Integrated Stochastic Discrete-Continuous Simulation-Based Optimization Framework for GHG Mitigation in Mining Operations

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ABSTRACT

This paper presents an integrated stochastic discrete-continuous simulation-based optimization framework specifically designed to address greenhouse gas (GHG) mitigation in operational decision-making processes in open pit mines. Our framework not only addresses the economic imperative of minimizing transportation costs but also prioritizes environmental sustainability by concurrently reducing carbon dioxide emissions. A case study is conducted on a specific copper mine to address the challenge of determining the optimal size of the transportation fleet, while concurrently minimizing transportation costs and the fleet's CO2-equivalent emissions. Furthermore, a novel approach for allocating trucks to shovels is introduced in this work. This method not only contributes to cost reduction and carbon emission mitigation, but also leads to the enhancement of key performance indicators, such as tonnage hauled and cycle time. Sensitivity analysis is performed to examine the influence of various parameters on the objective functions and performance indicators. The findings provide valuable insights for researchers focused on GHG mitigation in mining and contribute to the development of sustainable mining practices.

Keywords: *Sustainable production, GHG emission control, equipment selection and sizing, allocation problem, stochastic simulation-based optimization*

1. Introduction

Mining operations, crucial to global economic activities, heavily rely on fleets of trucks and shovels for material handling, constituting a significant portion of operational costs. The main material handling system in open pit mines is the truck-shovel system [1] which consumes over 50% of the operational budget [2-4]. Adding to the operational cost, these operations come with a hefty environmental cost, marked by substantial greenhouse gas (GHG) emissions, necessitating urgent mitigation efforts in the face of climate change concerns. Besides, the transportation fleet is accounted to consume around 30% of total energy in an open pit mine [5, 6]. Therefore, proper selection, sizing, and utilization of truck and shovel fleets not only will have substantial economic gains but also could lead to mitigating the possible environmental footprints. As presented in the literature section of this paper, several research papers addressed the selection, sizing, and the utilization problems in open pit mines.

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Lack of a proper tool accounting for the associated operational uncertainties and decisional conflicts while sizing the fleet and simultaneously considering economic gains and environmental footprints while utilizing the fleet motivated the authors to conduct this research resulting in introduction of a hybrid stochastic simulation and optimization framework taking a step closer to responsible open pit mining operations.

In the past few years, we have seen a growing emphasis on the development of sustainable mining practices aimed at minimizing environmental impact while maximizing economic efficiency [7-11]. Despite its inevitably crucial role, mine planning has not received its deserved attention in this regard. Developing and applying fleet management systems (FMSs) can be named as a cost-effective strategy widely used to improve overall fleet utilization. The main purpose of implementing an FMS is to apply mathematical models helping to efficiently utilize the equipment leading to production increase [2]. This implementation subsequently causes a reduction in GHG emissions as well as the operational costs, [12] addressing the two fundamental pillars of sustainable practices namely economic and environmental impact.

By considering economic and environmental objectives simultaneously, alongside factors such as uncertainty in maintenance and repair, downstream processes, and conducting sensitivity analysis, our framework offers a holistic approach to sustainable mining practices. The significance of our research lies in its ability to provide practical applications for both academics and industry professionals, fostering the development of mining strategies that balance economic viability with environmental responsibility, thus contributing to the long-term sustainability of mining operations. The presented framework was applied to a case study of a copper mine for performance evaluation. In addition, we performed sensitivity analysis to examine the impact of different parameters on the legitimacy of the framework and accuracy of the performance indicators. The analysis identifies important and influential parameters in economic productivity as well as environmental issues, further enhancing the applicability and effectiveness of the framework.

The following section of this paper includes an extensive review of the literature related to the topic. Following that, a step-by-step elaboration on the components of the framework including the simulation modelling and the optimization algorithm is presented. Model verification and validation using the case study are discussed in the fourth section. Section five provides a detailed comparative representation of results, and subsequently, in section six, results of the sensitivity analysis are laid out. Finally, section seven provides conclusions and proposes possible directions for future research in the field.

2. Literature Review

Finding optimal solutions for the equipment selection and sizing (ESS) problem plays a critical role in open pit mining operations, significantly influencing operating costs and the efficiency of the production fleet [13-14]. Over the years, diverse methodologies have emerged to address the ESS problem, which can be categorized into: considering the concept of equipment matching factor, applying the operations research techniques, implementing the artificial intelligence approaches, introducing the new life cycle costing techniques, and utilizing the discrete event simulation method [15]. This review focuses on research related to operations research techniques and simulation methods.

Early attempts, such as the application of linear programming models by Edwards et al., and the linear programming model by Burt et al., primarily aimed to optimize the selection of shovels and minimize costs. Ta et al. introduced a mathematical model focused on reducing truck fleet size, limited by its applicability to homogeneous fleets [16-18]. Addressing this limitation, Moradi Afrapoli et al. presented a framework integrating the optimization approach and the simulation modeling considering FMS and operational uncertainties. Mohtasham et al. implemented a two-stage framework to optimally dispatch trucks, making decision on the size of the transportation fleet, allocation of the available equipment, and dispatching of the transporters in real-time [4, 19]. Their subsequent work [15] explored strategies to optimize fleet size, emphasizing matching factor targets. Souza et al. [20] utilized a mixed-integer programming (MIP) model with incorporation of truck dispatching to reduce the possible deviations from the tonnage and grade targets. Yeganejou et al. [21] integrated the Monte-Carlo simulation technique with the MIP to optimize truck fleet allocation leading to enhancement of the fleet productivity. Meanwhile, Mohtasham et al. [22] applied multi-objective decision making technique to develop a framework with which production is maximized while fuel consumption and grade deviations are minimized. Zhang and Xia [23] minimized operating costs by employing the integer programming, considering truck capacities and travel distances. Ahangaran et al. [24] defined transportation cost as the decision variable and used integer programming to minimize it, albeit with a constraint on the number of available trucks. Alexandre et al. [25] explored multi-objective genetic algorithms for minimizing transportation costs and maximizing production. Afrapoli et al. [3] proposed a multi-objective model optimizing truck allocation based on assignment request time, addressing idle time, cumulative truck wait time, and deviations from flow rates.

Mohtasham et al. [12] presented a chance-constrained goal programming model for truck destination optimization, considering uncertainties and minimizing total operating costs. Ta et al. [26] and Afrapoli et al. [27] also presented stochastic models, addressing uncertainties in operational parameters and quality requirements. Both and Dimitrakopoulos [28] introduced a stochastic optimization model considering geological and operational uncertainties trying to investigate impact of short-term strategic plans on the allocation of trucks.

Studies examining environmental factors in open-pit mining include Topal and Ramazan, Peralta et al., Mane et al., Walnum and Simonsen, Aksoy et al., Alinaghian and Naderipour, Winebrake and Green, and Montiel and Dimitrakopoulos [29-36]. These studies investigated the impact of factors such as truck age, maintenance, driver behavior, infrastructure, and vehicle specifications on fuel consumption and greenhouse gas emissions.

The limitations of deterministic models in handling uncertainties, as highlighted by Dindarloo et al., led to the adoption of discrete event simulation (DES). Rist pioneered the application of DES in mine haulage, followed by notable studies by Kolonja and Mutmansky, Ataeepour and Baafi, Yuriy and Vayenas, Que et al., and Chaowasakoo et al., Upadhyay and Askari-Nasab, Forsman et al., Torkamani and Askari-Nasab, Hashemi and Sattarvand, and Moradi Afrapoli and Askari-Nasab [2, 37-47].

Recent studies by Awuah-Offei et al., Suglo and AlHassan, Tan et al., Ortiz et al., Tiile et al., Kaba et al., Zeng et al. and Chaowasakoo et al. have applied simulation to optimally address open-pit mining operational and strategic problems [48-55]. Readers are encouraged to navigate the work by Burt and Caccetta [14] for further investigation on ESS problem.

Recent works by Anaraki and Afrapoli [11] propose a multi-objective optimization model for fleet management, incorporating carbon emission minimization. Mohtasham et al. [15] introduce strategies for equipment sizing using mixed-integer non-linear programming (MINLP) models. Abolghasemian et al. [56] present a modified-NBI optimization method for copper open-pit mine extraction systems, emphasizing multi-objective optimization. Another work by Abolghasemian et al. [57] focuses on the hauling system in an Iranian copper mine, employing a simulation-based optimization approach for increased production. Table 1provides a detailed high level comparative analysis of the current advancements in the field.

Table 1. High level comparative representation of available models.

Year	Paper	Contributions						Model	Objective functions								Software
									Economic				Environmental				
		Simulation	Optimization	Case study	Discrete	Continues	Maintenance problems		#	Min	Max	Type	#	Min	Max	Type	
2013	[18]	*	*		*		*	LIP	1	*		Total number of allocated trucks					C# / CPLEX
2015	[23]		*		*		*	IP	1	*		Total truck operating costs					
2019	[3]	*	*	*	*			MILP	3	*		idle and wait time of equipment and deviation from target production					Arena / CPLEX / VBA
2019	[25]	*	*		*	*			2	*	*	Min: Total cost of the trucks in operation / Max: Total production					
2020	[56]	*	*	*	*			MINLP	1		*	Total production					Arena / OptQuest
2021	[15]	*	*	*	*			MINLP	1	*		Match factor					GAMS / Arena / OptQuest
2021	[12]		*	*	*	*	*	CCGP	4	*		Deviation from production, grade requirements, ore tonnage, total operating costs					MATLAB / CPLEX / Visual C#
2021	[22]		*	*	*			MILGP	4	*		Difference between production / material content / material sent / fuel consumption					CPLEX / GAMS
2021	[27]	*	*	*	*	*	*	FLP	3	*		Deviation from the production target / idle and wait time of equipment					Arena

2022	[57]	*	*	*	*		*	MINLP	2	*	*	Max: total extraction amount / Min: travel time					Arena / Maple / Lingo
2022	[19]	*	*	*	*			NLP	1	*		Deviation in the match facto					Arena / OptQuest
2023	[11]		*	*	*			MILP	1	*		Transportation costs	1	*		CO_2 emission	CPLEX
2024	This study	*	*	*	*	*	*	MILP	1	*		Transportation costs	1	*		CO_2 emission	Arena / OptQuest

LIP: Linear integer program, MILP: Mixed-integer linear programming, MILGP: Mixed-integer linear goal programming, MINLP: Mixed-integer nonlinear programming, CCGP: Chance-constrained goal programming, NLP: Nonlinear programming, IP: Integer programming, FLP: Fuzzy linear programming.

In conclusion, the literature provides a rich landscape of methodologies and models addressing equipment selection, sizing, and allocation in open pit mining. While various studies have made significant contributions, gaps remain in addressing uncertainties, environmental considerations, and integrating fleet management systems. The proposed framework aims to bridge these gaps and contribute to the advancement of sustainable and efficient mining practices. The following are the key contributions of our research work:

- Considering both environmental and economic issues;
- Considering stochastic maintenance parameters to account for uncertainties;
- Modelling downstream processes; and
- Sensitivity analysis in identifying effective parameters.

3. Framework and Formulations

The proposed framework consists of several interactive models and sub-models imitating open pit mine planning and operational activities, simultaneously simulating the way material handling systems in mines work and optimizing the decisions mining engineers make considering stochastic factors that impacting the operational excellence. 1 conceptualizes a high-level scheme of the proposed framework, illustrating the integrated stochastic discrete-continuous simulation-based optimization framework and highlighting the dynamic interactions between the optimization and simulation models.

We present a multi-objective optimization algorithm that optimizes decision making both economically and environmentally. The model considers various parameters, including fleet size, maintenance and repair of shovels and trucks, post-crushing processes, and allocation of trucks to shovels. One of the principal contributions of our research is the comparison and investigation of truck allocation methods. In this paper, we not only employ the locked-in method based on the match factor [2] but also introduce a novel approach for allocating trucks to shovels. This method not only leads to cost reduction and carbon emission mitigation but also improves key operational performance indicators such as tonnage hauled and cycle time.

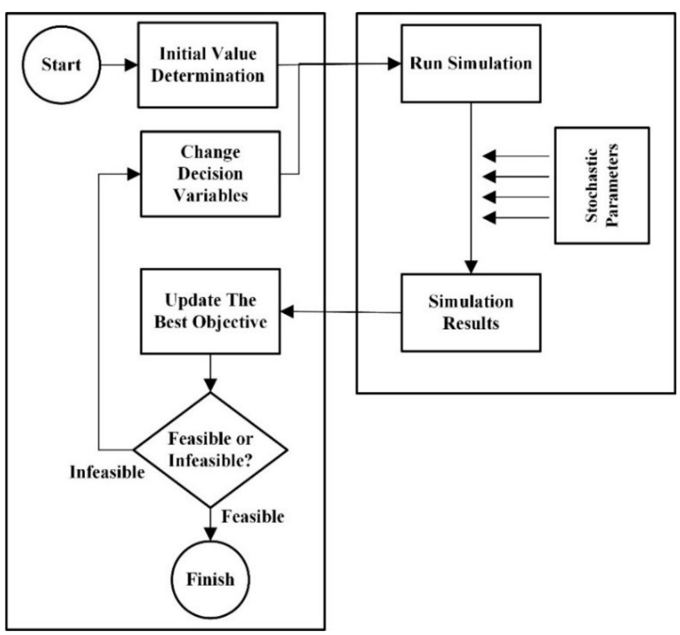

Figure 1. High-level schematic representation of the proposed simulation-based optimization framework.

3.1. Optimization Model

Our proposed multi-objective model aims to minimize transportation costs and enhance environmental sustainability by reducing carbon dioxide emissions. This MILP approach considers various aspects of FMS, such as transportation costs, truck types, ages, and velocities, as well as the emissions generated by each truck. It is important to note that costs, emissions, and velocities vary based on the specific truck type and its age. This model seeks to identify the most efficient set of trucks, including their quantity and age within each closed system (Loading point to Dumping point). However, driver proficiency and weather conditions are not accounted for in this model. The subsequent section outlines the specified indices, sets, parameters, decision variables, the objective function, and the constraints of the optimization model.

i	Indices for truck type (i ϵ {1, 2, … I})
j	Truck age group indices (j ϵ {1, 2, … J})
s	Indices for closed system (s ϵ {1, 2, … S})
o	Ore sites indices (o ϵ {1, 2, … O})
w	Waste sites indices (w ϵ {1, 2, … W})

Parameters

FC_{ijs}	Fix cost of truck of type *i* age *j* in closed system *s*
CL_{ijs}	Cost of trucks of type *i* age *j* in closed system *s* when loaded per kilometer
CUL_{ijs}	Cost of trucks of type *i* age *j* in closed system *s* when unloaded per kilometer
D_{ijs}	Distance traveled by truck *i* age *j* in closed system *s*
NL_{ijs}	Average loaded trip numbers of trucks of type *i* age *j* in closed system *s*
NU_{ijs}	Average unloaded trip numbers of trucks of type *i* age *j* in closed system *s*
CL_{ijs}	Amount of carbon produced by loaded trucks of type *i* age *j* in closed system *s* per trip
CE_{ijs}	Amount of carbon produced by unloaded trucks of type *i* age *j* in closed system *s* per trip
TN_{ijs}	Average tonnage hauled by trucks of type *i* age *j* in closed system *s*
LPR	Lower bound of production requirement
UPR	Upper bound of production requirement
T_i	Total number of truck type *i*
T_j	Total number of truck age *j*
T_s	Total number of truck in closed system *s*
SR	Stripping ratio

Decision Variable

X_{ijs}	Number of trucks of type *i* with age *j* in system *s*

$$Min\ Z1 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(FC_{ijs}X_{ijs}\right) + \left(CL_{ijs}NL_{ijs}D_{ijs}X_{ijs}\right) + \left(CUL_{ijs}NU_{ijs}D_{ijs}X_{ijs}\right) \tag{1}$$

$$Min\ Z2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(CL_{ijs}X_{ijs}NL_{ijs}\right) + \left(CE_{ijs}X_{ijs}NU_{ijs}\right) \tag{2}$$

Subject to:

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(TN_{ijs}X_{ijs}NL_{ijs}\right) \geq LPR \tag{1}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{S}\left(TN_{ijs}X_{ijs}NL_{ijs}\right) \leq UPR \tag{2}$$

$$\sum_{j=1}^{J}\sum_{s=1}^{S} X_{ijs} = T_i \quad \forall i \in I \tag{3}$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} X_{ijs} = T_j \quad \forall j \in J \tag{4}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ijs} = T_s \quad \forall s \in S \tag{5}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{W} X_{ijs} = SR\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s=1}^{O} X_{ijs} \tag{6}$$

$$X_{ijs} \geq 0 \tag{7}$$

The first objective function, as illustrated in Equation **Error! Reference source not found.**), focuses on reducing transportation costs. This involves considering the cost differential between using new and used trucks, and loaded and empty trucks, as well as the distance between shovels and dumpsites. Furthermore, as demonstrated in Equation **Error! Reference source not found.**), the second objective function aims to reduce carbon emissions by assessing the amount of carbon generated. Constraints (1) and (2) are implemented to guarantee compliance with the plant capacity requirement in terms of the number of trucks. In fact, these refer to the targeted upper and lower limits of material tonnage to be transported during each shift. Constraints (3), (4), and (5) represent the cumulative count of trucks for each category, the aggregate number of trucks within distinct age brackets, and the collective count of trucks within individual systems, respectively. These represent operational constraints concerning the quantity, type, and age combinations of trucks. For instance, in constraint 5, it ensures that the total count of type i trucks across various ages and systems does not exceed the planned number. Constraint (6) controls the standard ratio of trucks in the ore closed system to the waste closed system. Finally, Constraint (7) guarantees that the solution is an integer number.

3.2. Simulation Model

One major part of the framework was built applying the DES modelling techniques which itself includes several sub-models for proper imitation of cradle-to-gate processes and operations. One of the significant aspects here is the integration of discrete and continuous process modelling techniques, making the framework capable of simulating various aspects of mining operations, including comminution processes, slurry transfer, and plant processes as a cohesive package. Figure 2 and Figure 3 provide an operational level descriptive layout of integrated DES package where two scenarios were simulated to compare different allocation methods. The first allocation method is a locked-in method based on the match factor [2] (Figure 2), while the second method is a new allocation method that considers trucks' waiting time and loading process queue length (Figure 3).

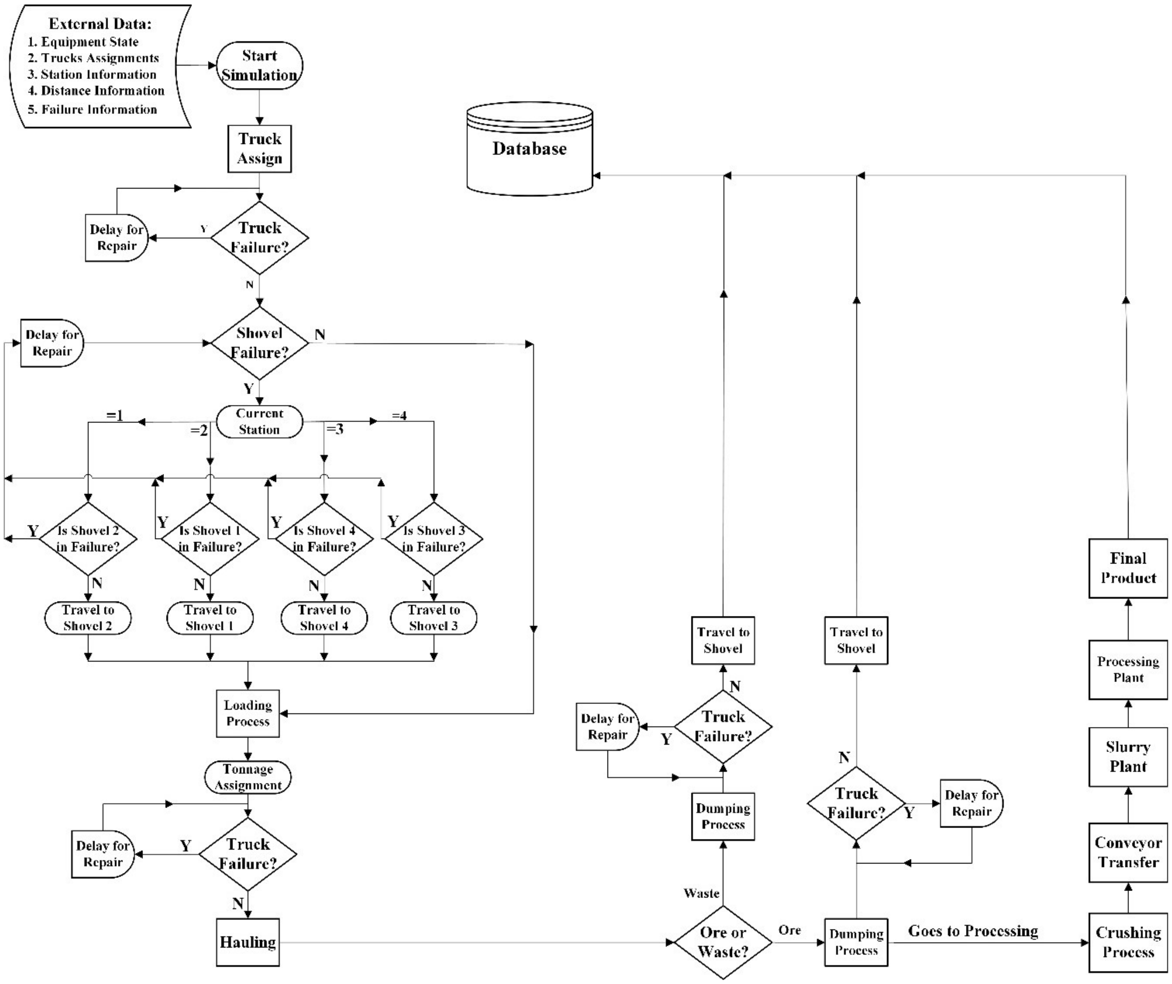

Figure 2. Flow chart of locked-in method.

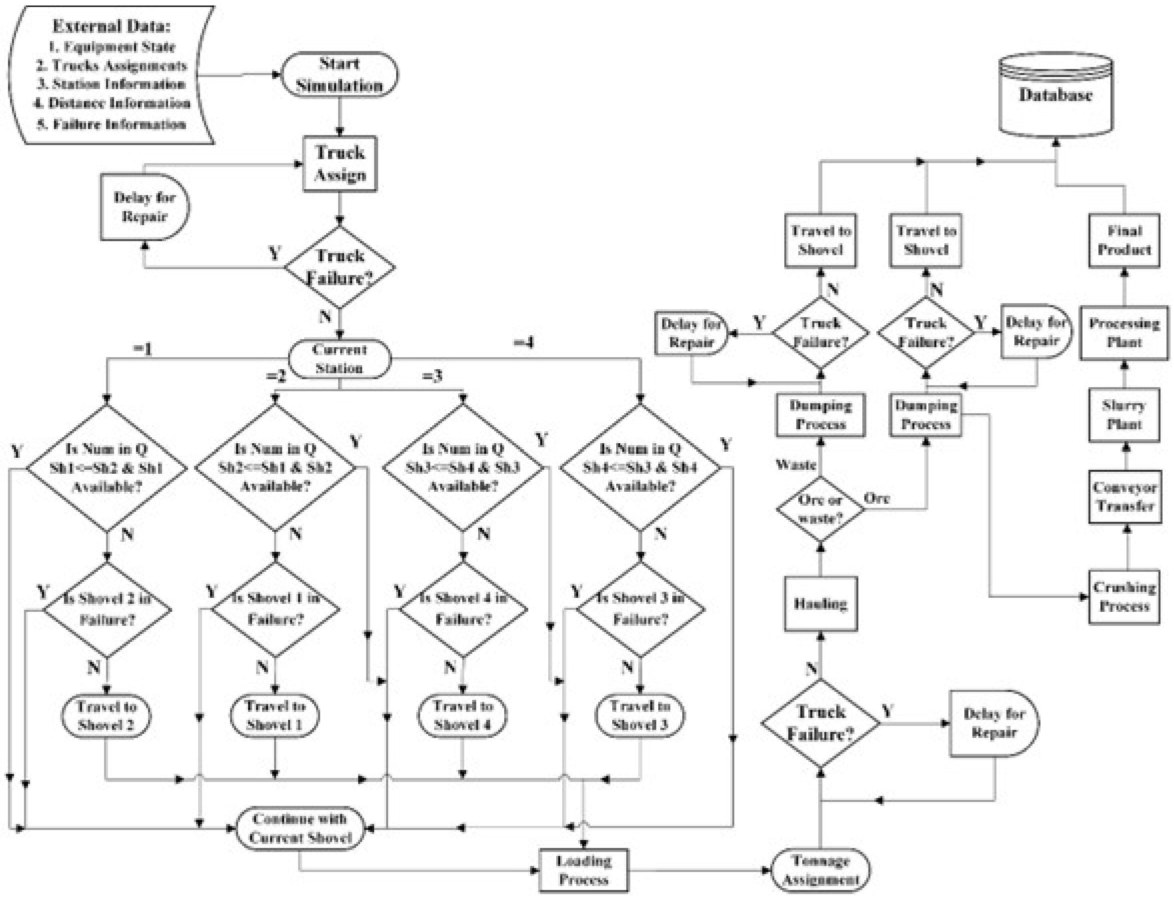

Figure 3. Flow chart of new allocation method.

First, external data, including equipment state, truck assignments, station information, distance information, and maintenance information, is entered into the model before starting the simulation process. Trucks are assigned to fixed shovel stations based on the pre-defined external data. Then, imitating the operation starts with the first step being loading, after two logic controls are performed to check the maintenance program such as emergency or preventive maintenance for trucks and shovels. If a truck fails, it will be taken out of service until the repair or inspection process is completed. However, when a shovel fails, logic control is implemented to ensure that the process does not stop and the trucks do not wait in a queue, allowing them to travel between stations.

After the failure controls, trucks travel to and are loaded by shovels and the loading tonnage is determined. The loaded trucks then haul materials (ore or waste) to a specific dumpsite, where they dump the materials and return to their initial station. Simultaneously, a continuous process is conducted. The ore fed into the crusher undergoes crushing before being conveyed to the slurry plant through a conveyor system. The output of the slurry plant is then transferred to the processing plant, where the final product is produced. It is noteworthy that the framework, as shown in Figure 2 and Figure 3, has an integrated databases built on Microsoft SQL Server, that seamlessly works together with the simulation models to record and store statistics and results of all the production steps.

4. Framework Validation and Evaluation

In the previous sections, authors established a comprehensive framework for optimizing and simulating mining methods. In this section, the proposed framework is first verified and then validated, and the results of its performance evaluation are presented. In this regard, the framework was implemented in a copper mine case study, illustrated in detail in the following sections, considering both abovementioned dispatching methods, and the consequent results served as a benchmark for subsequent evaluation. The validation process performed in this paper started with running the framework for 10 replications (calculated based on the desired production half-width). Subsequently, a comparison was made between the results and actual operating records in various aspects to confirm the efficacy of the framework. After validation, an extensive comparison was conducted between the locked-in method and the new allocation method, resulting in the determination that the new allocation method performs better than the locked-in method across multiple indicators.

4.1. Case study

To assess the efficacy of the hybrid stochastic simulation optimization framework proposed, Sungun open pit copper mine, situated in the northwestern region of Iran and renowned as a leading copper mine globally, has been selected for analysis. Figure 4 demonstrates a specific segment of the mine profile, showcasing the road network and the tasks related to trucks and shovels, which are responsible for the transportation of materials from loading to dumping points [15] Table 2 presents a concise overview of the gathered data.

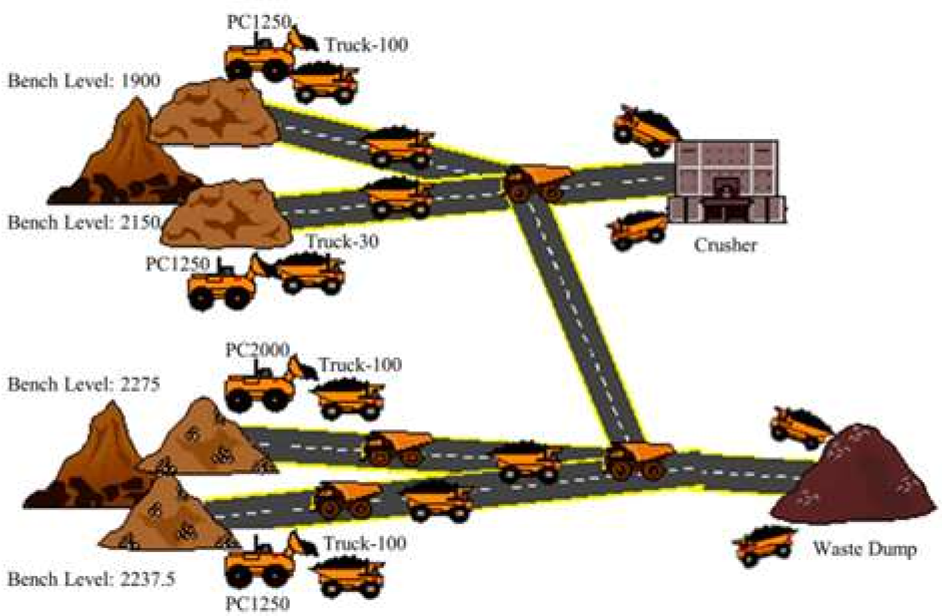

Figure 4. Schematic of the mining operation in the Sungun mine (reproduced after [15]).

Table 2. Main production and transportation systems and their components [11].

Closed system	Loading point	Dumping point	Distance (km)	Mean head grade	Loaders (Komatsu)		Hauler		
					Type	No	Type	Capacity (ton)	No
1	1900	Crushing unit	2.1	0.75	PC-1250	1	HD-785	100	3
2	2150	Crushing unit	3.15	0.42	PC-1250	1	HD-325	30	4
3	2275	Waste disposal	2.5	-	PC-2000	1	HD-785	100	5
4	2237.5	Waste disposal	3.65	-	PC-1250	1	HD-785	100	7

Furthermore, it is necessary for the crusher to maintain a copper grade ranging from 0.62% to 0.63% per shift. The designated tonnage of materials that should be moved during each shift is established at a minimum of 15300 tons and a maximum of 26600 tons. Moreover, the extraction process necessitates a stripping ratio within the range of 2 to 3. The mine operates round-the-clock with three 8-hour shifts, operating 363 days annually.

To categorize the trucks, they are separated based on their working years into two distinct groups. Trucks with under fifteen years of service are categorized as new, whereas those exceeding fifteen years are deemed old. Additionally, the hourly carbon emissions, transportation costs, and cycle time are all equally regarded for both types of trucks within the mine. A summary of the trucks' age groups information is provided in Table 3.

Table 3. Trucks age groups information.

Closed system	Hauler (Komatsu)			New trucks	Old trucks
	Type	Capacity (ton)	No	No	No
1	HD-785	100	3	2	1
2	HD-325	30	4	2	2
3	HD-785	100	5	3	2
4	HD-785	100	7	4	3

It is noteworthy that the Equation **Error! Reference source not found.** was used to calculate the carbon emission of trucks on truck fuel consumption [5].

$$F\left(\frac{L}{cycle}\right) = 1.37071 + 0.00483 \times PL + 0.00398 \times LT + 0.00499 \times ES + 0.01471 \times ETR + 0.00278 \times LS + 0.0519 \times LTR \quad (10)$$

F: Fuel consumption (liters per cycle)

PL: Payload (metric tons)

LT: loading time (seconds)

ES: Empty idle time (seconds)

ETR: Empty travel time (seconds)

LS: Loaded idle time (seconds)

LTR: Loaded travel time (seconds)

4.2. Validation

Verification is to double check if the conceptualized model of the real operation works properly. The main question answered in verification step as mentioned by Banks et al is: *"Is the conceptual model accurately represented by the operational model?"*[58]. Validity testing assesses the model's compatibility with the real system. To validate the framework, the head grade criteria are examined by comparing them between the actual system and the computer framework. This process confirms the model's validity. To do so, an assumption test is conducted on the mean of the normal population with an unknown variance. The alpha level for this test is set at 0.05, with a sample size of 10, representing simulation replications. Table 4 presents percentage information, averages, and standard deviations for both scenarios in the real system.

Table 4. Information about averages and standard deviations.

Closed system	**Case study**	**Scenario 1 (locked-in method)**		**Scenario 2 (new allocation method)**	
	Average	**Mean**	**std**	**Mean**	**std**
1	0.75	0.74	0.0085	0.74	0.0087
2	0.42	0.42	0.0084	0.42	0.0075

Assumption tests are applied to each closed system, calculating the test score as follows:

$$H_0: \mu = \mu_0 \tag{8}$$

$$H_1: \mu \neq \mu_0 \tag{9}$$

$$t_0 = \frac{x - \mu_0}{\frac{S}{\sqrt{n}}} \tag{10}$$

If the test statistic falls within the range $\left[-t_{\frac{\alpha}{2}.n-1}.\, t_{\frac{\alpha}{2}.n-1}\right]$, there is no basis to reject the H_0 hypothesis, confirming the model's validity. Referring to the t-distribution table, the acceptance interval for a two-tailed test with 9 degrees of freedom and a significance level of 0.05 is [-2.26, 2.26]. Table 5 displays the test statistics for each system.

Table 5. Test statistics for each system.

Closed system	**Test score**	
	Scenario 1	**Scenario 2**
1	-1.57	-1.59
2	1.84	1.91

Thus, there is no grounds to reject the null hypothesis for this test, meaning the head grade percentage resulting from the simulation model implementation is not significantly different from the percentages obtained in the case study at the 5% significance level.

The key performance indicators (KPIs) are defined, as presented in Table 6, to analyze the state of two models.

Table 6. Key performance indicators.

KPIs
Total tonnage hauled to dumpsite (Ore and Waste)
Average waiting time per shovel
Average cycle time
Average fuel consumption per cycle
Average CO2 emission per cycle

5. Results and Discussion

The proposed framework with several simulation models and sub-models and a multi-objective optimization model with one decision variable was developed and evaluated using Arena 16.1 software on a windows 10 operating system, equipped with an Intel 7 Core CPU of 2.20 GHz and an 8GB RAM.

OptQuest solver provides a potent tool that uses tabu search and scatter search heuristics to choose an optimal candidate for each decision variable in each simulation run [59]. The assessment of the objective function for each potential solution is conducted by the Arena model, which operates over a period of 12 months with a warm-up period lasting 15 days. To minimize errors and enhance the reliability of results, this process is repeated 10 times. OptQuest employs a variable number of replications, allowing for swift elimination of poor-quality solutions after ten replications to expedite the overall search time. Utilizing the current assessment of the candidate solution and the list of previously examined solutions, OptQuest determines the subsequent candidate solution to be evaluated. The search process continues until the specified stopping criterion is satisfied. A visual representation of the search methodology employed by OptQuest is presented in Figure 5.

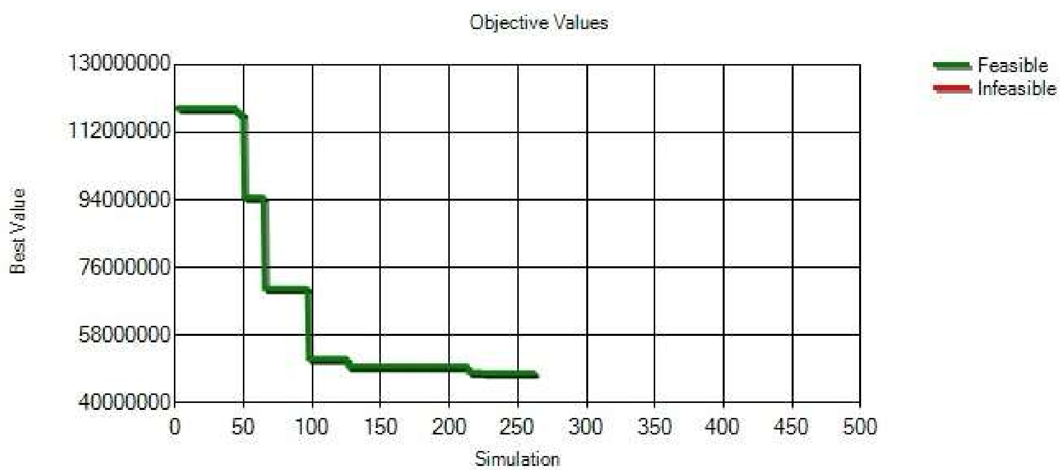

Figure 5. Search method in OptQuest.

Finally, after approximately 500 simulation runs, the optimal results were found in run number 224, as illustrated in Table 7 and Table 8.

Table 7. Optimum size of the truck fleet in different systems.

Item	Quantity
Type 1 trucks	9
Type 2 trucks	10
Closed system 1: sum of trucks	4
Closed system 2: sum of trucks	3
Closed system 3: sum of trucks	5
Closed system 4: sum of trucks	7

Table 8. Optimum number of trucks per each age group to be present in each closed production system

Closed System	Truck type 1		Truck type 2		Total
	Age bin 1	Age bin 2	Age bin 1	Age bin 2	
1	1	2	1	0	4
2	1	0	1	1	3
3	1	1	2	1	5
4	1	2	2	2	7

After obtaining the optimal values, we applied the new allocation method for the same period. The differences in objective functions among the three models are illustrated in Table 9 and Table 10, as well as Figure 6, Figure 7, and Figure 8. The case study model represents the current situation in the mine, whereas the other two models, namely the locked-in and new allocation method, were developed based on optimal values of decision variable. The difference between these models, as discussed in Section 3.2, refers to the logic of truck allocation within each system.

Table 9. Differences between the optimal costs and emissions of the operation using three different decision making models.

Model	Objective 1 (Transportation Costs -$M)	Objective 2 (CO2 Emission – M Kg)
Case Study	37.796	156.234
Locked-In	23.550	47.522
New allocation method	23.059	43.396

Table 10. Optimum fixed and variable costs of the material transportation for each decision making method.

Model	Fix transportation cost ($M)	Loaded travel costs ($M)	Empty travel costs ($M)
Case Study	8.3	15.716	13.78
Locked-In	18.1	2.904	2.546
New allocation method	18.1	2.643	2.316

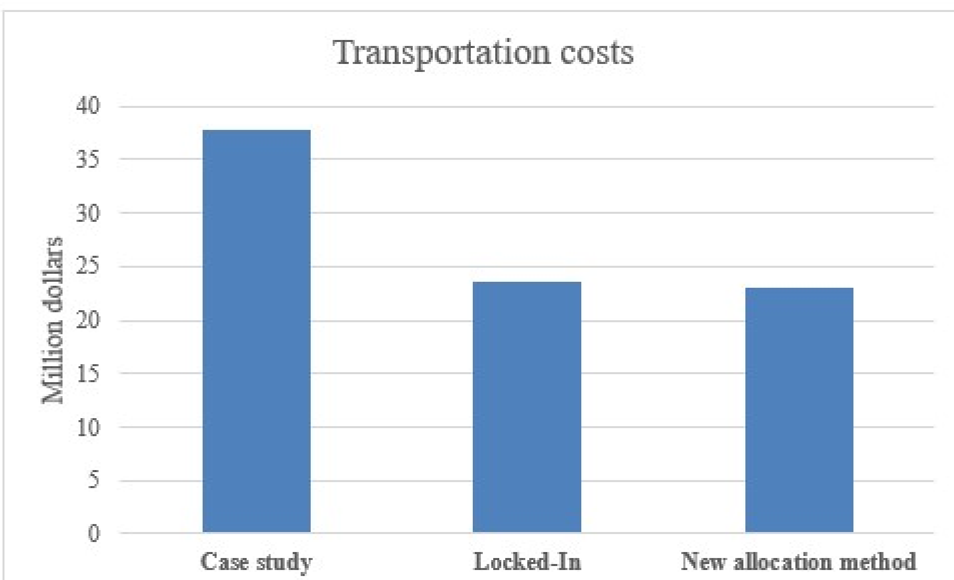

Figure 6. The transportation costs comparison between the case study, locked-in, and new allocation method.

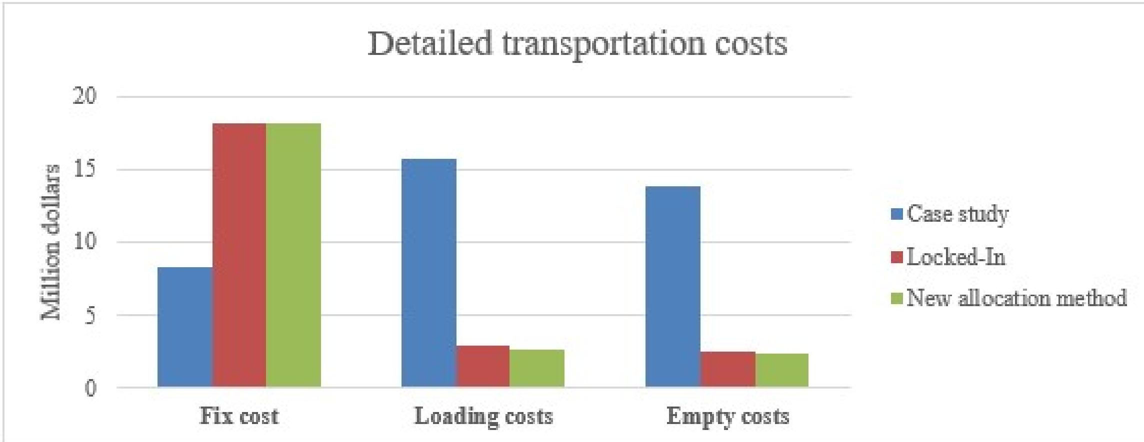

Figure 7. The detailed comparison of transportation costs between the case study, locked-in, and new allocation method.

As shown in Figure 6, the locked-in model and new allocation method have successfully reduced transportation costs by an impressive 38% and 39% respectively. This significant reduction highlights the superior efficiency of these models compared to the current situation in the mine. Furthermore, when referring to Figure 7, we observe a noteworthy 218% increase in fixed costs, attributed to the fleet renewal. However, this increase in fixed costs is counterbalanced by an average decrease of 83% in variable costs, which include loading mode and empty transportation costs.

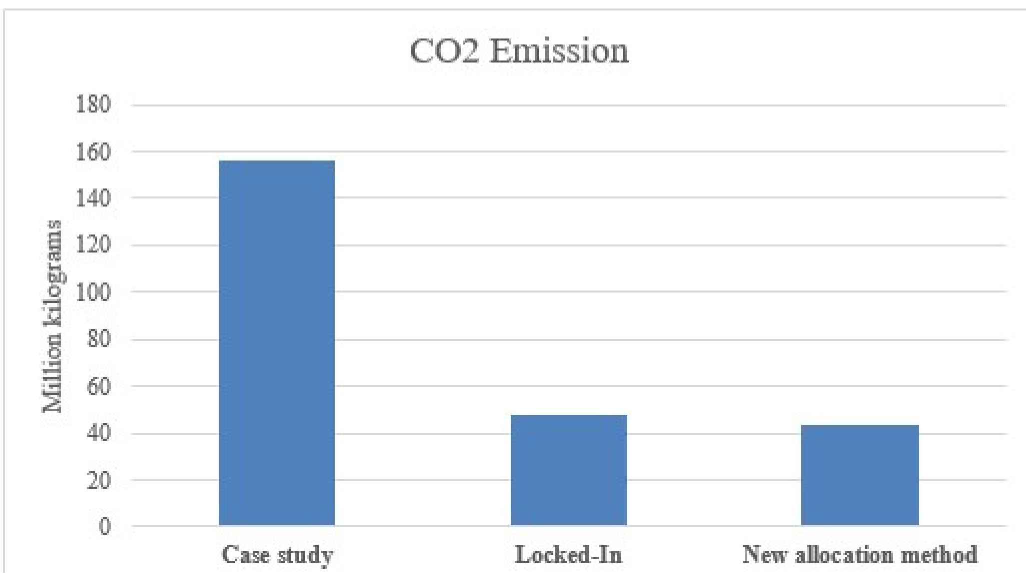

Figure 8. The comparison of CO_2 emission between the case study, locked-in, and new allocation method.

As depicted in Figure 8, the renovation of the fleet has led to a remarkable reduction of 70% and 72% in CO_2 emissions for the locked-in model and the new allocation method, respectively. These findings highlight the significant impact that the renovation of the fleet has on reducing harmful environmental pollutants. Additionally, these results suggest that investing in fleet renovation can be an effective strategy for combatting climate change and promoting sustainability.

5.1. Comparison of Results

In this section, an evaluation of the outcomes achieved by all three models will be conducted with a focus on defined KPIs. The findings of this comparative analysis are presented in Table 11, along with visual representations in Figure 9.

Table 11. Differences between KPIs.

KPI	Case Study	Locked in	New allocation method
Total tonnage hauled to dumpsite (Ore and Waste) (million tons)	16.803	17.613	18.195
Average waiting time per shovel (min)	3.08	2.73	1.94
Average cycle time (min)	40.33	23.45	22.54
Average fuel consumption per cycle (liter)	56.52	36.72	35.83
Average CO2 emission per cycle (Kg)	146.95	95.47	93.16

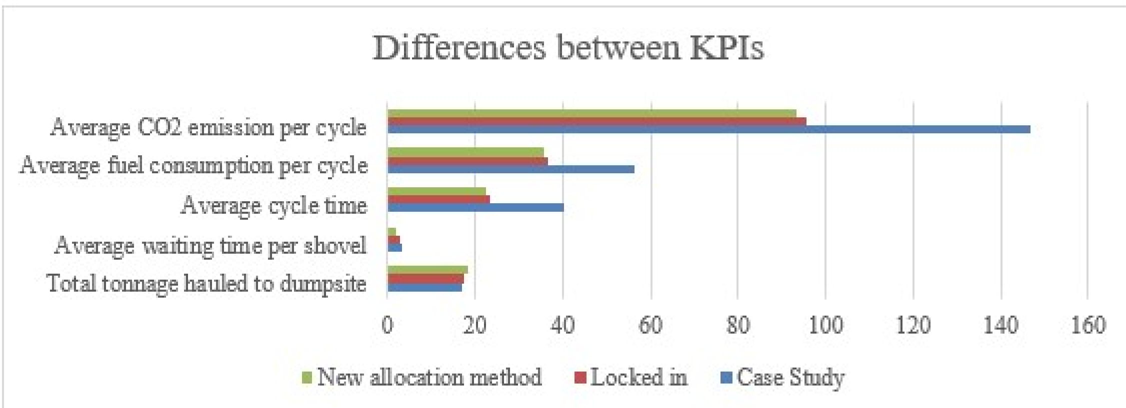

Figure 9. The comparison of KPIs.

By examining Figure 9, it becomes evident that the implementation of both the locked-in model and the new allocation method results in a notable increase in the total tonnage hauled. Specifically, an increase of 5% and 8% is observed respectively for each method, showcasing the significant efficiency improvements brought about by the new approach.

Moreover, it is evident that the locked-in and new allocation method models exhibit a reduction in the average waiting time per shovel by 11% and 37% respectively. Additionally, implementation of different allocation method leads to a significant decrease of 42% and 44%. These findings can be attributed to the adoption of optimal policies for truck allocation, resulting in minimized waiting and cycle times. These significant improvements in efficiency highlight the potential benefits associated with the utilization of advanced allocation strategies.

By analyzing Figure 9 and Table 11, it becomes evident that through fleet renewal and the optimal allocation of trucks, there is a notable average reduction of 36% in fuel consumption as well as carbon dioxide emissions. As a result, this issue demonstrates that fleet renewal has a substantial impact on both the economic and environmental aspects.

6. Sensitivity Analysis

In this section, set pf sensitivity analysis with changes in the parameters of maintenance policies, truck velocity, and changes in the age of trucks has been applied for further analysis of the framework performance. This analysis is done on the new allocation method by examining the objective functions and KPIs. The findings of the analysis are presented in Table 12. As mentioned, the scenarios are categorized into three areas, detailed as follows:

Maintenance:

- Improvement in maintenance policies, entailing a 5% reduction in failures.
- Improvement in maintenance policies, entailing a 10% reduction in failures.

Velocity:

- Increase in truck velocity by 5%.
- Increase in truck velocity by 10%.

Age:

- Depreciation of trucks over 5 years.
- Depreciation of trucks over 10 years.
- Renovation of trucks over 5 years.
- Renovation of trucks over 10 years.

Table 12. Results of sensitivity analysis.

Scenario	Objective 1						Objective 2		KPIs									
	Fix cost ($M)	**COV**	**Loading costs ($M)**	**COV**	**Empty costs ($M)**	**COV**	**CO2 Emission (M Kg)**	**COV**	**Total tonnage hauled (million tons)**	**COV**	**Average waiting time (min)**	**COV**	**Average cycle time (min)**	**COV**	**Average fuel per cycle (liter)**	**COV**	**Average CO2 (Kg)**	**COV**
New allocation method	18.1	-	2.643	-	2.316	-	43.396	-	18.195	-	1.94	-	22.54	-	35.83	-	93.16	-
Reduction in failure (5%)	18.1	1.00	2.871	1.09	2.516	1.09	44.791	1.03	19.765	1.09	1.67	0.86	20.59	0.91	36.94	1.03	95.94	1.03
Reduction in failure (10%)	18.1	1.00	2.938	1.11	2.547	1.10	46.686	1.08	21.119	1.16	1.12	0.58	19.36	0.86	38.69	1.08	100.61	1.08
Increase trucks velocity (5%)	18.1	1.00	2.739	1.04	2.409	1.04	46.234	1.07	21.834	1.20	1.90	0.98	19.51	0.87	38.05	1.06	99.87	1.07
Increase trucks velocity (10%)	18.1	1.00	2.995	1.13	2.618	1.13	50.396	1.16	23.504	1.29	1.89	0.97	17.93	0.80	41.48	1.16	108.86	1.17
Increase trucks age (5 years)	15.6	0.86	2.876	1.09	2.499	1.08	48.604	1.12	17.940	0.99	2.08	1.07	23.94	1.06	40.24	1.12	104.53	1.12
Increase trucks age (10 years)	12.8	0.71	3.145	1.19	2.745	1.19	52.510	1.21	16.557	0.91	2.25	1.16	26.37	1.17	43.00	1.20	112.72	1.21
Decrease trucks age (5 years)	20.7	1.14	2.352	0.89	2.108	0.91	39.491	0.91	18.198	1.00	1.86	0.96	22.31	0.99	32.61	0.91	84.78	0.91
Decrease trucks age (10 years)	23.5	1.30	2.061	0.78	1.853	0.80	34.717	0.80	18.326	1.01	1.78	0.92	21.93	0.97	28.66	0.80	74.53	0.80

After reviewing the results of the sensitivity analysis, we have identified the following findings:

- Fixed costs: The age of trucks has the most significant impact on the fixed costs of the project.
- Variable costs: Changes in the age of trucks have the greatest effect on variable costs. Additionally, truck velocity and improved maintenance policies have a similar impact on variable costs.
- The emissions: The age of trucks is the most influential factor in changes to the amount of carbon gas emission. Following this, changes in truck velocity have the most significant effect on pollution levels.
- Amount of hauled tonnage: Truck velocity is the most influential factor in this index, followed by the implementation of improved maintenance policies.
- Average waiting time: Improvement in maintenance policies is the most effective factor in reducing average waiting time.
- Average cycle time: Truck velocity is the main determinant of the cycle time.

6.1. Maintenance Improvement

Improving maintenance policies and reducing the duration of failure times does not affect fixed costs. However, reducing the duration of breakdowns increases the availability time of trucks, which impacts the number of trips they can make. This, in turn, directly increases the values of the objective functions. Generally, improvements in maintenance policies result in a 9 to 10% increase in transportation costs and around 3% to 8% increase in CO_2 emissions. It is noteworthy that the increase in the objective function values is primarily due to the reduction in breakdown duration, leading to a potential 9-16% increase in the amount of tonnage hauled. Additionally, this policy improvement significantly affects time related KPIs such as average cycle time and waiting time. The implementation of this policy is expected to result in a 9-14% reduction in cycle time and a 14-42% reduction in expected time. The results of these analyzes are shown in Figure 10.

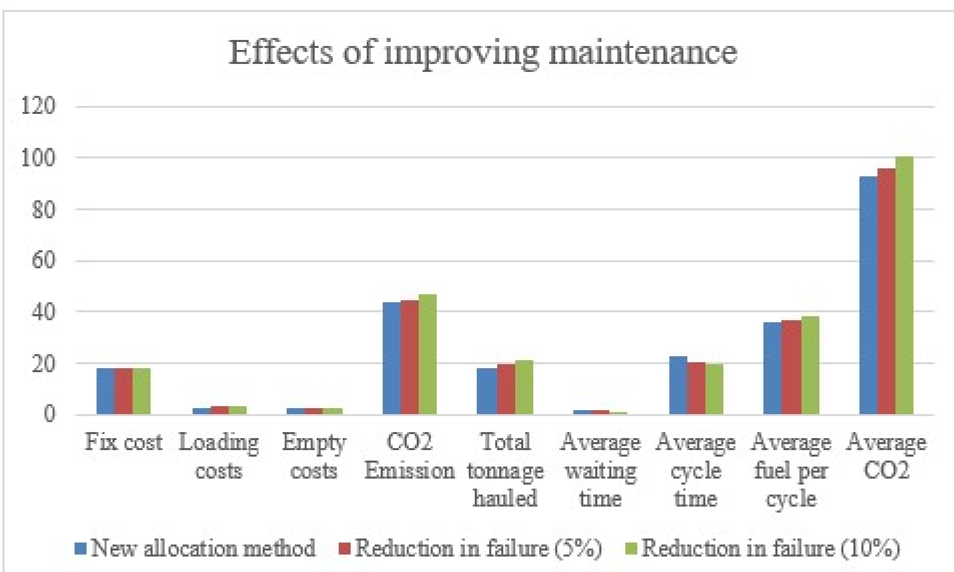

Figure 10. Effects of improving maintenance.

6.2. Increase Truck's Velocity

In this analysis, we examined the effect of increasing the velocity of trucks by 5 and 10 percent. As a result, we observed no change in fixed costs, but we did observe an increase of 4 and 13 percent in variable costs. Furthermore, there was an increase of 7 and 16 percent in carbon emissions. However, the increase in truck velocity had a positive impact on their performance. Specifically, the amount of tonnage carried increased by 20 and 29 percent, while the cycle time decreased by 13 to 20 percent. It is noteworthy that the increase in truck velocity did not have a significant effect on waiting time. In fact, the reduction in waiting time was only between 2 and 3 percent in this scenario. The graph illustrating these changes can be found in Figure 11.

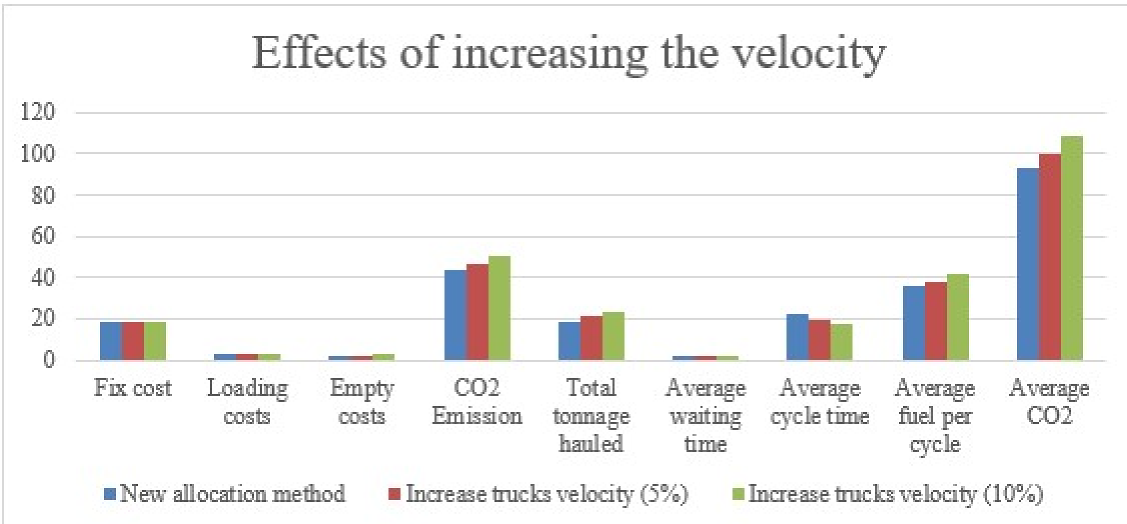

Figure 11. Effects of increasing velocity.

6.3. Changes in the Age of Transport Fleet

In this section, we aim to analyze the impact of truck renovation and depreciation on objective functions and key indicators for our research paper. During this analysis, we tested truck renewal and depreciation over periods ranging from 5 to 10 years. As the trucks' age increases, we observed a decrease in fixed costs, attributed to newer trucks having higher fixed costs initially. This decrease in fixed costs ranged between 14 and 29 percent as the trucks aged. Conversely, increasing the age of trucks led to an increase in variable costs, ranging between 9 and 19 percent. Furthermore, the aging of trucks had a significant impact on carbon emissions, showing an increase of between 12 and 21 percent. Apart from influencing objective function values, aging also negatively affected truck performance. For instance, the amount of tonnage moved decreased by 1 to 9 percent, while cycle time and waiting times increased by 6 to 17 percent.

Now, let us explore the scenario of reducing the age of trucks and considering their renovation. It is evident that truck renovation will result in increased fixed costs, ranging between 14 and 30 percent. However, due to the modernization of trucks and their improved performance, we observed a reduction in variable costs of 9 to 20 percent. Additionally, newer trucks exhibited a 9-20% decrease in carbon emissions. When it comes to measuring truck performance in terms of indicators, the age reduction did not significantly impact the amount of transported tonnage, resulting in a minimal 1% increase. Conversely, cycle time and waiting time experienced a reduction of 4 to 8 percent. These analyses are shown in Figure 12.

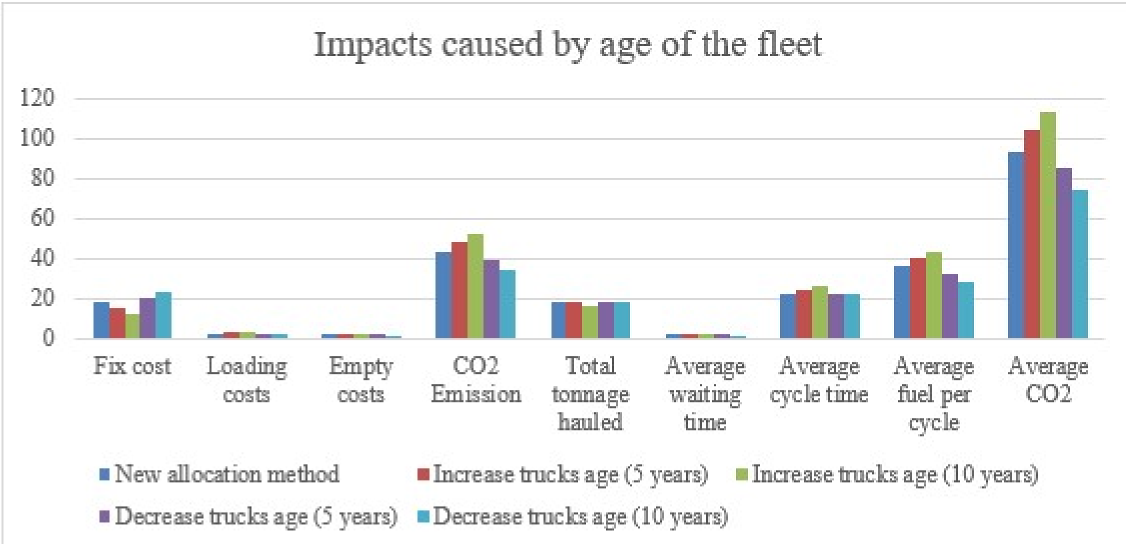

Figure 12. Impacts caused by age of the fleet

7. Conclusion

In this study, we introduced a comprehensive integrated stochastic discrete-continuous simulation-based optimization framework for GHG mitigation in open pit mines. Our framework not only addresses the economic imperative of minimizing transportation costs but also prioritizes environmental sustainability by concurrently reducing carbon dioxide emissions. Furthermore, our novel approach to allocating trucks to shovels stands out for its dual benefits, enhancing both economic efficiency and environmental performance.

The significance and distinction of present work is concurrent addressing of both strategic and tactical level mine planning with simultaneous consideration of economic, environmental, and operational advantages and disadvantages in one frame. Although the presented framework, as the scope mandated, targets the open pit mining operations, the analogy, both the simulation and optimization modeling approaches, and the main structure of the framework can be adapted or translated to other production environments.

In conclusion, the presented framework was effectively evaluated through a real currently in operation copper mine case study. The use of sensitivity analysis allowed for an examination of the influence of factors such as uncertainty in maintenance and repair, as well as downstream processes, on the legitimacy of the framework and accuracy of the performance indicators. Through this analysis, it was possible to identify significant parameters that impact economic productivity and environmental concerns, thus further enhancing the applicability and effectiveness of the framework. Based on our study, the remarkable findings of implementing our novel method for allocating trucks to shovels are as follows:

- Our proposed model led to a significant decrease in transportation costs compared to the existing situation and the use of old truck allocation policies. We observed an 83% reduction in variable costs and a 39% reduction in total costs. These results highlight the economic justification of implementing this model in the strategic planning of the mine.
- Aligned with the growing importance of sustainable development and environmental concerns, a primary accomplishment of our study was the prioritization of these matters. Through the utilization of our new allocation method, we were able to contribute to a 72%

reduction in carbon dioxide emissions. This reduction is crucial for addressing current environmental challenges.

- Our model also demonstrated satisfactory results in terms of time savings and productivity. Notably, we observed a 37% reduction in waiting time and a 44% decrease in the duration of cycle time. Additionally, the model displayed good efficiency, resulting in an approximately 8% increase in tonnage and material transfer. These findings are indicative of the effectiveness and efficiency of our proposed approach.
- Another significant finding of this research was the identification of factors influencing both environmental and economic concerns. Through sensitivity analysis and simulation tests, we discovered that the truck age parameter is the most influential factor in increasing transportation costs, pollution levels, and greenhouse gas emissions.

8. References:

[1] Ozdemir, B., and M., Kumral, *Simulation-based optimization of truck-shovel material handling systems in multi-pit surface mines*. Simulation Modelling Practice and Theory, 2019. **95**, pp. 36–48. https://doi.org/10.1016/j.simpat.2019.04.006

[2] Moradi Afrapoli, A., and H., Askari-Nasab, *Mining fleet management systems: a review of models and algorithms*. International Journal of Mining, Reclamation and Environment, 2019. **33**, pp. 42–60. https://doi.org/10.1080/17480930.2017.1336607.

[3] Moradi Afrapoli, A., M., Tabesh, and H., Askari-Nasab, *A multiple objective transportation problem approach to dynamic truck dispatching in surface mines*. European Journal of Operational Research, 2019. **276**, pp. 331–342. https://doi.org/10.1016/j.ejor.2019.01.008.

[4] Moradi Afrapoli, A., M., Tabesh, and H., Askari-Nasab, *A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines*. Mining Technology: Transactions of the Institute of Mining and Metallurgy, 2019. **128**, pp. 9–20. https://doi.org/10.1080/25726668.2018.1473314.

[5] Dindarloo, S.R., and E., Siami-Irdemoosa, *Determinants of fuel consumption in mining trucks.* Energy, 2016. **112**, pp. 232–240. https://doi.org/10.1016/j.energy.2016.06.085.

[6] Siami-Irdemoosa, E., and S.R., Dindarloo, *Prediction of fuel consumption of mining dump trucks: A neural networks approach*. Applied Energy, 2015. **151**, pp. 77–84. https://doi.org/10.1016/j.apenergy.2015.04.064.

[7] Azapagic, A., *Developing a framework for sustainable development indicators for the mining and minerals industry*. Journal of Cleaner Production, 2004. **12**(6), pp. 639–662. https://doi.org/10.1016/S0959-6526(03)00075-1.

[8] Hilson, G., and B., Murck, *Sustainable development in the mining industry: Clarifying the corporate perspective.* Resources Policy, 2000. **26**(4), pp. 227–238. https://doi.org/10.1016/S0301-4207(00)00041-6.

[9] Shen, L., K. Muduli, and A., Barve, *Developing a sustainable development framework in the context of mining industries: AHP approach*. *Resources Policy*, 2015. **46**, pp. 15–26. https://doi.org/10.1016/j.resourpol.2013.10.006.

[10] Yakovleva, N., Corporate Social Responsibility in the Mining Industries. 2017. https://doi.org/10.4324/9781315259215.

[11] Anaraki, M.G., and A.M., Afrapoli, *Sustainable open pit fleet management system: integrating economic and environmental objectives into truck allocation*. Mining Technology: Transactions of the Institute of Mining and Metallurgy, 2023. **132**(3), pp. 153–163. https://doi.org/10.1080/25726668.2023.2233230.

[12] Mohtasham, M., H., Mirzaei-Nasirabad, and B., Alizadeh, *Optimization of truck-shovel allocation in open-pit mines under uncertainty: A chance-constrained goal programming approach*. Mining Technology: Transactions of the Institute of Mining and Metallurgy, 2021. **130**(2), pp. 81–100. https://doi.org/10.1080/25726668.2021.1916170.

[13] Alarie, S., and M., Gamache, *Overview of solution strategies used in truck dispatching systems for open pit mines*. International Journal of Surface Mining, Reclamation and Environment, 2022. **16**, pp. 59–76. https://doi.org/10.1076/ijsm.16.1.59.3408.

[14] Burt, C.N., and L., Caccetta, *Equipment selection for surface mining: A review*. Interfaces, 2014. **44**(2), pp. 143–162. http://doi.org/10.1287/inte.2013.0732.

[15] Mohtasham, M., H., Mirzaei-nasirabad, H., Askari-nasab, and M., Mohtasham, *Truck fleet size selection in open-pit mines based on the match factor using a MINLP model*. Mining Technology: Transactions of the Institute of Mining and Metallurgy, 2021. **130**(3), pp. 159–175. https://doi.org/10.1080/25726668.2021.1919374.

[16] Edwards, D.J., H., Malekzadeh, and S.B., Yisa, *A linear programming decision tool for selecting the optimum excavator*. *Structural Survey*, 2001. **19**(2), pp. 113–120. https://doi.org/10.1108/EUM0000000005628.

[17] Burt, C., L., Caccetta, S., Hill, and P., Welgama, *Models for mining equipment selection*, in *Conference of International Congress on Modelling and Simulation: Advances and Applications for Management and Decision Making, MODSIM05*. 2005. pp. 1730–1736.

[18] Huu, C., T.S., Canada, A., Ingolfsson, J., Doucette, and C.H., Ta, *A linear model for surface mining haul truck allocation incorporating shovel idle probabilities*. European Journal of Operational Research, 2013. **231**(3), pp. 770-778. https://doi.org/10.1016/j.ejor.2013.06.016.

[19] Mohtasham, M., H., Mirzaei-Nasirabad, H., Askari-Nasab, and B., Alizadeh, *Multi-stage optimization framework for the real-time truck decision problem in open-pit mines: A case study on Sungun copper mine*. International Journal of Mining, Reclamation and Environment, 2022. **36**(7), pp. 1–31. https://doi.org/10.1080/17480930.2022.2067709.

[20] Souza, M.J.F., I.M., Coelho, S., Ribas, H.G., Santos, and L.H.C., Merschmann, *A hybrid heuristic algorithm for the open-pit-mining operational planning problem*. European Journal of Operational Research, 2010. **207**(2), pp. 1041–1051. https://doi.org/10.1016/j.ejor.2010.05.031.

[21] Yeganejou, M., M.M., Badiozamani, A., Moradi-Afrapoli, and H., Askari-Nasab, *Integration of simulation and dispatch modelling to predict fleet productivity: An open-pit mining case*. Mining Technology: Transactions of the Institute of Mining and Metallurgy, 2022. **131**(2), pp. 67–79. https://doi.org/10.1080/25726668.2021.2001255.

[22] Mohtasham, M.,, H., Mirzaei-Nasirabad, H., Askari-Nasab, and B., Alizadeh, *A multi-objective model for fleet allocation schedule in open-pit mines considering the impact of prioritising objectives on transportation system performance*. International Journal of Mining, Reclamation and Environment, 2021. **35**(10), pp. 1–19. https://doi.org/10.1080/17480930.2021.1949861.

[23] Zhang, L., and X., Xia, *An integer programming approach for truck-shovel dispatching problem in open-pit mines*. Energy Procedia, 2015. **75**, pp. 1779–1784. https://doi.org/10.1016/j.egypro.2015.07.469.

[24] Ahangaran, D.K., A.B., Yasrebi, A., Wetherelt, P., Foster, and A.B., Yasrebi, *Real–time dispatching modelling for trucks with different capacities in open pit mines*. Archives of Mining Sciences, 2012. **57**, pp. 39-52. https://doi.org/10.2478/v10267-012-0003-8.

[25] Alexandre, R.F., F., Campelo, and J.A., Vasconcelos, *Multi-objective evolutionary algorithm for truck dispatching in open pit mining operations*. Learning and Nonlinear Models, 2019. **17**(2), pp. 53–66. http://dx.doi.org/10.21528/lnlm-vol17-no2-art5

[26] Ta, C.H., J.V., Kresta, J.F,. Forbes, and H.J., Marquez, *A stochastic optimization approach to mine truck allocation*. International Journal of Surface Mining, Reclamation and Environment, 2005. **19**(3), pp. 162–175. https://doi.org/10.1080/13895260500128914.

[27] Moradi-Afrapoli, A., S., Upadhyay, and H., Askari-Nasab, *Truck dispatching in surface mines - Application of fuzzy linear programming*. Journal of the Southern African Institute of Mining and Metallurgy, 2021. **121**(9), pp. 505-512. https://doi.org/10.17159/2411-9717/522/2021.

[28] Both, C., and R., Dimitrakopoulos, *Joint stochastic short-term production scheduling and fleet management optimization for mining complexes*. Optimization and Engineering, 2020. **21**(4), pp. 1717–1743. https://doi.org/10.1007/s11081-020-09495-x.

[29] Topal, E., and S., Ramazan, *A new MIP model for mine equipment scheduling by minimizing maintenance cost*. European Journal of Operational Research, 2010. **207**(2), pp. 1065–1071. https://doi.org/10.1016/j.ejor.2010.05.037.

[30] Peralta, S., A.P., Sasmito, and M., Kumral, *Reliability effect on energy consumption and greenhouse gas emissions of mining hauling fleet towards sustainable mining*. Journal of Sustainable Mining, 2016. **15**(3), pp. 85–94. https://doi.org/10.1016/j.jsm.2016.08.002.

[31] Mane, S., B., Djordjevic, and B., Ghosh, *A data-driven framework for incentivising fuel-efficient driving behaviour in heavy-duty vehicles*. Transportation Research Part D: Transport and Environment, 2021. **95**, p. 102845. https://doi.org/10.1016/j.trd.2021.102845.

[32] Walnum H.J., and M., Simonsen, *Does driving behavior matter? An analysis of fuel consumption data from heavy-duty trucks*. Transportation Research Part D: Transport and Environment, 2015. **36**, pp. 107–120. https://doi.org/10.1016/j.trd.2015.02.016.

[33] Aksoy, A., İ., Küçükoğlu, S., Ene, and N., Öztürk, *Integrated emission and fuel consumption calculation model for green supply chain management*. Procedia - Social and Behavioral Sciences, 2014. **109**, pp. 1106–1109. https://doi.org/10.1016/j.sbspro.2013.12.595.

[34] Alinaghian, M., and M., Naderipour, *A novel comprehensive macroscopic model for time-dependent vehicle routing problem with multi-alternative graph to reduce fuel consumption: A case study*. Computers and Industrial Engineering, 2016. **99**, pp. 210–222. https://doi.org/10.1016/j.cie.2016.07.029.

[35] Winebrake, J.J., and E.H., Green, *Environmental policy, decision making, and rebound effects in the U.S. trucking sector.* Research in Transportation Business and Management, 2017. **23**, pp. 54–63. https://doi.org/10.1016/j.rtbm.2017.02.008.

[36] Montiel, L., and R., Dimitrakopoulos, *Optimizing mining complexes with multiple processing and transportation alternatives: An uncertainty-based approach.* European Journal of Operational Research, 2015. **247***,* pp. 166–178. https://doi.org/10.1016/j.ejor.2015.05.002.

[37] Dindarloo, D.R., M., Osanloo, and S., Frimpong, *A stochastic simulation framework for truck and shovel selection and sizing in open pit mines*. Journal of the Southern African Institute of Mining and Metallurgy, 2015. **115**(3), pp. 209–219.

[38] Rist, K., *The solution of a transportation problem by use of a Monte Carlo technique*, in *Applications for computers and operations research in the minerals industries (APCOM)*. 1961.

[39] Kolonja, B., and J.M., Mutmansky, *Analysis of truck dispatching strategies for surface mining operations using SIMAN*. Society for Mining, Metallurgy & Exploration, 1995. **296**, pp. 1845–1850.

[40] Ataeepour, N., and E.Y., Baafi, *ARENA simulation model for truck-shovel operation in despatching and non-despatching modes*. International Journal of Mining, Reclamation and Environment, 1999. **13**(3), pp. 125–129. http://doi.org/10.1080/09208119908944228.

[41] Yuriy, G., and N., Vayenas, *Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms*. International Journal of Mining, Reclamation and Environment, 2008. **22**, pp. 70–83.

[42] Que, S., A., Anani, and K., Awuah-Offei, *Effect of ignoring input correlation on truck–shovel simulation*. International Journal of Mining, Reclamation and Environment, 2016. **30**(5), pp. 405–421. http://doi.org/10.1080/17480930.2015.1099188.

[43] Chaowasakoo, P., H., Seppälä, H., Koivo, and Q., Zhou, *Digitalization of mine operations: Scenarios to benefit in real-time truck dispatching.* International Journal of Mining Science and Technology, 2017. **27**(2), pp. 229–236. http://doi.org/10.1016/j.ijmst.2017.01.007.

[44] Upadhyay, S.P., and H., Askari-Nasab, *Truck-shovel allocation optimisation: A goal programming approach*. Mining Technology: Transactions of the Institutions of Mining and Metallurgy, 2016. **125**(2), pp. 82-92. https://doi.org/10.1179/1743286315Y.0000000024.

[45] Forsman, B., E., Ronnkvist, and N., Vagenas, *Truck dispatch computer simulation in Aitik open pit mine*. International Journal of Surface Mining, Reclamation and Environment, 1993. **7**(3), pp. 117–120. https://doi.org/10.1080/17480939308547571.

[46] Torkamani, E., and H., Askari-Nasab, *A linkage of truck-and-shovel operations to short-term mine plans using discrete-event simulation*. International Journal of Mining and Mineral Engineering, 2015. **6**(2), pp. 97–118. http://doi.org/10.1504/IJMME.2015.070367.

[47] Saadatmand Hashemi, A., and J., Sattarvand, *Simulation based investigation of different fleet management paradigms in open pit mines-a case study of Sungun copper mine*. Archives of Mining Sciences, 2015. **60**, pp. 195-208. https://doi.org/10.1515/amsc-2015-0013.

[48] Awuah-Offei, K., V.A., Temeng, and S., Al-Hassan, *Predicting equipment requirements using SIMAN simulation - A case study*. Mining Technology: Transactions of the Institutions of Mining and Metallurgy, 2003. **112**(3), pp. 180–184. http://doi.org/10.1179/037178403225003609.

[49] Suglo, S., and S., Al-Hassan, *Use of simulation techniques in determining the fleet requirements of an open pit mine*. Ghana Mining Journal, 2007. **9**, pp. 25-32. https://doi.org/10.4314/gm.v9i1.42606.

[50] Tan, Y., K., Miwa, U., Chinbat, and S., Takakuwa, *Operations modeling and analysis of open pit copper mining using GPS tracking data*, in *Proceedings of the 2012 Winter Simulation Conference (WSC)*. 2012. https://doi.org/10.1109/WSC.2012.6465062.

[51] Enrique, C., A., Curi and P.H., Campos, *The use of simulation in fleet selection and equipment sizing in mining*, in *Mine Planning and Equipment Selection*. 2014. pp. 869–877. https://doi.org/10.1007/978-3-319-02678-7_84.

[52] Tiile, R.N., F.A., Kaba, N., Aouad, and F., Arthur, *Shovel-truck haulage analysis using stochastic discrete event simulation*. International Journal of Science and Research, 2016. **5**(11), pp. 495–500. http://dx.doi.org/10.21275/ART20162683 .

[53] Kaba, F.A., V.A., Temeng, and P.A., Eshun, *Application of discrete event simulation in mine production forecast*. Ghana Mining Journal, 2016. **16**, pp. 40–48.

[54] Zeng, W., E., Baafi, and D., Walker, *A simulation model to study bunching effect of a truck-shovel system*. International Journal of Mining, Reclamation and Environment, 2019. **33**(2), pp. 102–117. https://doi.org/10.1080/17480930.2017.1348284.

[55] Chaowasakoo, P., H., Seppälä, H., Koivo, and Q., Zhou, *Improving fleet management in mines: The benefit of heterogeneous match factor*. European Journal of Operational Research, 2017. **261**(3), pp. 1052–1065. https://doi.org/10.1016/j.ejor.2017.02.039.

[56] Abolghasemian, M., A.G., Kanafi, and M., Daneshmandmehr, *A two-phase simulation-based optimization of hauling system in open-pit mine*. Interdisciplinary Journal of Management Studies, 2020. **13**(4), pp. 705–732. https://doi.org/10.22059/IJMS.2020.294809.673898.

[57] Abolghasemian, M., A.G., Kanafi, and M., Daneshmand-Mehr, *Simulation-based multiobjective optimization of open-pit mine haulage system: A modified-NBI method and meta modeling approach*. Complexity, 2022. **2022**(4), pp. 1-15. https://doi.org/10.1155/2022/3540736.

[58] Banks, D., J., Carson, J., Nelson, B., Nicol, Discrete-Event System Simulation. 2004.

[59] Kelton, D.W., Simulation with Arena. 2014.