Shahrood University of Technology

Iranian Society of Mining Engineering (IRSME)

Journal of Mining and Environment (JME)

journal homepage: www.jme.shahroodut.ac.ir

THOMSON REUTERS

Design of Loading and Transportation Fleet in Open-Pit Mines using Simulation Approach and Metaheuristic Algorithms

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Article Info

Received 4 November 2021

Received in Revised form 6 December 2021

Accepted 14 December 2021

Published online 14 December 2021

DOI:10.22044/jme.2022.11450.2131

Keywords

Optimization
Open-pit mines
Loading and haulage
Simulation
Firefly algorithm

Abstract

The production cycle in open-pit mines includes the drilling, blasting, loading, and haulage. Since loading and haulage account for a large part of the mining costs, it is very important to optimize the transport fleet from the economic viewpoint. Simulation is one of the most widely used methods in the field of fleet design. However, it is unable to propose an optimized scenario for which the appropriate metaheuristic method should be employed. This paper considers the Sungun copper mine as the case study, and attempts to find the most feasible transportation arrangement. In the first step, in this work, we compare the flexible dispatching with the fixed allocation methods using the Arena software. Accordingly, the use of flexible dispatching reveals the increase in the production rate (20%) and productivity (25%), and the decrease (20%) in the idle time. The firefly metaheuristic algorithm used in the second step shows that the combined scenario of the 35-ton and 100-ton trucks is the most suitable option in terms of productivity and cost. In another attempt, comparing different heterogeneous truck fleets, we have found that the scenarios 35-100 and 35-60-100-144 increase the production rate by 39% and 49%, respectively. Also, in both scenarios, the production cost decreases by 11% and 21%, respectively.

1. Introduction

Transportation in open-pit mines accounts for up to 60% of the mining operating costs. Therefore, optimizing the mining operations and fleet management has a significant effect on the operational efficiency [8]. The shovel-truck system is one of the most widely used transportation systems in mines. Nowadays, the increase in the equipment efficiency, transportation planning, truck allocation, and dispatching strategy can significantly reduce the costs in this sector [16]. Simulation is one of the best ways to identify the current situation and improve the performance of systems, especially the manufacturing systems. Providing an optimization approach is one of the critical issues in this area. Simulation is the imitation of performance in a process or system over time. Whether manual or computer-aided, simulation creates a system history and checks the system to achieve the results related to the functional characteristics of the system [1].

The first manual simulation of the mining fleet took place in the late 1960s in northern Sweden in the Kirona underground iron mine [21]. Rist (1961) ran the first computer simulation of an underground mine's operation in order to determine the optimal number of wagons for reducing the waiting time for loading and unloading [23]. Herbar (1979) used the simulation to select the dragline type in an open-pit mine [9]. Castillo and Cochran (1987) developed a program based on the FITPLUS and SLAM II languages for the simulation and statistical analysis of mining models [7]. Bonates and Lizotte (1988) developed a simulation model for open-pit mining using the FORTRAN programming language in order to achieve the required long-term production and

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maximize the productivity of the shovel-truck system [6]. Baafi and Ataee-pour (1996) for the first time applied Arena to the mining industry. They used the discrete event simulation to investigate a truck-shovel system of discontinuous open-pit mines [3]. Temeng and Amoako (1997) used a computer model to optimize the flexible dispatching of trucks in open-pit mines and managed to provide a solution for reducing the waiting time for the system equipment [26]. Sturgul (2001) described the importance of simulation in mining and described GPSS/H and SIMAN-based ARENA as the two most commonly used discrete event simulation languages in this field [25]. Amel *et al.* (2012) used the intelligent movement simulation based on the real-time control system to flexibly dispatch trucks to the transportation system of an open-pit mine [13]. Hashemi and Sattarvand (2015) studied different management systems of the open-pit mining equipment including non-dispatching, dispatching, and blending solutions using simulation modeling [11]. Azadi *et al.* (2015) used the simulation technique to model the transportation system of the mine in the Arena software, and then by defining new systems, the efficiency of the available fleet was improved [2]. Zeng *et al.* (2016) used a discrete event simulation model with 3D animation in order to estimate the productivity of a truck-shovel network system, shovel efficiency, truck cycle time, truck utilization, and the optimal fleet size [34]. Upadhyay *et al*, (2016) developed a simulation optimization framework/tool to account for the uncertainties in mining operations for robust short-term production planning and proactive decision-making. This framework/tool uses a discrete event simulation model of mine operations, which interacts with a goal-programming-based mine operational optimization tool to develop an uncertainty-based short-term schedule [28]. In another research work, Upadhyay *et al.* (2019) presented a simulation framework to estimate the productivity of haulage fleet for the open-pit mining operations with the truck-and-shovel system. The historical data was used to fit probability distributions for the haulage cycle components, and the mine road network and long-term production schedule were the main inputs to the model [29]. Table 1 presents some research-works on designing the mining transportation systems.

Table 1. Some research works on designing mining transportation

Ref.	Case	Method
Zhang *et al.,* 2021 [35]	Optimization of autonomous truck trips and speed to reduce fuel consumption	TABU search algorithm
Bakhtavar *et al.,* 2021 [4]	Estimating the impacts of the uncertainty on the efficiency of truck-shovel systems	Chance-constrained goal programming model
Mohtasham *et al.,* 2021 [18]	Equipment sizing (ES) problem to verify the overall efficiency of the fleet	Mixed-integer non-linear programming (MINLP) models
Jamil *et al.,* 2021 [12]	Multi-type vehicle routing problem (MTVRP)	Firefly algorithm
Yeganejou *et al.,* 2021 [33]	Mimicking the real truck-and-shovel operations and measure trucks' productivity in terms of Tonne Per Gross Operating Hour (TPGOH).	Monte-Carlo simulation

An optimization problem refers to the maximization or minimization of an objective function by setting suitable values for the variables from a set of feasible values. These problems appear not only in complex scientific studies but also in our day-to-day activities. For instance, when a person wants to go from one place to another, and has multiple possible routes, a decision is required to be made on which route to take. The decision can be with the objective to minimize the travel time, fuel consumption, and so on. However, these kinds of problems with fewer number of alternatives can easily be solved by looking at the outcome of each one of the alternatives. However, in the real problems such as optimizing the mining transportation fleet, it is not always the case to have a finite and small number of alternatives. Hence, different solution methods are proposed based on the behavior of the problem [15]. Since the introduction of evolutionary algorithms, many studies have been conducted on the heuristic algorithms. Currently, there are more than 40 metaheuristic algorithms [27]. Most of these new algorithms have been introduced by mimicking a scenario from the nature. For instance, the genetic algorithm is inspired by the Darwin theory of survival of the fittest [19]; particle swarm optimization is another metaheuristic algorithm, mimicking how a swarm moves by following each other [14]; the firefly algorithm is inspired by how fireflies signal each other using the flashing light to attract for mating or to identify predators [31], and the prey predator algorithm is another new algorithm inspired by the behavior of a predator and its prey [27]. These algorithms use different degrees of exploration and exploitation based on their different search mechanisms [15]. Among these new algorithms, it has been shown that the firefly algorithm is very efficient in dealing with the multi-modal, global optimization problems. FA has two major advantages over the other algorithms. First, FA is based on attraction, and attractiveness decreases with distance. This leads to the fact that the whole population can automatically sub-divide into sub-groups, and each group can swarm around each mode or local optimum. Among all these modes, the best global solution can be found. Secondly, this subdivision allows the fireflies to be able to find all optima simultaneously if the population size is sufficiently higher than the number of modes [30].

As it can be concluded from the literature, using the intelligent algorithms in solving the mining transportation problems has recently become widespread due to their ability and speed in determining the possible answers. The present paper aims to study and analyze the performance of the Sungun copper mine's transportation system using the ARENA software. Also the obtained simulation scenarios are optimized using the firefly metaheuristic algorithm in the MATLAB environment.

2. Methodology

In this work, we used the discrete event simulation for the systems in which the state variable changes in a set of discrete time instants, such as the mining transportation system. In general, a complete simulation process involves defining a goal, collecting the data, developing a model, validating the model, verifying the model, using the model, and analyzing the results [5].

2.1. Modeling using ARENA software

ARENA (ver. 14) is a relatively new simulation software developed by the ROCKWELL Company based on SIMAN/CINEMA [22]. During the modeling with ARENA, two terms, module and template, are used extensively. Module is an image object in ARENA used to display a number of system components, and is actually a combination of SIMAN blocks and CINEMA elements [24]. Figure 1 shows the two most widely used modules in ARENA.

Figure 1. Two most widely used modules in ARENA.

Template is the place of gathering and organization of a group of modules with almost equal importance. The three most important ARENA templates used in this work are Common, Support, and Transfer.

The steps for generating a simulation model in ARENA are [24]:

1. Create a scheme of the problem
2. Define the problem logic by selecting the appropriate modules in ARENA to show the real system components and their operations and then to put them in a schematic design.
3. Enter the model data with specific available structures.

2.2. Optimization with firefly algorithm (FA)

Swarm intelligence belongs to a branch of artificial intelligence that has attracted attention in the last decade. It is inspired by the collective behavior of social groups of ants and termites, worms, birds, and fish [10]. FA is one of the swarm intelligence methods that was developed by Yang (2008). and inspired by the light emitted by the firefly. FA is a randomized algorithm, meaning that it uses random selection to search for a set of solutions [31]. This algorithm relies on the physical formula of light intensity (*I*), which decreases by increasing the distance by r^2. However, as the distance to the light source increases, the light becomes weaker due to light absorption. This phenomenon can be optimized along with the objective function. In general, the firewall algorithm follows the following rules [31]:

(1) Fireflies are unisex; therefore, they are attracted to other worms regardless of sex.

(2) In the firefly algorithm, the absorption increases in proportion to the brightness and the reduced distance between the two fireflies. Hence, in two flashing fireflies, the brighter fireflies attract other surrounding worms. If none of them are brighter, there is a random movement.

(3) The brightness of a firefly is determined by the objective function.

The steps of the firefly algorithm is presented in Appendix 1.

In order to properly design FA, two important issues should be defined: light intensity and attractiveness. The attractiveness of fireflies is determined by the brightness or light intensity obtained from the objective function. The intensity of light can be obtained based on the following equation [32]:

$$I = I_0 e^{-\gamma r} \tag{1}$$

where, I_0= Primary light intensity and γ= Absorption coefficient.

The attractiveness of fireflies is quite relative and should be seen in the eyes of the observers or judged by other fireflies. Thus, the attractiveness changes with the distance r between firefly *i* and firefly *j* [20]:

$$r = |X_i - X_j| = \sqrt{\sum_{k=1}^{n} (X_{i,k} - X_{j,k})^2} \tag{2}$$

where $X_{i,k}$= *Part k of firefly i,* $X_{j,k}$= *Part k of firefly j*, and n = problem aspect.

Table 2. Sungun mine's fleet characterization.

Subsystem name	Model
Shovel	Liebherr R9350
Loader	Caterpillar 988B
Dump truck	Komatsu HD-785-5
Dump truck	Komatsu HD 325

The following formula can be used to describe the attractiveness [32]:

$$\beta = \beta_0 e^{-\gamma r} \tag{3}$$

where, β_0= *Amount of attractiveness at zero distance* and γ= *Absorption coefficient*

The movement of firefly *i* towards the more attractive firefly *j* is obtained from the following equation [32]:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha \varepsilon_i \tag{4}$$

where, ε_i= *A random number obtained from Gaussian distribution*

3. Sungun Copper Mine

3.1. Geographical location and access routes of Sungun copper mine

The Sungun copper mine is located in the East Azerbaijan province, Iran, in the coordinates of 46° 43' longitude and 38° 43' latitude in the vicinity of Republics of Azerbaijan and Armenia. The average elevation of the region is 2000 m above the sea level, and the main access road to the mine is through the Tabriz-Varzeqan-Sungun asphalt road. Cold and freezing winter and mild summer describe the climate characteristics of this region [17].

3.2. Sungun copper mine's transportation fleet

The mining operation is managed in the mine site by employing a fleet of dump trucks, loaders, shovels, excavators, bulldozers, and drilling rigs. The characteristics of the mining fleet and its block diagram are illustrated in Table 2. The loading and haulage system studied in the Sungun copper mine includes three loaders at the L2, L4, and L6 loading stations. There are two shovels at the L3 and L5 loading stations and one excavator at the L1 station. The system includes six 100-ton trucks and twelve 35-ton trucks. Figure 3 shows a schematic view of the system arrangement.

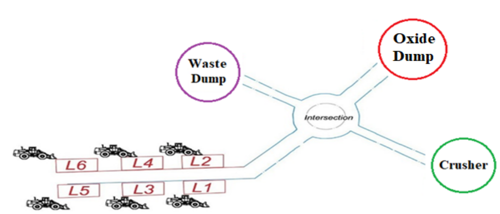
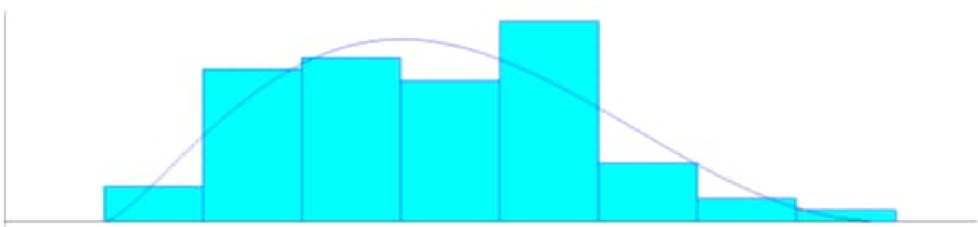


Figure 3. Schematic view of system component arrangement.

4. Modelling and Results

4.1. ARENA modelling

One of the main steps in a simulation operation is to gather information about the system. The time required to perform the activities is one of the most important pieces of information. The timing of the Sungun copper mine is the direct observation of the active sectors. Other information is required to run a simulation is the specific gravity of the transported materials to determine the capacity of trucks. In this work, the specific gravity of minerals is 2.5 tons per cubic meter, waste is 2.3 tons per cubic meter and copper oxide is 2.5 tons per cubic meter. Also the working hours in each shift, effective working time of a shift, and number of working shifts per day are among the essential information used. Considering the delays and timing of the study system, the useful working time during the day and night is 990 minutes. The primary function of simulation is to find the right distribution for the input data from the viewpoints of time and required resources. This research work uses the Arena's input analyzer software to fit and select the appropriate distribution. This software is an input data analysis package that is also available from the ARENA software. The software package allows to adapt possible distributions to the data and estimate the parameters. Figure 2 shows the histogram and probability distribution of the traveling time of a 100-ton truck between intersection to the Loader 1 (L1) in Sungun mine, which are generated by the input analyzer of ARENA, and Table 3 summarizes the timing of the Sungun mine.



Distribution: Beta (min)
*Expression: 1.18+1.81*BETA (2.4, 3.33)*
Square error: 0.010535
Chi Square test
Number of intervals= 5
Degrees of freedom= 2
Test statistic= 4.4
Corresponding p-value= 0.117
Kolmogorov-Smirnov test
Test statistic= 0.0676
Corresponding p-value > 0.15

Figure 4. Histogram and probability distribution of traveling time of a 100-ton truck between intersection and loader 1 in Sungun mine generated by ARENA.

The length of each iteration of the simulation is considered to be seven working days, of which 990 minutes run per day. The half-width confidence interval of the system performance criteria is 15. In order to calculate the system warm-up time, the behavior of some system performance criteria has been studied, and the time it takes for them to reach a steady state has been considered as the system warm-up time. Figure 5 shows the average trend of fleet equipment efficiency in two different iterations. As it can be seen from this graph, in all repetitions, after a period of 14 hours, the productivity has reached a steady state. Therefore, the warm-up time of the system is considered to be 14 hours.

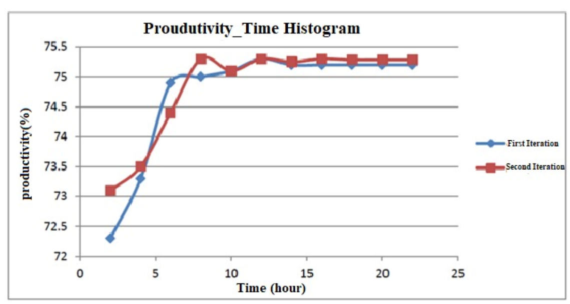


Figure 5. Average trend of fleet equipment efficiency in two different iterations.

In this research work, the following steps were taken to validate the model:

- More detailed review of the model by professional experts;

- Checking the model outputs for different inputs; and
- Preparing model animation to understand and correct the model shape errors.

As simulation is an estimate of the real world, it should be noted that it is not possible to validate 100% of the model with the real system. In the first step, the sensitivity analysis was used to check the apparent validity of the model. For this purpose, the number of entities (number of trucks) changed to examine its effect on the current situation and the efficiency of equipment. As a result, with increase in the number of trucks, the efficiency of equipment increased as expected. In the second stage, the hypotheses related to the model structure and model information were examined with the cooperation of the mining experts in an experimental and intuitive manner. In the last step, the results of the transportation system simulation model including the production and cost were compared with the actual fleet. It was found that the results did not differ significantly in the simulation mode and the mining fleet.

After running the model simulation for 7 days, 15 iterations, and 14 hours of system warm-up time, some results of the current mining allocation system (fixed allocation) and the flexible dispatching are given in Tables 4 and 5.

Table 3. Some examples of timing equations in Sungun mine.

Variable type	Type of distribution and its parameters (BETA (min))	Mean	Standard deviation
Loader L1 load time	2.6 + 0.59 * BETA(1.36, 1.47)	1.41	0.065
Moving time from loader L1 to the intersection	1.56 + 2 * BETA(2.78, 3.05)	2.91	0.036
Moving time from the intersection to crusher	4.58 + 4.5 * BETA(1.28, 1.52)	1.4	0.065
Return time from crusher to the intersection	2.56 + 3.58 * BETA(1.64, 1.16)	1.4	0.063
Return time from the intersection to loader L1	1.26 + 1.45 * BETA(2.76, 3.24)	3	0.035
Loader L2 load time	2.54 + 1.3 * BETA (1.46, 1.86)	1.66	0.057
Moving time from loader L2 to the intersection	3.58 + ERLA(0.614, 3.5)	2.05	0.024
Moving time from the intersection to crusher	4 + 4.96 * BETA(1.27, 1.45)	1.36	0.066
Return time from crusher to the intersection	2.3 + 3.66 * BETA(1.75, 1.13)	1.44	0.061
Return time from the intersection to loader L2	NORM(2.93, 0.293)	1.61	0.019
Loader L3 load time	3.72 + 0.68 * BETA(1.45, 1.4)	1.42	0.064
Moving time from loader L3 to the intersection	3.15 + ERLA(0.173, 4.5)	2.33	0.006
Travel time from the intersection to the dump	3 + 2.73 * BETA(0.734, 1.18)	0.95	0.081
Return time from tailings dump to the intersection	1.54 + 3.1 * BETA(2.56, 2.3)	2.43	0.050
Return time from the intersection to loader L3	2 + 2.89 * BETA(1.9, 2)	1.95	0.044
Loader L4 load time	0.89 + 1.3 * BETA(2.5, 2)	2.25	0.018
Moving time from loader L4 to the intersection	NORM(4, 0.53)	2.26	0.083
Travel time from the intersection to the dump	2.55 +2.87 * BETA(0.73, 1.13)	0.93	0.038
Return time from waste dump to the intersection	1.45 + 3.2 * BETA(2.6, 2.85)	2.72	0.056
Return time from the intersection to loader L4	2 + 2.23 * BETA(1.54, 1.84)	1.69	0.048
Unloading time in the crusher	1 + LOGN(2.12, 0.685)	1.4	0.070
Duration of unloading in the waste dump	UNIF(0.855, 1.45)	1.15	0.059
Loader L5 load time	3.54 + 1.53 * BETA(1.65, 1.54)	1.59	0.010
Moving time from loader L5 to the intersection	2.24 + GAMM(0.215, 3.78)	1.99	0.030
Travel time from the intersection to the dump	1.12 + WEIB(3.89, 3.27)	3.58	0.061
Return time from waste dump to the intersection	TRIA(1.45, 1.88, 2.54)	1.95	0.019
Return time from intersection to loader L5	1.14 + 1.41 * BETA(2.3, 2.95)	2.62	0.064
loader load time L6	2.74 + 0.54 * BETA(1.6, 1.69)	1.64	0.006
Moving time from loader L6 to the intersection	2.45 + LOGN(1.25, 0.694)	0.97	0.081
Moving time from the intersection to the oxide dump	1.18 + 1.81 * BETA(2.4, 3.33)	2.86	0.042
Return time from oxide dump to the intersection	UNIF(2.04, 4.5)	3.27	0.050
Return time from the intersection to loader L6	TRIA(2.98, 3.45, 4.92)	3.78	0.044
Dump time in oxide dump	0.869 + 0.832 * BETA(0.675, 1.13)	0.9	0.018

Table 4. Results of current mining allocation system (fixed allocation).

Loading station	Efficiency relative to scheduled time(%)	Minimum production (tons)	Maximum production (tons)	Average production (tons)	Half-length of 95% confidence interval (tons)	Average queue length (minutes)
L1	40	22995	23292	23130	39.8	1.47
L2	79	31662	31878	31770	37.14	1.97
L3	75	30123	30609	30339	64.54	1.77
L4	29	25155	35820	30337	1325	0.3
L5	57	77442	79080	78170	177	0.87
L6	59	83903	84540	84267	74.16	0.12
Entire system	56.5	271280	285219	278013	1717.64	1.08

Table 5. Results of flexible dispatching.

Loading station	Efficiency relative to scheduled time (%)	Minimum production (tons)	Maximum production (tons)	Average production (tons)	Half-length of 95% confidence interval (tons)	Average queue length (minutes)
L1	82.9	40923	45516	43223	765	0.37
L2	97.5	34747	39526	37118	796	1.21
L3	94.7	34221	39253	36663	696	2.37
L4	54.3	49708	54992	52153	931	0.21
L5	75.5	101113	108633	105028	1296	0.17
L6	48.8	62589	70057	66234	1197	0.87
Entire system	75.6	323301	357977	340419	5681	0.86

By examining the results related to the flexible dispatching of the current mining fleet in comparison with the results of the fixed allocation, we found that the average productivity compared to the planned time and weekly production increased by 25% and 18%, respectively. Also the average length of the queue was reduced by 20%.

4.2. Firefly algorithm

In order to optimize the loading and transport fleet for reducing the costs and increasing the production in the Sungun copper mine, the firefly algorithm was used. Due to the fact that there are no multiple objective functions that accommodate all parameters, a neural network was used to determine the objective function. In fact, the neural network is responsible for simulating the objective function, which is recalled by the m.file command in the firefly algorithm. In this work, the average geometric cost function (cost and production) was used for the optimization. Table 6 displays the control parameters of the firefly algorithm, which was obtained using trial-and-error.

Initially, the model simulation was run with a different number of trucks, and the results including the production level and system cost were obtained in different cases. In the first scenario, the optimal number of 35-ton and 100-ton trucks was determined using the firefly algorithm. The decision variables are the number of 35-ton and 100-ton trucks marked by x1 and x2 in Table 7

Table 6. Control parameters of firefly algorithm.

Parameters	Symbol	Amount
Maximum number of iterations	Max It	200
Number of fireflies (Scenario 1)	N pop	130
Number of fireflies (Scenario 2)	N pop	190
Light absorption coefficient	γ	1
Amount of attractiveness at zero distance	β_0	0.7
Convergence coefficient	α	0.2
Space width	δ	0.05
Absorption coefficient exponent	m	2

Table 7. Decision variables in Scenario 1.

Truck type	Decision variable	Minimum value	Maximum value
35-ton truck	x_1	1	40
100-ton truck	x_2	1	40

In the second scenario, two 60-ton and 144-ton trucks were added to the system. It should be noted that the 60-ton and 144-ton trucks are not currently available in the mine, and this scenario is only proposed to compare the results of using larger trucks. The decision variables in this scenario are the number of 35-ton, 60-ton, 100-ton, and 144-ton trucks, which are marked by *x1, x2, x3,* and *x4* in Table 8.

Table 8. Decision variables in Scenario 2.

Truck type	Decision variable	Minimum value	Maximum value
35- ton truck	x_1	1	30
60- ton truck	x_2	1	30
100- ton truck	x_3	1	20
144- ton truck	x_4	1	20

In both cases, the optimal number of trucks was determined aiming to maximize the production and minimize the costs. It should be noted that in both scenarios, the number of loaders was kept constant. Table 9 presents some results of simulating the first scenario and Table 10 presents the results of optimizing this scenario.

Table 9. Results of simulating first scenario.

Total operating costs (dollars)	Production (tons)	X1	X2
251986	404631	17	11
508921	615535	19	26
252645	410553	23	9
360768	545064	27	14
420624	593049	29	17
258988	423100	30	7
420670	593130	30	18
333289	520307	31	11
651580	619247	35	30
426377	600032	36	15
399828	587705	37	13
228526	362652	37	3
529591	618911	47	18

Table 10. Results of optimizing first scenario.

Total operating costs (dollars)	Production (ton)	X1	X2
251986	404631	17	11
252645	410553	23	9

Table 11 presents some results of simulating the second scenario and Table 12 presents the results of optimizing the second scenario.

With the increase in the number of 35-ton and 100-ton trucks, the production of mines will increase by 32%. Also, the difference between production and cost is greater than the current fleet, which indicates the reduction in the fleet costs compared to the current situation. It can be observed that with the addition of higher-capacity trucks to the transport fleet, the production will increase by 49%. Also the difference between production and cost is greater than the current fleet of mines.

Table 11. Results of simulating second scenario.

Total operating costs (dollars)	Production (tons)	X1	X2	X3	X4
190935	312182	30	2	2	2
294937	545361	10	2	2	15
265304	505639	6	2	3	14
632832	916329	5	2	2	12
838796	972781	5	7	2	16
754586	964716	5	4	6	21
484411	793748	5	2	2	16
658095	945361	5	3	3	16
579384	878507	4	2	7	20
365710	639749	4	2	4	11
884411	974394	3	2	10	23
383664	661077	3	2	4	15
672916	957999	3	2	3	31
514148	827687	3	3	9	12
330025	596974	3	2	3	17
733533	961490	3	3	4	20
335565	623838	2	2	4	15
208363	378345	2	3	2	2
602656	899023	2	5	2	19
698446	959877	2	4	2	21
540551	859877	2	8	3	19
923007	976006	2	5	7	23
967942	789674	2	11	2	20

Table 12. Results of optimizing second scenario.

Total operating costs (dollars)	Production (tons)	X1	X2	X3	X4
294937	545361	10	2	2	15

5. Conclusions

In this work, the simulation method was used to model the current transport fleet of the Sungun mine and the proposed scenarios. The optimal state of the fleet in terms of number, capacity, production, and cost was then determined using the firefly metaheuristic algorithm. The general findings of this work are presented as follow:

With the flexible allocation of the mining fleet compared to the current state, which is of the fixed allocation type, the production level and productivity increase by 20% and 25%, respectively, and the waiting time decreases by 20%. By applying a scenario involving seventeen 35-ton trucks and eleven 100-ton trucks, the production will increase to 404,631 tons per week at the cost of $251,986. The difference in production and cost in this case is 11% higher than the current mining fleet. A scenario involving ten 35-ton trucks, two 60-ton trucks, two 100-ton trucks, and fifteen 144-ton trucks can increase the production to 545,361 tons per week at the cost of $294,937. The difference in production and cost in this case is 21% higher than the current mining fleet.

It is suggested for the future research work that the number of decision variables and goals in the objective function include more items. It is also possible to include manpower in the model simulation and to evaluate the impacts on the production and cost of the mining fleet.

Conflict of Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Appendix 1. Firefly algorithm pseudo-code

(1)	*Objective function f(x), x=(x1 ,….., xd)T*
(2)	*Initialize a population of fireflies x_i (i , , ….,n)*
(3)	*Define light absorption coefficient*
(4)	*While (t <Maxgeneration):*
(5)	*For i=1 : n all n fireflies:*
(6)	*For j=1 : n all n fireflies:*
(7)	*Light intensity I_i at x_i is determined by $f(x_i)$*
(8)	*If (Ij > Ii):*
(9)	*Move firefly i toward j in all d dimensions*
(10)	*End-if*
(11)	*Finding distance*
(12)	*Evaluate new solutions and update light intensity*
(13)	*End-for j*
(14)	*End-for i*
(15)	*Rank the fireflies and find the current best*
(16)	*End-while*
(17)	*Postprocess results and visualization*

طراحی ناوگان بارگیری و باربری معادن روباز با استفاده از رویکرد شبیه سازی و الگوریتم‌های فرا ابتکاری

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ارسال ۲۰۲۱/۱۱/۰۴، پذیرش ۲۰۲۱/۱۲/۱۴

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چکیده:

چرخه تولید در معادن روباز شامل حفاری، انفجار، بارگیری و باربری است. از آنجایی که بارگیری و باربری بخش بزرگی از هزینه‌های معدن را تشکیل می‌دهد، بهینه سازی آن از نظر اقتصادی بسیار مهم است. شبیه سازی یکی از پرکاربردترین روش‌ها در زمینه طراحی ناوگان است. با این حال شبیه سازی نمی‌تواند یک سناریوی بهینه را پیشنهاد کند که برای آن از روش فراابتکاری مناسب استفاده شود. این مقاله معدن مس سونگون را به عنوان مطالعه موردی در نظر گرفته و سعی در یافتن امکان پذیرترین سیستم حمل و نقل را دارد. در این پژوهش در مرحله اول به مقایسه تخصیص انعطاف پذیر با روش‌های تخصیص ثابت با استفاده از نرم افزار ARENA می‌پردازیم. بر این اساس، استفاده از تخصیص انعطاف پذیر افزایش نرخ تولید (۲۰ درصد) و بهره وری (۲۵ درصد) و کاهش (۲۰ درصد) در زمان بیکاری را نشان می‌دهد. الگوریتم فراابتکاری کرم شب تاب استفاده شده در مرحله دوم نشان می‌دهد که سناریوی ترکیبی کامیون‌های ۳۵ تنی و ۱۰۰ تنی از نظر بهره وری و هزینه مناسب‌ترین گزینه است. در تلاشی دیگر، با مقایسه ناوگان کامیون‌های ناهمگن مختلف، دریافتیم که سناریوهای ۳۵-۱۰۰ و ۳۵-۶۰-۱۰۰-۱۴۴ نرخ تولید را به ترتیب ۳۹ و ۴۹ درصد افزایش می‌دهند. همچنین در هر دو سناریو هزینه تولید به ترتیب ۱۱ و ۲۱ درصد کاهش می‌یابد.

کلمات کلیدی: بهینه سازی ، معادن روباز، بارگیری و باربری، شبیه سازی، الگوریتم کرم شب تاب.