a multi-stage approach that optimizes real-time dispatching and determines fleet size. The technique in their study, assessed through a case study in a copper ore mine. Anaraki and Afrapoli (2023) introduced a mathematical multi-objective model that aims to minimize transportation costs and carbon emissions associated with truck travel in open pit mines. The model takes into account various types of trucks with different age groups, recognizing their impact on carbon emissions. Huo et al. (2023) Utilized reinforcement learning in order to improve truck fleet dispatching efficiency in open-pit mining. Their primary objective was to develop a smart fleet management system and decrease greenhouse gas emissions. This study differs from previous research by introducing a real-time decision-making framework that integrates economic, environmental, and uncertainty considerations. The approach simultaneously addresses emissions, economic goals, and operational objectives, providing benefits to both economy and environment.

3. Methodology

This chapter delves into the theoretical foundations of an integrated simulation and optimization framework for open-pit mine truck dispatching. By introducing a new multi-objective mixed integer goal programming (MOMIGP) model, this chapter focuses on enhancing production efficiency through the reduction of shovel idle time, truck wait time, deviations from target production rates, and greenhouse gas (GHG) emissions arising from truck fuel consumption. Notably, the MOMIGP model adeptly manages dispatching decisions in the face of uncertain factors.

Within this chapter, there are two sections. The first section presents optimization models, while another section introduces the integrated simulation and optimization framework. Divided into three subsections, the optimization models section introduces three distinct truck dispatching optimization approaches: Modular Mining Dispatch (MODULAR MINING) by White and Olson (1993; 1986), Tri-Objective model by Moradi Afrapoli et al. (2019), and Quad-Objective model, which is the central model of this research.

3.1. Optimization Models

3.1.1. Modular Mining Dispatch

The Modular Mining Dispatch stands as one of the mining industry's most extensively utilized truck dispatching systems for open-pit mines. This system offers real-time dispatching, a crucial factor in optimizing mining operations. Within the Modular Mining Dispatch model, truck dispatching relies on the prioritization in two main lists: "needy shovels" and "available trucks." The first list encompasses shovels requiring trucks, ranked by urgency, while the second list ranks available trucks by their next availability. Dispatching entails assigning the foremost available truck to the top-listed shovel, a process repeated until all trucks are dispatched. Thanks to its effectiveness and widespread application, Modular Mining Dispatch has emerged as the dominant fleet dispatching system in the mining market. Given its extensive industry usage, the Modular Mining Dispatch model serves as one of benchmark models for comparison in evaluating the Quad-Objective dispatch model of this research. This choice stems from its established reputation as an efficient solution for mining fleet dispatching. This model also served as the benchmark in the study by Moradi Afrapoli et al. (2019).

3.1.2. Tri-Objective Model

To facilitate real-time truck dispatching in open-pit mines, Moradi Afrapoli et al. (2019) developed a Tri-Objective dispatching model that concurrently minimizes shovel idle times, truck wait times, and deviations from planned production rates. This model efficiently managed diverse fleets of varying sizes and types, operating autonomously to maintain the target production rate. The model is executed whenever a new truck assignment is needed including when the truck starts working, and when the truck dumps its load. Their model accounted for operational factors like stripping ratios, truck capacity, plant throughput, and shovel dig rates. Impressively, their Tri-Objective model achieved maximum plant capacity with 14% fewer trucks than the Modular Mining Dispatch model, utilizing just 86% of the intended fleet size while meeting production needs. Meeting the predefined production rate, this model holds the status of an additional benchmark in this context.

3.1.3. Quad-Objective Model

This study introduces a Quad-Objective mathematical optimization model designed for real-time truck dispatching. An exceptional aspect of this model is its incorporation of an extra objective function dedicated to minimizing overall trucks' fuel consumption, thus addressing carbon emissions and environmental concerns. The model is employed whenever a truck requires a new assignment, triggered by events like the initiation of a truck's operation, truck dumping, shovel breakdowns before loading, and the restart of a truck's operation after downtime. Numerous indices, parameters, and decision variables are available within the optimization model. The indices are listed below:

t	Index for set of trucks: $t = \{1, \dots, T\}$
s	Index for set of shovels: $s = \{1, \dots, S\}$
d	Index for set of dumping points: $d = \{1, \dots, D\}$
d'	Index for set of locations where trucks are required to dump their load before traveling to the new shovel: $d' = \{1, \dots, D\}$
w	Index for set of weights assigned to individual goals: $w = \{1, 2, 3, 4\}$
g	index for the group of trucks that are currently waiting in a queue of the shovel: $g = \{1, \dots, NTWS\}$

The decision variables are listed below:

x_{tsd}	Binary variable equals to 1 if truck t assigns to the path of shovel s to dumping point d , and 0 otherwise
y_{sd}^{-}	Negative deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d
y_{sd}^{+}	Positive deviation of the met path flow rate and the desired path flow rate for the path between shovel s and dumping point d

The parameters are listed below:

IT_{tsd}	Idle time for shovel s if truck t is assigned to transport material from shovel s to the dumping point d
WT_{tsd}	Wait time for truck t if it is assigned to transport material from shovel s to the dumping point d
N_w	Normalized weights of individual goals based on priority
AF	A factor balancing available trucks with the required capacity of plants
PC_d	Capacity of the plant d: $d = \{1, \dots, P\} \subset \{1, \dots, \mathrm{D}\}$
SC_s	Production capacity of shovel s
MP_{sd}	Path flow rate for the path from shovel s to the dumping point d that the production operation has met so far
TC_t	Actual capacity of truck t (tonne)
NTC_t	Nominal capacity of truck t (tonne)

P_{sd}	Path flow rate for the path from shovel s to the dumping point d
TR_{tsd}	Next time truck t reaches shovel s, if truck t is assigned to transport material from shovel s to the dumping point d
SA_{tsd}	Next time shovel s is available to serve truck t, if truck t is assigned to transport material from shovel s to the dumping point d
TNOW	Current time of the operation/simulation
$LD_{td'}$	The distance truck t must travel to reach the dumping point d' to dump its load
$ED_{td's}$	The distance truck t must travel from the dumping point d' to the next expected shovel s
ALT_t	Average loading time of truck t
APL_t	Average payload of truck t
$LV_{td's}$	Average loaded velocity of truck t traveling to dumping point d' and will travel to shovel s after dumping its load
$EV_{td's}$	Average empty velocity of truck t traveling from dumping point d' to the next expected shovel s
$DQ_{td'}$	Queue time for truck t in the queue of the dumping point d'
$DT_{td'}$	Dump time for truck t to dump its material in dumping point d'
$NTWS_s$	Number of trucks waiting in queue at shovel s
ST_g	Spotting time for the truck g in the queue
LT_g	Loading time for the truck g in the queue
α_t	Intercept of truck t for the fuel consumption
β_t	Payload coefficient of truck t for the fuel consumption
γ_t	Loading time coefficient of truck t for the fuel consumption
τ_t	Idle time coefficient of truck t for the fuel consumption
ω_t	Empty traveling time coefficient of truck t for the fuel consumption
φ_t	Loaded traveling time coefficient of truck t for the fuel consumption
SIT_{tsd}	Shovel idle time coefficient, by assigning truck t to the path of shovel s to dumping point d

TWT_{tsd}	Truck wait time coefficient, by assigning truck t to the path of shovel s to dumping point d
F_{tsd}	Truck fuel consumption coefficient, by assigning truck t to the path of shovel s to dumping point d

In order to determine the arrival time of each truck to be loaded by shovel, Eq. (1) is used. To calculate the shovel availability, Eq. (2) is used, which represents the next time the shovel will be available to load the truck. The coefficients for three objectives within the optimization problem can be calculated using Eqs. (3), (4) and (5). Accordingly, these coefficients correspond to the objective functions associated with shovel idle time, truck wait time, and fuel consumption, respectively.

$$TR_{tsd} = TNOW + \frac{LD_{td'}}{LV_{td's}} + DQ_{td'} + DT_{td'} + \frac{ED_{td's}}{EV_{td's}} \tag{1}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\} \;\&\; \forall d' \in \{1, \dots, D\}$$

$$SA_{tsd} = TNOW + \sum_{g=1}^{NTWS_s} \left(ST_g + LT_g\right) \tag{2}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

$$SIT_{tsd} = \max\left(0, TR_{tsd} - SA_{tsd}\right) \tag{3}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

$$TWT_{tsd} = \max\left(0, SA_{tsd} - TR_{tsd}\right) \tag{4}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\}$$

$$F_{tsd} = \alpha_t + \beta_t \times APL_t + \gamma_t \times ALT_t + \tau_t \times TWT_{tsd} + \omega_t \frac{ED_{td's}}{EV_{td's}} + \varphi_t \frac{LD_{td'}}{LV_{td's}} \tag{5}$$
$$\forall t \in \{1, \dots, T\} \;\&\; \forall s \in \{1, \dots, S\} \;\&\; \forall d \in \{1, \dots, D\} \;\&\; \forall d' \in \{1, \dots, D\}$$

The optimization model comprises four distinct objectives, each with a specific purpose. The initial objective focuses on minimizing active shovel idle time, calculated using Eq. (6). The second objective aims to reduce truck wait time during operation, computed through Eq. (7). The third objective adopts a goal programming approach to minimize deviations from path flow rates, as determined by Eq. (8). Lastly, the fourth objective function aims to minimize total fuel consumption by active trucks using Eq. (9). These objectives possess differing scales and varying degrees of influence on the system. The model is categorized as a Mixed Integer Linear Programming (MILP) model, necessitating a non-preemptive mixed integer linear weighted sum goal programming approach for resolution. Following are the objective functions of the model:

$$f_1 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} SIT_{tsd} x_{tsd} \tag{6}$$

$$f_2 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{d=1}^{D} TWT_{tsd} x_{tsd} \tag{7}$$

$$f_3 = \sum_{s=1}^{S}\sum_{d=1}^{D}(y_{sd}^{-} + y_{sd}^{+}) \tag{8}$$

$$f_4 = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{d=1}^{D}F_{tsd}x_{tsd} \tag{9}$$

To achieve the model's solution, the four objectives are converted into dimensionless forms through the application of Nadir and Utopia points, a concept proposed in (Grodzevich and Romanko, 2006). Within this method, Utopia defines lower boundaries for each objective, while Nadir establishes upper limits. By determining these points, a range is set for the objective functions within the Pareto optimal set. When considering a single objective, optimization directs towards the Utopia point, yielding minimal values. Conversely, upper limits are determined using components derived from the Nadir point. The process of normalization is achieved by employing Nadir and Utopia points, thereby scaling objectives within a range of 0 to 1 by Eq. (10). To establish the necessary priority weights for the weighted sum method, each component of the objective function outlined in Eq. (11) represents a weighted and normalized version of an individual objective from Eqs. (6) to (9).

$$\bar{f_i} = \frac{f_i - U_i}{N_i - U_i} \qquad \forall i \in \{1,2,3,4\} \tag{10}$$

$$f = N_1\bar{f_1} + N_2\bar{f_2} + N_3\bar{f_3} + N_4\bar{f_4} \tag{11}$$

Following are the constraints of the model:

$$\sum_{s=1}^{S}\sum_{d=1}^{D}TC_t x_{tsd} \le NTC_t \qquad \forall t \in \{1, \dots, T\} \tag{12}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S}TC_t x_{tsd} \ge AF \times PC_d \qquad \forall d \in \{1, \dots, P\} \tag{13}$$

$$\sum_{t=1}^{T}\sum_{d=1}^{D}TC_t x_{tsd} \le SC_s \qquad \forall s \in \{1, \dots, S\} \tag{14}$$

$$\sum_{t=1}^{T}TC_t x_{tsd} + MP_{sd} + y_{sd}^{-} - y_{sd}^{+} = P_{sd} \qquad \forall s \in \{1, \dots, S\}\ \&\ \forall d \in \{1, \dots, D\} \tag{15}$$

$$x_{tsd} \in \{0,1\} \qquad \forall t \in \{1, \dots, T\}\ \&\ \forall s \in \{1, \dots, S\}\ \&\ \forall d \in \{1, \dots, D\} \tag{16}$$

$$y_{sd}^{-} \ge 0 \qquad \forall s \in \{1, \dots, S\}\ \&\ \forall d \in \{1, \dots, D\} \tag{17}$$

$$y_{sd}^{+} \ge 0 \qquad \forall s \in \{1, \dots, S\}\ \&\ \forall d \in \{1, \dots, D\} \tag{18}$$

$$AF = \frac{\sum capacity\ of\ available\ trucks}{\sum required\ flow\ rate\ at\ paths} \tag{19}$$

In order to ensure the system's efficient operation, a number of constraints are placed on it. According to constraint (12), the amount of tonnage that a truck can transport in one payload is limited to its nominal capacity. For constraint (13) it is considered that the material hauled to the processing plants using all the trucks must meet the processing target determined by each plant in AF times the percentage. AF, or the adjustment factor, is calculated using Eq. (19), and it is used to adjust the amount of material required for each processing plant. This means that only the AF portion of the plant's requirements can be met. It is indicated by constraint (14) that the total haulage capacity directed to a shovel will be limited to the nominal digging rate for that shovel. Constraint (15) calculates the deviation of the path flow rate from the desired path flow rate for each path connecting a source to a destination. Finally, constraint (16) ensures that the first set of decision variables are binary, and constraints (17) and (18) ensure that the goal programming variables are not negative. After the model has been solved, trucks will be dispatched to shovels in order to ensure that the system operates efficiently.

3.2. Integrated Simulation and Optimization Framework

The simulation segment of the framework follows a structured procedure, outlined in Figure 1. Initially, the model identifies active trucks awaiting assignment to suitable shovels and destinations. Subsequently, the multi-objective optimization model takes charge, efficiently assigning unassigned trucks to their respective tasks, ensuring optimal utilization. Throughout the simulation, the optimization model is recurrently executed upon specific events, such as a truck commencing work, completing a dump, or reactivating after a failure. These events trigger a reevaluation of the optimal truck assignment decision. The optimization process for truck assignments persists throughout the simulation runtime until the designated time period is reached.

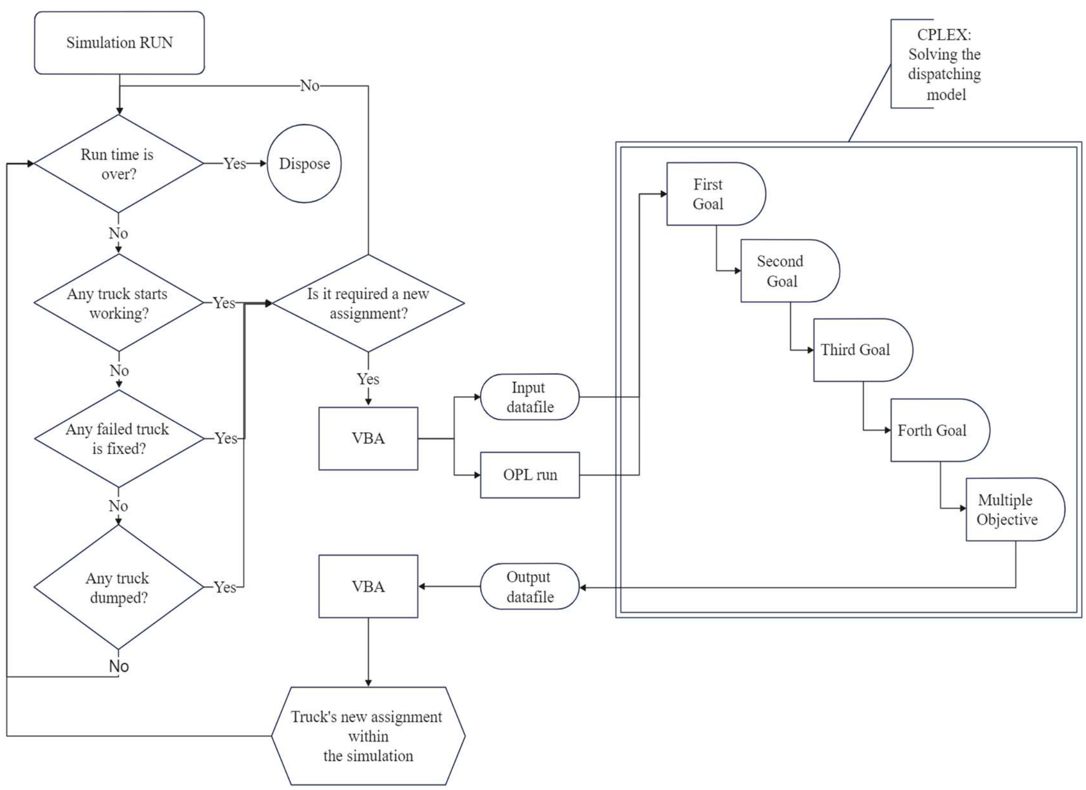

Figure 1. An overview of the simulation and optimization integration process.

4. **Design of Experiments and Results**

The assessment of the developed model in this study is carried out using a case study based on historical data from the Gol-E-Gohar iron ore open-pit mine in Iran. Figure 2 illustrate the layout of loading and dumping points, along with the operational road network. Five shovels are active at the loading points, with two assigned for ore extraction and three for waste. Trucks have three destinations: two processing plants and a waste dump.

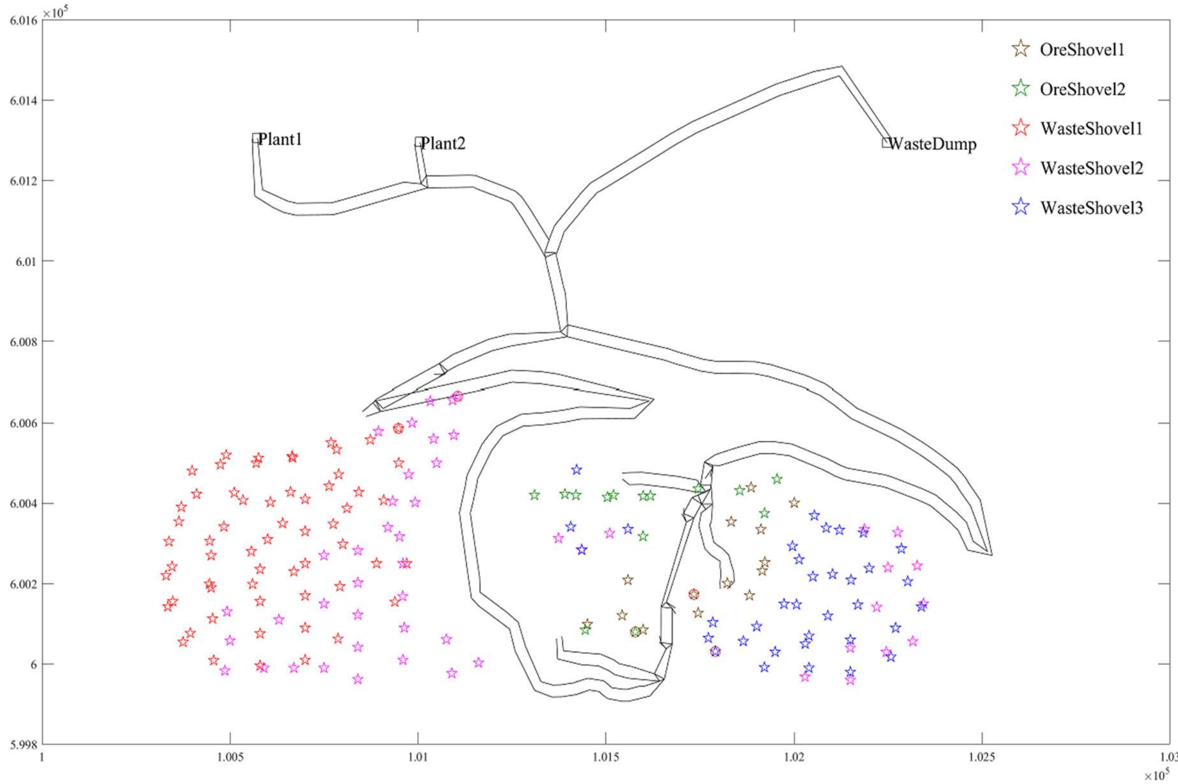

Figure 2. Gol-E-Gohar iron ore mine network.

The ore shovels utilized are Hitachi EX2500, while waste shovels 1 and 2 are Hitachi EX5500, and waste shovel 3 is a Hitachi EX2500. The available fleet comprises 30 CAT 785C trucks.

Fuel consumption for each CAT 785C truck is computed using the regression formula derived from (Dindarloo and Siami-Irdemoosa, 2016) specific to the CAT 785C truck type. The formula is depicted in Eq. (20):

$$F\left(\frac{l}{cycle}\right) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \quad (20)$$

The equation's variables signify the following quantities: fuel consumption (F) in liters per cycle, payload (PL) in metric tons, loading time (LT) in seconds, empty idle time (ES) in seconds, empty travel time (ETR) in seconds, loaded idle time (LS) in seconds, and loaded travel time (LTR) in seconds.

The simulation was conducted over a span of 10 days, operating for 12 hours each day. The runtime and the quantity of replications are pivotal for precise and dependable outcomes, as multiple simulation iterations diminish randomness and enhance resilience, particularly for intricate systems or uncertain conditions. The targeted ore and waste material productions for the planned 10-day mining operations are 552, and 718 kilotonnes respectively. The input data comprises deterministic and stochastic information, with stochastic input distributions calibrated using historical data through the Arena Input Analyzer tool (Rockwell Automation, 2019).

Key Performance Indicators (KPIs) introduced below (Table 1) are essential variables within the fleet management system of an open-pit mine, exerting a substantial influence on operational efficiency and overall performance. KPIs are crucial when comparing different models, as they provide a basis for evaluating performance and making informed decisions.

Table 1. Key Performance Indicators.

Key Performance Indicator (KPI)	**Significance**
Shovel's Utilization	Measures efficiency and productivity
Truck's Waiting Time	Indicates operational flow
Truck's Fuel Consumption	Displays environmental impact
Production of Ore and Total Tonnages	Shows the efficiency of production planning and resource utilization
Ore Tonne Per Gross Operating Hour (OTPGOH)	Quantifies the efficiency of ore production per hour of operation, the mining productivity and resource utilization

Selecting appropriate weights for multi-objective optimization is vital and requires understanding of the problem domain and objectives. Sensitivity analysis helps determine weights, reflecting stakeholder preferences and trade-offs among objectives. Table 2 presents scenarios with different objective's weights and

Table 3 showcases corresponding KPIs for each scenario.

Table 2. Weights of the objective functions.

Scenario	W1(SIT)	W2(TWT)	W3(PD)	W4(FC)
S1	0.1	0.25	0.55	0.1
S2	0.3	0.1	0.5	0.1
S3	0.1	0.2	0.5	0.2
S4	0.1	0.1	0.4	0.4
S5	0.1	0.3	0.4	0.2
S6	0.2	0.3	0.4	0.1
S7	0.25	0.25	0.25	0.25
S8	0.1	0.1	0.7	0.1
S9	0.1	0.1	0.2	0.6
S10	0.6	0.1	0.2	0.1
S11	0.1	0.6	0.2	0.1
S12	0.1	0.35	0.55	0
S13	1	0	0	0
S14	0	1	0	0
S15	0	0	1	0
S16	0	0	0	1

Table 3. Weighted scenarios' KPIs.

Scenario	Util. Ore (%)	Util. Waste (%)	Queue Time (mins)	Fuel Cons. (kl)	Ore Tonnage (kt)	Total Tonnage (kt)	Ore TPGOH (t)
S1	81.2	56.0	3.66	416	552	1273	4602
S2	81.2	56.1	3.73	414	552	1273	4603
S3	81.2	56.2	3.75	413	552	1278	4601
S4	81.1	56.4	3.66	415	552	1279	4602
S5	81.2	56.2	3.68	415	552	1278	4603
S6	81.3	56.2	3.71	414	552	1276	4602
S7	81.2	56.2	3.66	416	552	1277	4603
S8	81.0	56.3	3.66	415	552	1277	4604
S9	81.2	56.2	3.85	410	552	1278	4603
S10	81.3	56.2	3.61	417	552	1277	4602
S11	81.2	56.3	3.62	416	552	1278	4603
S12	81.2	55.9	3.62	417	552	1271	4603
S13	81.2	56.2	3.64	416	552	1275	4603
S14	81.2	55.3	3.59	420	552	1263	4603
S15	81.2	51.0	4.16	417	552	1205	4603
S16	81.1	55.7	4.18	403	552	1269	4603

Most KPIs remain stable despite weight adjustments, except Total Tonnage and Fuel Consumption. The fuel consumption weight (W4) strongly negatively correlates (-0.91) with total fuel consumption. Other weights also correlate with their KPIs. Notably, Total Fuel Consumption and Average Queue Time negatively correlate (-0.63). To achieve minimal fuel consumption and acceptable production in 10 days, weight scenario 9 is chosen for further comparison with benchmarks. Figure 3, and Figure 4 depict Total production, Average truck queue time, and total fuel consumption across all scenarios.

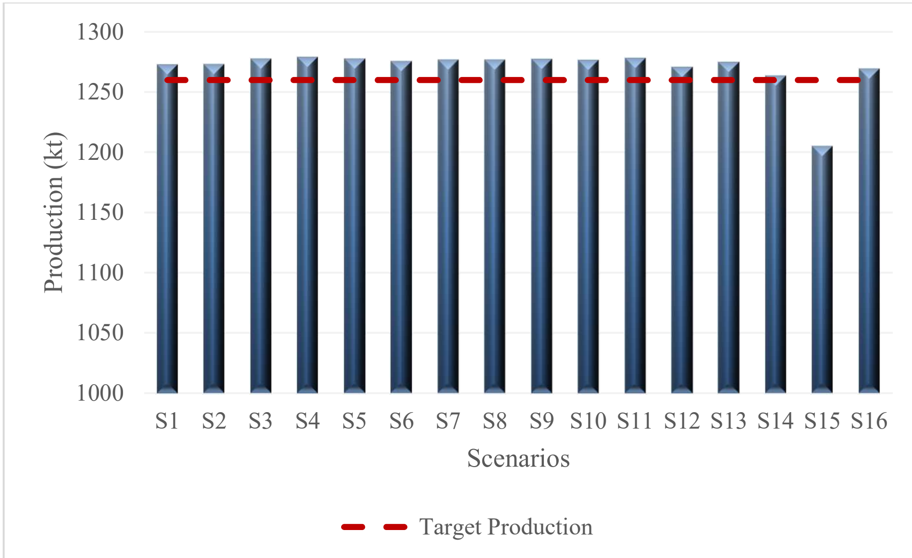

Figure 3. Production for different scenarios.

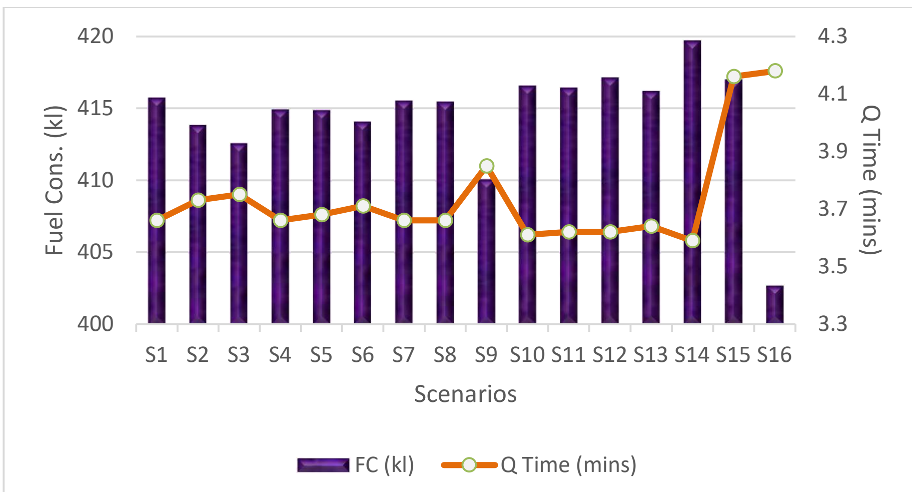

Figure 4. Each scenario's fuel consumption and queue time.

4.1. Comparison

The comparison of the Quadratic Objective (Quad-Obj.) model (designated as model number 3) introduced in this study against the Modular Mining Dispatch model (model number 1) and the Tri-Objective (Tri-Obj.) model (model number 2) extracted from the work of Moradi Afrapoli et al. (2019) is shown by various figures below. This comparison involves the assessment of multiple significant Key Performance Indicators (KPIs).

For Plant 1, the Quad-Obj. and Tri-Obj. models transported about 16% more material on average than the Modular Mining Dispatch model. Similarly, for Plant 2, both models outperformed the Modular Mining Dispatch model by approximately 11%. Figure 5 reveals material quantities transported to the plants and the waste dump across all models. The Modular Mining Dispatch model moved more waste, yielding a higher stripping ratio (SR). However, this model couldn't meet the target ore production. In contrast, both Tri-Obj. and Quad-Obj. models succeeded. However, the Quad-Obj. model had a higher SR than Tri-Obj., moving more waste by 3.7%, equivalent to 26.2 kt. Figure 6 presents the daily average TPGOH along with their corresponding confidence levels. The Tri-Obj. and Quad-Obj. models demonstrate higher TPGOH values when contrasted with the

Modular Mining Dispatch model. Furthermore, the average TPGOH levels remain fairly constant across all days for all models.

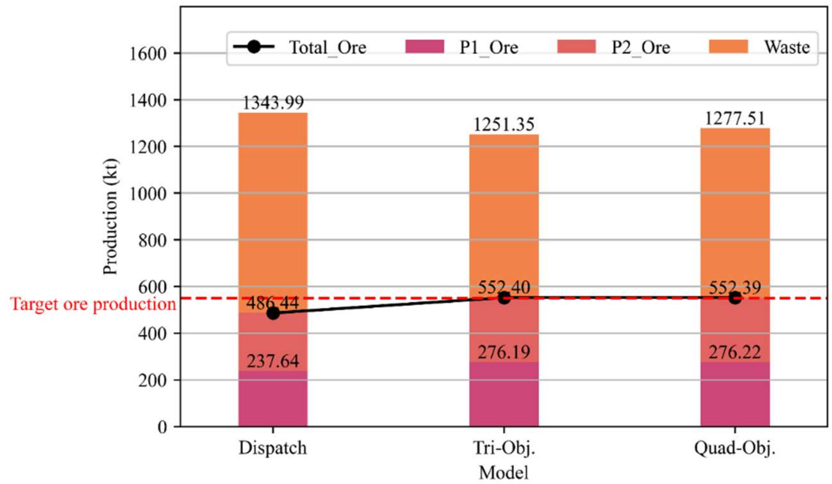

Figure 5. Tonnage Statistics for Plant1, Plant2, and Waste Dump for all models.

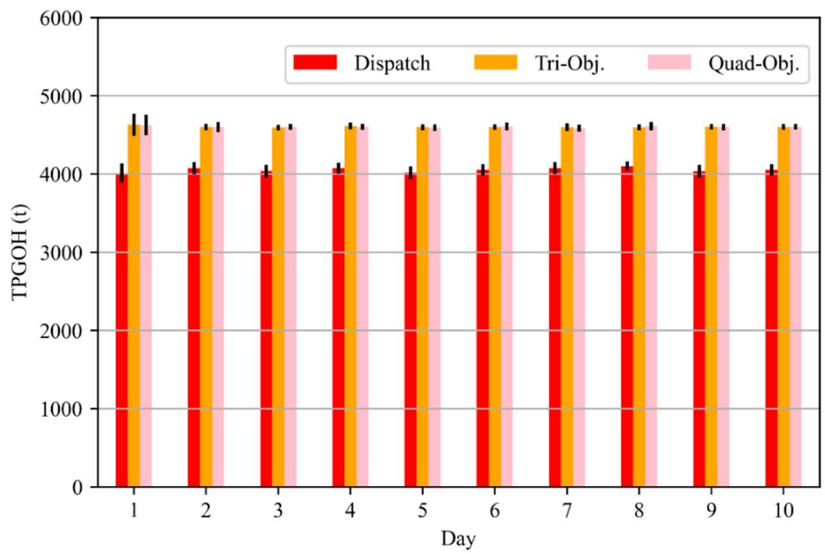

Figure 6. Average TPGOH in each day for each model.

Figure 7 highlights the consistent waste delivery superiority of the Quad-Obj. model over the Tri-Obj. model every day. Notably, the Modular Mining Dispatch model surpasses both models in waste delivery, yet it falls short in meeting required ore tonnage delivery for each plant.

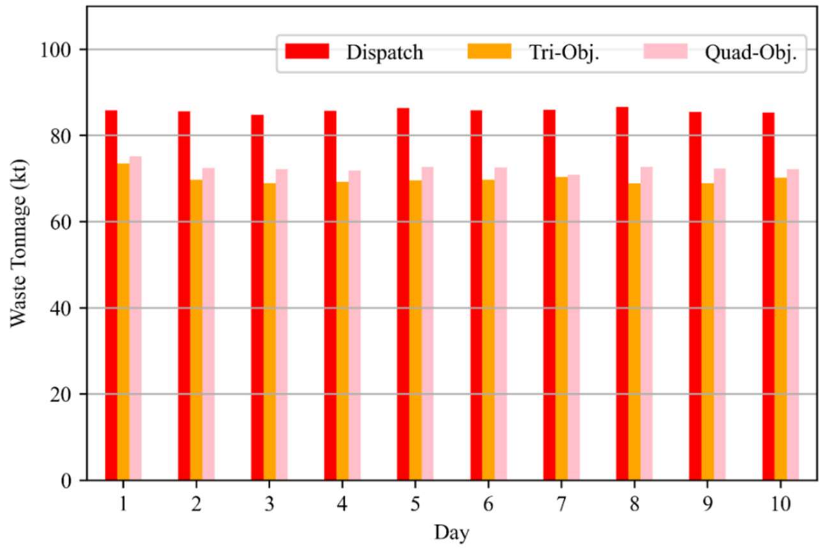

Figure 7. Average Waste tonnage in each day for each model.

Figure 8 presents the fuel consumption details for generating 1000 tonnes of ore for each model, along with a total fuel consumption bar chart. Notably, the Quad-Obj. model consumes 12190 liters less fuel than the previous Tri-Obj. benchmark model. The Modular Mining Dispatch model boasts the lowest fuel consumption due to its focus on selecting shortest paths for trucks and prioritizing waste materials over ores. This choice is influenced by shorter distances between waste polygons and the waste dump compared to those between ore polygons and plants. The Quad-Obj. model shines with the lowest fuel consumption per tonne of ore, yielding a 2.88% reduction, equivalent to roughly 22050 liters saved, compared to the Tri-Obj. model. The reduction increases to 4.88% when total production, including waste, is considered.

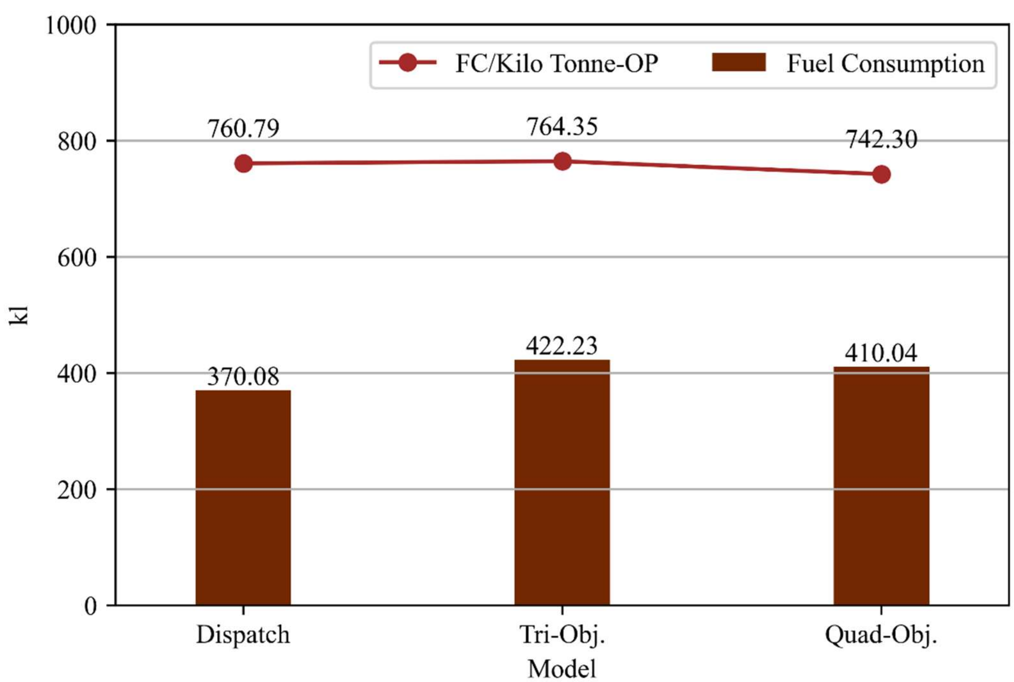

Figure 8. Fuel consumption per a kilotonne ore production.

Figure 9 depicts shovel utilization across models. The Modular Mining Dispatch model shows lower ore shovel utilization but higher waste shovel utilization. Quad-Obj. and Tri-Obj. models exhibit similar utilizations, differing only in waste shovel 4, where Quad-Obj. model surpasses Tri-Obj. model.

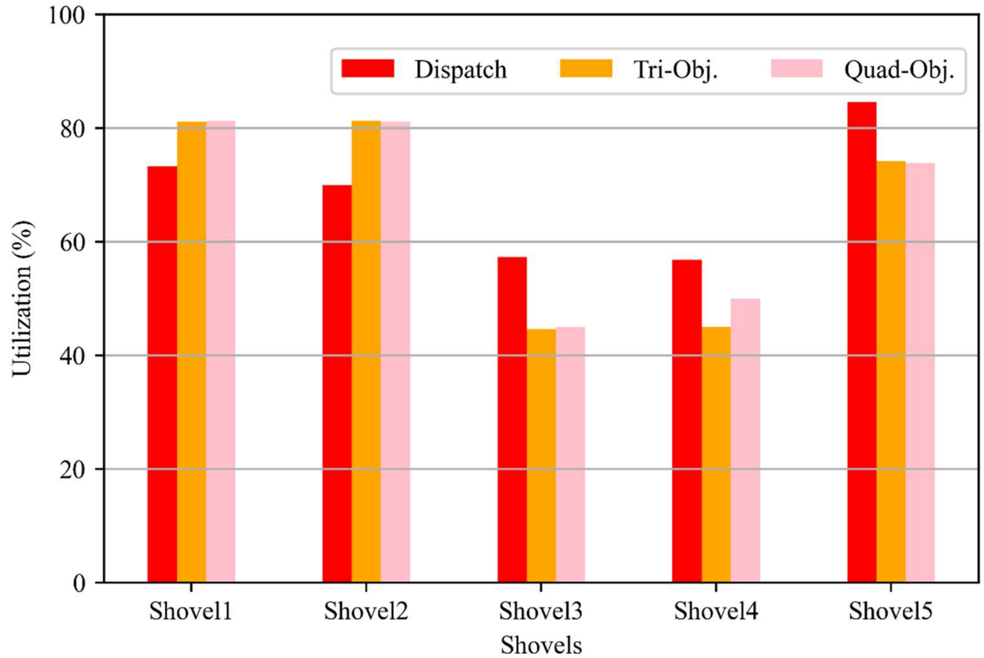

Figure 9. Shovels Utilization.

In Figure 10, and Figure 11 the truck average waiting time for each model is shown. The first figure shows the waiting time for shovels, and the second figure shows the waiting time in processing plants. Among the models, the Modular Mining Dispatch model has the shortest queue times for ore shovels while experiencing the longest queue times for waste shovels, with waste shovel 5 showing a notable variation. Concerning queue times at destinations, waste dumps exhibit no queue time due to multiple available dumping points. Additionally, the Modular Mining Dispatch model avoids processing plant queues by assigning more trucks to the waste dump. Another important observation is that, across both processing plants, the Quad-Obj. model demonstrates lower average queue times compared to the Tri-Obj. model.

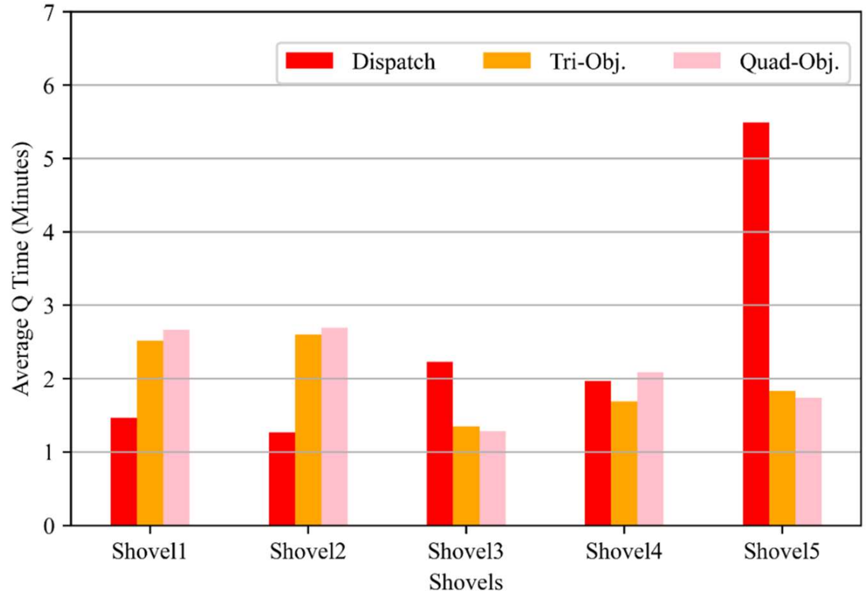

Figure 10. Trucks Average Queue Time at Each Shovel (Minutes).

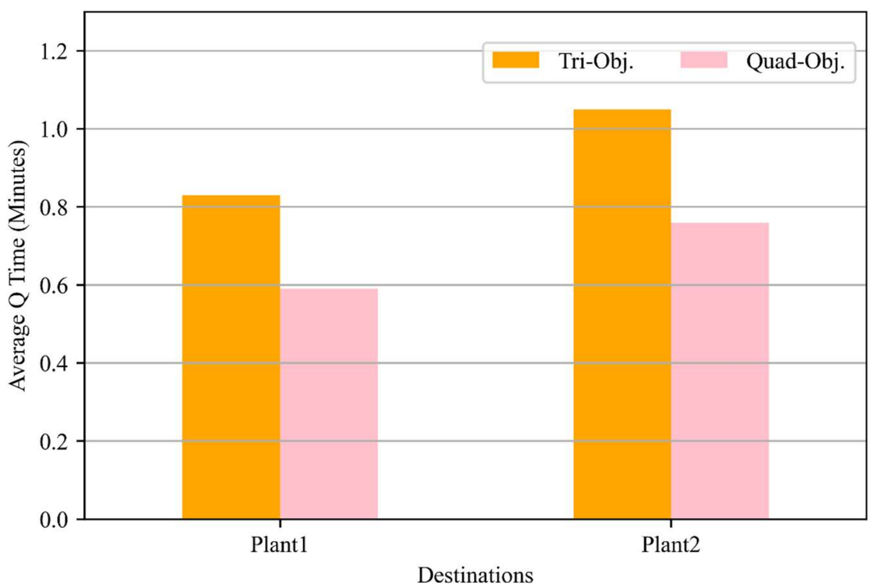

Figure 11. Destinations Average Queue Time (Minutes).

Finally, the S16 scenario (within objective's weight scenarios), as the most fuel-efficient scenario, is evaluated against the Tri-Obj. benchmark model in Figure 12. Notably, implementing the Quad-Obj. model within the S16 scenario resulted in a 4.6% reduction in total fuel consumption, a 1.4% increase in total production, and a 6% decrease in fuel consumption per tonne of production.

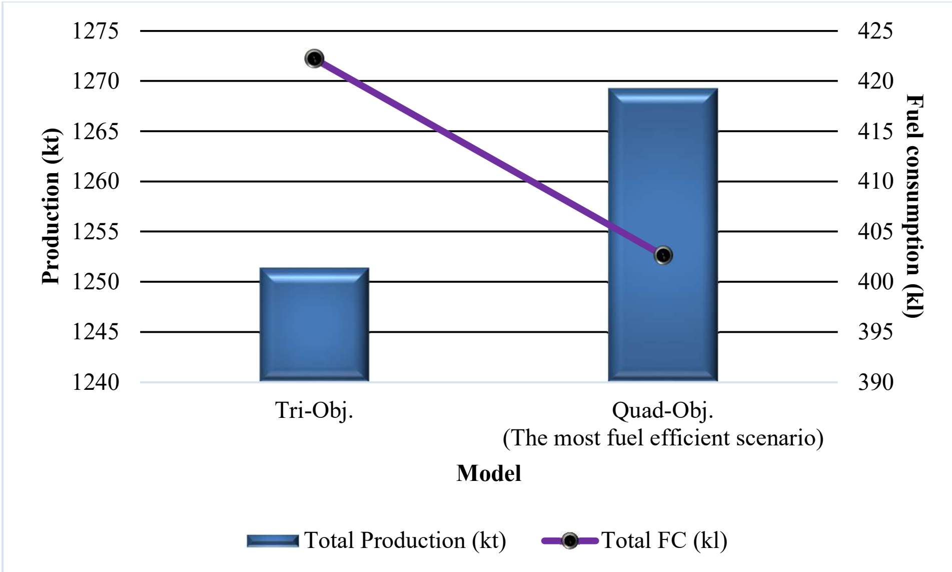

Figure 12. Production and fuel consumption of the most fuel-efficient scenario and Tri-Obj. models.

5. **Conclusions**

This study primarily focuses on optimizing truck dispatching. The developed framework aims to minimize path flow rate deviations, shovel idle time, truck wait time, and fuel consumption. A notable contribution of the study is the integration of fuel consumption reduction as an objective in the dispatching model, yielding economic and environmental advantages. To address the uncertainty in open-pit mining, a discrete event simulation model was developed using Arena software (Rockwell Automation, 2019). Scenarios with varied objective weights were explored, with application in the Gol-E-Gohar iron ore mine as a case study. The Quad-Objective model yielded a 4.88% reduction in fuel consumption per tonne of production compared to the Tri-Objective benchmark, saving over 12,000 liters. Prioritizing fuel consumption led to a potential 6% reduction per tonne, corresponding to a noticeable 20,000 liters overall decrease. The model-maintained production rates while increasing waste extraction by 3.74%, equivalent to about 26.2 kilotonnes over ten operational days.

In future studies, it will be important to consider the age of trucks when developing simulation and optimization models. Truck age significantly impacts performance, including speed, fuel use, and emissions. Integrating age data can yield insights into efficiency, costs, and environmental effects, informing maintenance and replacement strategies. Moreover, applying In-pit crushing and conveying (IPCC) in mine haulage systems is worth investigating. IPCC involves crushing ore in the pit and conveying it using belts, reducing costs, energy consumption, GHG emissions, and truck transport requirements.

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Appendix

LIST OF ABBREVIATIONS:

CAT	Caterpillar
HIT	Hitachi
TPGOH	Tonne Per Gross Operating Hours
OTPGOH	Ore Tonne Per Gross Operating Hours
SR	Stripping Ratio
Q	Queue
SIT	Shovel Idle Time
TWT	Truck Wait Time
PD	Production Deviation
FC	Fuel Consumption
Min	Minutes
Hrs	Hours
t / kt	Tonnes / Kilo Tonnes
l / kl	Liters / Kilo Liters
Tph	Tonne Per Hour