Journal of Mining and Environment (JME) Vol. 18, No. 4, 2026, 1445-1455

Shahrood University of Technology

Journal of Mining and Environment (JME)

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

Iranian Society of Mining Engineering (IRSME)

Development of a Match Factor for Optimizing Haulage Fleet Efficiency in Open-Pit Mining Operations

Mehrnaz Mohtasham*

Department of Mining Engineering, Faculty of Technology and Engineering, University of Mohaghegh Ardabili, Ardabil, Iran

Article Info

Received 4 June 2025

Received in Revised form 25 June 2025

Accepted 9 September 2025

Published online 9 September 2025

DOI: 10.22044/jme.2025.16360.3188

Keywords

Haulage system

Equipment selection

Developed match factor

Fleet efficiency improvement

Open-pit mining

Abstract

In open-pit mining, haulage equipment accounts for a significant portion of total operating costs. Optimizing fleet performance is therefore crucial for reducing costs and improving productivity. Within this system, loading equipment plays a key role, as truck efficiency depends heavily on loader performance. The match factor, a metric that evaluates compatibility between loaders and trucks, is commonly used to enhance fleet efficiency. However, many existing approaches fail to account for practical mining conditions such as equipment downtime, accurate truck cycle times, and material fragmentation resulting from blasting. These omissions can lead to inaccurate fleet performance evaluations and higher operational costs. This study proposes an improved match factor method that incorporates these critical variables. It includes equipment downtime, truck cycle time estimates based on travel routes, and material fragmentation. The model applies to both homogeneous and heterogeneous fleet configurations and integrates the operational efficiency coefficient of each machine to reflect real conditions more accurately. The model was tested using data from the Sungun copper mine. The match factor values were calculated both with and without accounting for equipment downtime, and loader capacities were adjusted according to the size distribution of blasted material. Results showed that in heterogeneous fleet operations, the match factor increased from 0.74 to 0.85 when operational efficiency was included. Subsystem analyses also revealed match factor values below 1, indicating a need for additional trucks. Overall, the enhanced model enables more efficient equipment use, reduces loader idle time, and contributes to substantial operating-cost savings.

1. Introduction

In open-pit mining, material transportation is one of the most crucial and complex components of the process of mineral extraction, having direct implications on the productivity, cost, and time of operation. Optimizing the use of loading and hauling equipment is a vital component in achieving this objective. Fleet productivity improvement is impacted by a wide range of factors that include equipment selection, allocation and dispatching of the fleet, drilling and blasting outcomes, facility layout, and numerous other variables. Given the typically large scale of open-pit operations, the selection of an appropriate system of transportation and its optimization are of extreme importance in enhancing the efficiency of haulage equipment. Equipment selection plays a pivotal role in both the mining and construction industries. Despite their distinct operational requirements, both sectors typically employ a similar methodological framework for choosing machinery. In mining, this process centers on selecting a fleet of haulers and loaders that can meet material-transport demands at the lowest possible cost, thereby maximizing operational efficiency and profitability. On the other hand, the construction industry focuses more on the end date of the project, with recognition that project initiation early can influence operating expenses just as significantly as delays. Moreover, mining operations typically involve transporting

Corresponding author: m_mohtasham@uma.ac.ir (M. Mohtasham)

substantially larger material volumes over much longer time horizons. From this perspective, the equipment age, residual value, and fleet heterogeneity are more relevant factors in equipment selection models applied to the mining industry. Considering the inherent complexities in the transportation of material in mining operations, the selection of the best fleet of equipment not only aids in lowering the cost but also significantly contributes to overall mine performance and system productivity. Herein, a number of factors such as mineral nature, geographical and climatic conditions, operating and maintenance costs, and downtime of equipment play a critical role. Equipment selection involves obtaining an appropriate combination of loaders and trucks based on various objectives and constraints. Generally, the equipment selection and sizing problem in mine planning is usually divided into two sets of subproblems: the loader-related subproblem, including loader type and fleet size determination, and the truck-related subproblem, including truck type selection and fleet size determination (Figure 1) [1]. The assumptions and the nature of constraints applied in the models are very different. Consequently, a wide range of methods with varying degrees of success have been proposed to solve this problem. Several methods are applied for the equipment selection problem in open pit mines. These solution methods vary in complexity as well as performance. In general, these methods can be classified into five categories: life cycle costing, match factor, operations research, artificial intelligence, and simulation methods. One of the most important tools for managing and choosing transportation fleets is the life cycle costing method. This method thoroughly examines every expense related to the fleet, from purchase to disposal. The main goal of this analysis is to economically distinguish between two or more alternative options so that the best investment option can be chosen [2, 3]. Numerous studies have proposed the use of operations research techniques, including goal programming, integer programming, and linear programming, to determine the optimal fleet size in the transportation of mining operations. Operations research methods, in contrast to other approaches, are employed for optimal solutions and have the capability of guaranteeing optimality. Artificial intelligence techniques, such as fuzzy set theory, expert systems, multi-criteria decision-making, and genetic algorithms, have been implemented to assist in making decisions about how many trucks and shovels are needed for open-pit mining operations. The majority of studies have focused on discrete-event simulation due to its ability to account for the stochastic nature of the transportation fleet while simultaneously incorporating constraints related to the quality and quantity of mined materials, as dictated by short-term production planning. The description of the methods for equipment selection, along with their advantages and disadvantages, is summarized in Table 1. The first study to address the match factor was undertaken by Douglas in 1964, who introduced the concept of truck–shovel productivity [4]. Four years later, Morgan and Patterson (1968) reformulated this idea in terms of truck–shovel cycle time, coining the term “match factor” [5]. A significant drawback of their work was the assumption of a homogeneous fleet. To account for the diversity of truck and shovel types used in mining transport, Burt (2008) extended the match factor formulation to cover both homogeneous and heterogeneous fleets [6]. Dabbagh and Baqerpour (2019) proposed a new definition of the match factor by refining and modifying the existing relationships [7]. Other researchers have applied the match factor concept to determine the optimal truck–shovel fleet composition in open-pit mining operations (see Table 1). Generally, fleet selection using this method is calculated by considering the productivity of hauling and loading equipment to ensure that equipment efficiency is optimized. The haulage fleet must be selected so that the intended mine rate of production is achieved without idle time for loaders and haulers during production. However, there are three major shortcomings of the studies developed on the basis of the match factor concept: (1) failure to account for equipment downtime, (2) improper estimation of truck cycle time, and (3) failure to consider material fragmentation when estimating the loading capacity of loading equipment. These limitations can lead to second-best solutions and limit the applicability of the method under real mining conditions. This study, thus, aims to address the limitations in match factor calculation for various fleet compositions to enhance haulage operations in open-pit mining.

The rest of the paper is arranged as follows: Section 2 explains the proposed method in detail; Section 3 defines the case study; Section 4 presents the implementation of the proposed method in the case study and compares the results; and finally, Section 5 provides concluding remarks.

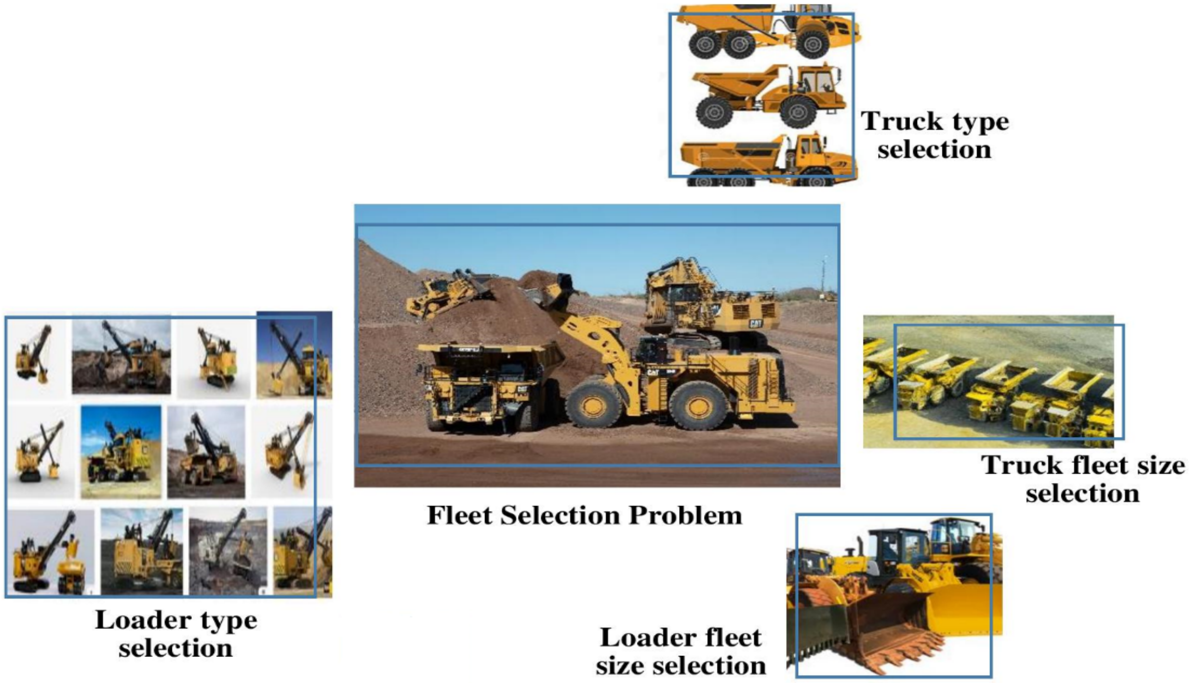

Figure 1. Equipment selection and sizing problem in open-pit mining

Table 1. Approaches for solving the haulage fleet selection problem in the mining industry

Approach	Description	Advantages	Disadvantages	Related Researches
Life Cycle Costing (LCC)	Calculates the total cost of equipment ownership over its entire lifespan, including purchase price, operational expenses, maintenance costs, and disposal fees.	• Comprehensive cost evaluation • Considers long-term economic performance	• Requires accurate cost data • May overlook operational compatibility factors	[8], [9]
Match Factor (MF)	Evaluates compatibility between loaders and trucks based on loading capacity and cycle times.	• Easy to use • Useful for initial planning stages • Commonly adopted in industry	• Often ignores real operational variables (downtime, fragmentation, route variability)	[10], [4], [5], [11], [6], [7], [12], [13]
Operations Research (OR)	Uses optimization techniques such as linear programming, integer programming, and goal programming to determine optimal fleet composition.	• Produces mathematically optimal solutions • Can handle multiple objectives	• Complex modeling • Requires accurate data • May not capture dynamic mine conditions	[10], [14], [15], [16], [17], [18], [19], [20], [21]
Artificial Intelligence (AI)	Applies machine learning, expert systems, and fuzzy logic for decision-making based on large data sets and uncertain information.	• Handles uncertainty and complex variables • Adapts to new data • Can improve over time	• Requires large historical data • High computational demands • Black-box solutions may lack transparency	[22], [23], [24], [25]
Simulation	Uses discrete-event or continuous simulation models to replicate fleet operations and test different scenarios.	• Captures system dynamics • Allows scenario testing • Accounts for variability in operations	• Time-consuming model development • Requires detailed data • High computational requirements	[26], [27], [28], [29], [30], [31]

2. Extended Match Factor for Various Fleet Combinations

The match factor in the mining industry is a critical performance indicator with two principal applications. At the equipment selection stage, it can be utilized to compute the ideal fleet size in such a way that the productivity of the truck fleet equals that of the loader fleet. Once the fleet has been selected, the match factor subsequently becomes a measure to assess the relative efficiency of the fleet. The match factor is technically defined as the truck arrival rate divided by the loader service rate. A match factor of one signifies trucks never have to wait for loaders and loaders never have to wait for trucks, resulting in 100% productivity for both fleets. A match factor of less than one indicates that trucks never wait, but loaders are idle while waiting for trucks (i.e., truck productivity is 100%, but loader productivity is less than 100%). Conversely, a match factor of greater than one indicates that trucks wait in line to be loaded, but loaders are always busy (i.e., loader productivity is 100%, but truck productivity is less than 100%). The calculation of the match factor relies on the fleet configuration and can be divided into four cases: (1) homogeneous fleet, (2) homogeneous truck fleet, (3) homogeneous loader fleet, and (4) heterogeneous fleet. Formulations for all of these cases have been shown in previous research studies, but in most cases, the models do not have the capability to portray the actual efficiency and performance of fleets in real-world operating environments. Specifically, such models typically assume 100% equipment availability and optimal truck arrival synchronization, where all trucks arrive just as the preceding truck leaves with loaded material. In actual open-pit mining practice, however, such situations are rarely attainable due to many unexpected factors. Even when there are enough trucks to carry all the material loaded by the current loaders in a shift, loaders and trucks still experience downtime for numerous reasons. These reasons prevent mining operations from achieving maximum equipment performance and efficiency. Throughout the production cycle, part of the fleet is constantly out of action due to breakdowns, adverse weather, truck traffic in road intersections, speed reduction due to overtaking restrictions, road unevenness, inefficient rock breakage through drilling and blasting (leading to long loading cycles), equipment wear and tear, and operating skills affecting truck speed, among others. Neglecting such factors leads to match factor estimates that are far from actual and optimal values, creating practical problems. In addition, ignoring such factors contributes to low levels of operational efficiency and causes significant financial burdens on the system. In order to improve the applicability and accuracy of these models to actual mining operations, this study develops an expanded version of the match factor. This expanded model incorporates an operating performance coefficient for the hauling and loading system across the four different fleet configurations. Moreover, the proposed match factor model is developed based on several simplifying assumptions in mining operations. It is assumed that equipment downtimes can be accurately represented by average historical downtime values and that random, unexpected breakdowns are rare or negligible during the analyzed period. The model takes static dispatching of haul trucks, without incorporating dynamic allocation strategies that may respond to real-time fluctuations in equipment availability or operational conditions. It also assumes that haul routes remain constant throughout the operation, with minimal variability in travel path conditions such as road congestion, temporary obstructions, or detours. It does not deal directly with the impact of adverse weather conditions, such as heavy rain, snow, or extreme temperatures, on equipment performance, road conditions, and cycle times. In addition, it is assumed that the fragmentation effects derived from blasting are well represented in the adjusted loader capacities and that these changes remain consistent throughout the operational cycles.

In summary, this study contributes to the field of open-pit mining haulage optimization by developing an enhanced match factor model that incorporates critical operational variables often overlooked in the literature, such as equipment downtime, route-based truck cycle times, and material fragmentation effects. Unlike traditional models, the proposed approach provides a more realistic and practical assessment of fleet efficiency, enabling better allocation of trucks and loaders. The method's applicability to both homogeneous and heterogeneous fleets further extends its versatility.

2.1. List of Symbols

The notation used in the match factor equations for various fleet configurations is presented in Table 2. Notation is introduced to shorten expressions and to represent more easily the significant variables and parameters involved.

2.2. Homogeneous Fleet Case

In a loading and haulage system, truck and loader fleet performance must be as balanced as possible to achieve maximum system efficiency. Loaders are the key equipment and the central point in the haulage system, and trucks and other machines depend on their operation for performance. The loading equipment's efficiency directly affects the system's overall productivity. Thus, the primary purpose of loaders is to ensure high performance in the haulage system, and the primary function of trucks is to support and attain this performance. By comparing theoretical (possible) truck fleet output and actual loader fleet output, the system overall can be brought into balance by determining the optimal number of trucks required to support loader production. In the event that both fleets are uniform pieces of equipment (i.e., identical equipment), the methodology to calculate the actual loader fleet per shift output is as follows in Equation (1). To calculate loader productivity in actual operating conditions, an operational performance coefficient for loading and haulage is employed, as used in Equation (2). It reflects effective usage of the fleet by including all downtime and the availability of the equipment, except for truck waiting time, because that is also included in truck cycle time.

The equation for calculating the theoretical performance of the truck fleet per shift is given in Equation (3). The extended match factor is calculated as the ratio of the actual performance of the loader fleet to the theoretical performance of the truck fleet, and it is provided in Equation (6). For the sake of simplicity, the intermediate relationships are presented in Equations (4) and (5).

Table 2. Symbols used in the presented mathematical formulations

Parameter	Definition	Parameter	Definition
P_{shovel}	Loader production capacity (cubic meters per shift)	t_{si}	Average loading time of each truck i at loading location s (hours)
P_{truck}	Truck production capacity (cubic meters per shift)	d_{sdi}	Travel distance of truck i from loading location s to unloading location d (meters)
c_s	Loader bucket capacity (cubic meters)	v_{sdi}	Average speed of truck i from loading location s to unloading location d (meters per hour)
c_t	Tuck capacity (cubic meters)	t_{di}	Average unloading time of truck i at unloading location d (hours)
t_s	Average time of a loader cycle to fill a truck (hours)	t_{wdi}	Average waiting time of truck i at unloading location d (hours)
N_s	Total number of loaders	t_{mdi}	Average maneuvering time of truck i to unload materials at unloading location d (hours)
T_{shift}	Work shift time (hours)	d_{dsi}	Travel distance of truck i from unloading location d to loading location s (meters)
λ_{LTF}	Operational performance coefficient of the loading and unloading system	v_{dsi}	Average speed of truck i from unloading point d to loading point s (m/h)
Dt_j	Total stopping times of each loader j (hours)	n_s	Number of buckets required to fill the truck
Dt_i	Total stopping times of each hauler i (hours)	t_{st}	Total time for loading the truck by the loader (hours)
N_t	Total number of loaders	TAR	Truck arrival rate
$\overline{t_t}$	Average time of a truck cycle (hours)	LRS	Loader service rate
t_h	Average time of a truck cycle of type h (hours)	MF	Match factor
n_h	Number of trucks of type h	DMF	Extended match factor
t_i	Average time of a truck cycle of each truck i (hours)	N_l	Number of type l loaders
t_{wsi}	Average waiting time of each truck i at loading location s (hours)	t_l	Average time for loading a truck by type l loader (hours)
t_{msi}	Average maneuvering time of each truck i to load materials at loading location s (hours	t_{lh}	Average time for loading a truck of type h by type l loader (hours)

$$P_{shovels} = \frac{c_s}{t_s} \times N_s \times T_{shift} \times \lambda_{LTF} \tag{1}$$

$$\lambda_{STF} = 1 - \frac{\sum_{j=1}^{N_s} Dt_j + \sum_{i=1}^{N_t} Dt_i}{T_{shift}(N_s + N_t)} \tag{2}$$

$$P_{trucks} = \frac{c_t}{\overline{t_t}} \times N_t \times T_{shift} \tag{3}$$

$$\frac{c_t}{c_s} = n_s \tag{4}$$

$$n_s \times t_s = t_{st} \tag{5}$$

$$DMF = \frac{P_{trucks}}{P_{shovels}} = \frac{c_t \times t_s \times N_t}{c_s \times \overline{t_t} \times N_s \times \lambda_{LTF}} = \frac{N_t \times t_{st}}{N_s \times \overline{t_t} \times \lambda_{LTF}} \tag{6}$$

2.3. Heterogeneous Truck Fleet Case

In cases where there are multiple types of trucks functioning with a single type of loader to perform the haulage operations in a mine, the extended match factor is calculated from Equation (10). Here, the rate of truck arrivals is given by Equation (7), referring to the frequency of trucks arriving at the loading unit per unit time. Additionally, the loader service rate is provided by Equations (8) and (9). The operational performance coefficient of the haulage and loading system is taken as given above in Equation (2).

$$TAR = \frac{N_t}{\overline{t_t}} \tag{7}$$

$$LRS = \frac{N_s}{t_{st}} \times N_t \times \lambda_{LTF} \tag{8}$$

$$t_{st} = \sum_{h=1} t_h \times N_h \tag{9}$$

$$DMF = \frac{t_{st}}{N_s \times \overline{t_t} \times \lambda_{LTF}} \tag{10}$$

2.4. Heterogeneous Loader Fleet Case

In this case, various loaders and a single category of truck are assumed. The time taken to load a truck may vary depending on the loader type. Service rate for loaders specifies how many trucks are loaded in a particular period of time. For a heterogeneous fleet of loaders, the time to service a truck could vary by loader category. The extended match factor for this setup is given in Equation (12), which follows from the intermediate relations in Equations (11) and (7). During the calculation of the extended match factor, the operational performance coefficient of the hauling and loading system is used as given in Equation (2).

$$LSR = \sum_{l=1} \frac{N_l}{t_l \times N_t} \times N_t \times \lambda_{LTF} \tag{11}$$

$$DMF = \frac{1}{\overline{t_t} \times \sum_{l=1} \frac{N_l}{t_l \times N_t} \times \lambda_{LTF}} \tag{12}$$

2.5. Heterogeneous Truck and Loader Fleet Case

In the case of a heterogeneous fleet of trucks and loaders in mining operations, the service time of each loader can vary based on the type of truck being loaded. For this case, the loader service rate and truck arrival rate are provided by Equations (13) and (7), respectively. Based on these formulations, the extended match factor is provided by Equation (14). As in the preceding examples, the operational performance coefficient of the loading and hauling system is incorporated as developed in Equation (2).

$$LSR = \sum_{h=1} \sum_{l=1} \frac{N_l}{t_{lh} \times N_h} \times N_t \times \lambda_{LTF} \tag{13}$$

$$DMF = \frac{1}{\overline{t_t} \times \sum_{h=1} \sum_{l=1} \frac{N_l}{t_{lh} \times N_h} \times \lambda_{LTF}} \tag{14}$$

2.6. Calculation of the Average Truck Cycle Time

In any material haulage system, trucks operate on multiple incoming and outgoing paths for material delivery. This produces varying cycle times for a specific truck. If a fixed cycle time is supposed for every vehicle type in any of the arrangements mentioned above, the ensuing match factor will no longer be optimal or realistic. This is due to the possibility that different types of trucks will have varying cycle times based on the haul route. To offset this, the cycle time for each truck is calculated individually using Equation (17) and added to all the aforementioned formulations. As indicated earlier, waiting times of trucks are also included in calculating the cycle time. Subsequently, the average truck cycle time for each type may be obtained from Equations (15) or (16). Most notably, in Equation (15), the mean cycle time for each truck category is derived from the mean of individual truck cycle times in that particular category.

$$\overline{t_t} = \frac{\sum_{h=1} (t_h \times n_h)}{N_t} \tag{15}$$

$$\overline{t_t} = \frac{\sum_{i=1}^{N_t} t_i}{N_t} \tag{16}$$

$$t_i = t_{wsi} + t_{msi} + t_{si} + \frac{d_{sdi}}{v_{sdi}} + t_{wdi} + t_{mdi} + t_{di} + \frac{d_{dsi}}{v_{dsi}} \tag{17}$$

3. Case Study

To compare the performance of the haulage system using the proposed extended method and to allow for comparison with the conventional match factor method, the Sungun copper mine was selected as a case study. The Sungun copper mine is located approximately 130 kilometers north of Tabriz and about 30 kilometers from Varzeghan County. As of late 2024, the Sungun copper mine hosts proven reserves of approximately 1.15 billion tons, within a broader total of 2.49 billion tons of copper-bearing ore, grading at an average of 0.53% Cu. The on-site concentration plant currently produces around 170,000 tons of copper concentrate annually, with expansion plans to increase this output to 300,000 tons per year.

Since the haulage operation in this mine is conducted by different contractors separately, the present study takes into account the data from the haulage operation of a single contractor. The fleet used for the transport of materials in the operational shift under consideration is heterogeneous in nature. There are five working faces and three dump points (crusher, waste dump, and low-grade ore dump) in the selected operational shift. The detailed operating requirements for this shift are presented in Table 3. Note that, due to the limited availability of detailed downtime data for the fleet, only average downtime due to mechanical failure has been considered in the analysis. Additionally, loader capacities were determined based on the fragmentation size produced by the drilling and blasting operations at each working face.

Table 3. Haulage system specifications for a single shift conducted by one contractor at the Sungun copper mine (L: Loader, H: Haul Truck)

Working Face ID	Equipment Type			Loading Level and Travel Path		Average Loading and Haulage Time (seconds)	Average Failures (seconds)
	Loading	Hauling	Number				
1	Hyundai500	Komatsu HD325	L: 1	2083.5		229.2	2641.3
			H: 3		Waste Dump (1200 m)	879.6	4944.3
2	CAT988	Komatsu HD325	L: 1	2037.5		198	2056.2
			H: 3		Crusher (1000 m)	855	4560
3	Hyundai500	Komatsu HD325	L: 1	2087.5 S		225.6	2245
			H: 3		Low-Grade Dump (2200 m)	1230	10868.4
4	Komatsu PC800	Komatsu HD785	L: 1	2025 S		321.6	2359.5
			H: 3		Waste Dump (1975 m)	1198.2	6720.4
5	Komatsu WA600	Komatsu HD785	L: 1	2100 S		310.2	2680.4
			H: 2		Crusher (2700 m)	1211.4	5640

4. Discussion

4.1. Considering Operations within an Integrated Mining System

In this case, operations are assumed to be executed as a merged system with a heterogeneous fleet. There are two kinds of trucks and four kinds of loaders in the mining system. The match factor, calculated without regard to the fleet's downtime, was found to be 0.74. However, when introducing the operational performance coefficient ($\lambda_{STF} = 0.88$), the match factor through Equation (16) was estimated at 0.85. In either situation, the match factor is less than one, indicating that in achieving the best fleet balance, the trucks need to be increased in quantity to offset loader idle hours. Using the determined match factor, the ideal number of trucks required can be calculated. The difference among these numbers greatly impacts the calculation of the ideal truck fleet size and, consequently, the mining cost. It can be understood that, unless fleet availability times are taken into account in the formulations, a match factor that does not reflect optimal conditions would result. Any such assessment of fleet performance on such assumptions would lead to significant operational losses. In the case study under discussion, the new approach offers an optimized number of trucks required, thereby yielding efficient fleet productivity at a lower cost.

4.2. Considering Operations within Each Mining Subsystem

In this section, haulage operations are discussed at the subsystem level, with a single subsystem consisting of one loader unit together with a specified number of haul trucks. Subsystem 1 comprises a Hyundai 500 loader and three 35-ton trucks as an example. For every subsystem, the trucks' and loader's average cycle times are determined from field data to facilitate a more detailed analysis of fleet performance. The values of the match factor for each subsystem under two scenarios are presented in Table 4: (i) the traditional match factor (MF), which does not take equipment downtimes into account, and (ii) the proposed match factor (DMF), which incorporates operational downtimes in its calculation. In all subsystems, for both instances, the match factor values are less than one, indicating fewer than optimal trucks per loader and suggesting that additional trucks would better balance hauling and loading activities. Notably, the inclusion of downtime factors in the DMF provides a more accurate approximation of equipment utilization and operational efficiency. In certain subsystems, the DMF is higher than the MF, indicating that, based on the actual utilization of the equipment, fewer additional trucks may be needed to achieve an optimal match. This adjustment leads to a more effective allocation of resources, reduced loader idling time, and can ultimately result in greater overall productivity and lower operating costs than decision-making processes based on the traditional match factor.

Table 4. Match factor calculation in two scenarios for each mining subsystem in Sungun copper mine

Subsystem	Average Truck Cycle Time (seconds)	Average Loading Cycle Time (seconds)	MF	DMF
1	879.5	30	0.87	0.84
2	855.5	45	0.69	0.74
3	1230	30	0.55	0.63
4	1198	25	0.81	0.88
5	1211.4	50	0.51	0.57

5. Conclusions

The haulage system is an essential component of any mining operation. Equipment used in the haulage system accounts for a significant portion of the total mining cost. Therefore, it is essential to ensure that the truck-loader fleet operates efficiently. Loaders are the central machinery of the haulage system, holding a central position, in that the operation of trucks and other machines or activities is dependent on the proper operation of the loaders. Conversely, the task of the trucks is to achieve the highest level of efficiency for the loaders. Hence, a balance between the hauling and loading equipment performance is required. The loading and hauling system efficiency and its match are quantified by the ratio of the truck arrival rate for loading to the loader service rate. This ratio is referred to as the match factor. Equipment availability was not considered in the match factor in earlier methodologies, and therefore, inaccurate and suboptimal estimates of equipment performance are obtained, resulting in increased mining costs. To address this issue, this study proposes an expanded match factor that incorporates haulage equipment stopping time (i.e., times when equipment is not utilized for production) under different fleets (homogeneous and heterogeneous). The equipment stopping time is accounted for through the incorporation of an operating performance coefficient for the loading and hauling machines in loader productivity analysis. Generally, this study advances the optimization of haulage operations in open-pit mining by introducing an improved match factor model that accounts for key operational factors often overlooked in previous studies, including equipment downtime, truck cycle times based on travel routes, and the impact of material fragmentation. To analyze and compare the proposed approach under real mining conditions, the Sungun copper mine was used as the case study. The match factor was calculated both with and without the consideration of equipment downtimes, for two scenarios: an integrated haulage system and individual subsystem analysis. Additionally, loader capacities were determined based on the fragmentation characteristics of blasted rocks. The results indicate that in combined operations with a mixed fleet, the match factor was 0.74 when equipment stopping time was not considered, increasing to 0.85 upon incorporating the operational performance coefficient. This suggests that additional trucks are necessary to compensate for fleet inefficiencies and to reduce loader idle time. Furthermore, subsystem-level analysis demonstrated that the match factor for each subsystem remained below 1 in both scenarios, scenario 1 with and scenario 2 without consideration of the operational performance coefficient, highlighting the need for extra trucks to optimize overall productivity. Notably, a comparison between the two scenarios revealed a higher match factor when the operational performance coefficient was accounted for (scenario 2) compared to when it was not (scenario 1). In conclusion, through the integration of actual operating conditions, the results demonstrate that the proposed extended match factor, applied to both the integrated mining system and its subsystems, enables improved estimation of fleet needs and can achieve effective loading and hauling operations employing fewer trucks, hence reducing operating costs.

While the developed match factor model offers a more comprehensive framework for evaluating haulage fleet efficiency by incorporating equipment downtimes, cycle time estimations, and material fragmentation, several limitations remain. The model relies on average downtime values, which may not fully capture unexpected equipment failures or abrupt operational disruptions. Additionally, the absence of a dynamic dispatching mechanism limits the model's ability to adapt to real-time fluctuations in equipment availability and haulage demands. The estimation of truck cycle times is based on predefined travel routes and assumes relatively stable haul road conditions, without accounting for temporary changes in route accessibility, traffic congestion, or other short-term operational variations. Furthermore, the potential impacts of extreme weather conditions, such as heavy precipitation, fog, or temperature extremes, on equipment performance, road conditions, and operational delays have not been explicitly integrated into the model. These factors suggest avenues for future refinement and emphasize the importance of context-specific validation when applying the model in diverse operational environments. In addition, integrating the proposed model with advanced optimization approaches such as discrete-event simulation, AI-driven dispatching, or hybrid algorithms could further enhance its adaptability and accuracy in the dynamic and complex mining environment.

References

[1]. Moradi Afrapoli, A., Tabesh, M., & Askari-Nasab, H. (2019). A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. *Mining Technology,* 128(1), 9-20.

[2]. Dhillon, B. S. (2009). Life cycle costing for engineers. *Crc Press*.

[3]. Fabrycky, W. J., & Blanchard, B. S. (1991). Life-cycle cost and economic analysis (Vol. 135383234). *Englewood Cliffs, NJ: Prentice Hall*.

[4]. Douglas, J. (1964). Prediction Shovel-Truck Production: A Reconciliation Of Computer And Conventional Estimates.

[5]. Morgan, W. C., & Peterson, L. (1968). Determining shovel-truck productivity. *Mining Engineering*, 20(12), 76-80.

[6]. Burt, C. N. (2008). An optimisation approach to materials handling in surface mines. *Curtin University*.

[7]. Dabbagh, A., & Bagherpour, R. (2019). Development of a match factor and comparison of its applicability with ant-colony algorithm in a heterogeneous transportation fleet in an open-pit mine. *Journal of Mining Science*, 55(1), 45-56.

[8]. Samanta, B., Sarkar, B., & Mukherjee, S. K. (2002). Selection of opencast mining equipment by a multi-criteria decision-making process. *Mining Technology*, 111(2), 136-142.

[9]. Markeset, T., & Kumar, U. (2018). Application of LCC techniques in selection of mining equipment and technology. *In Mine Planning and Equipment Selection* 2000 (pp. 635-640). Routledge.

[10]. Michiotis, A., Xerocostas, D., & Galitis, N. (1998). A new integrated system for selecting mining equipment. *Computers & industrial engineering,* 34(2), 391-397.

[11]. A. Krause, A., & Musingwini, C. (2007). Modelling open pit shovel-truck systems using the Machine Repair Model. *Journal of the Southern African Institute of Mining and Metallurgy*, 107(8), 469-476.

[12]. Burt, C., Caccetta, L., Welgama, P., & Fouché, L. (2011). Equipment selection with heterogeneous fleets for multiple-period schedules. *Journal of the Operational Research Society*, 62(8), 1498-1509.

[13]. Pasch, O., & Uludag, S. (2018). Optimization of the load-and-haul operation at an opencast colliery. *Journal of the Southern African Institute of Mining and Metallurgy,* 118(5), 449-456.

[14]. Edwards, D. J., Malekzadeh, H., & Yisa, S. B. (2001). A linear programming decision tool for selecting the optimum excavator. *Structural Survey*, 19(2), 113-120.

[15]. Fu, Z., Topal, E., & Erten, O. (2014). Optimisation of a mixed truck fleet schedule through a mathematical model considering a new truck-purchase option. *Mining Technology*, 123(1), 30-35.

[16]. Ercelebi, S. G., & Bascetin, A. (2009). Optimization of shovel-truck system for surface mining. *Journal of the Southern African Institute of Mining and Metallurgy*, 109(7), 433-439.

[17]. Mohtasham, M., Mirzaei-Nasirabad, H., Askari-Nasab, H., & Alizadeh, B. (2021). Truck fleet size selection in open-pit mines based on the match factor using a MINLP model. *Mining Technology*, 130(3), 159-175.

[18]. Rakhmangulov, A., Burmistrov, K., & Osintsev, N. (2024). Multi-criteria system's design methodology for selecting open pits dump trucks. *Sustainability*, 16(2), 863.

[19]. Navidi, S., Motamedi, M., Aghsami, A., & Jolai, F. (2023). AG/M/C//M queueing model for revenue management of shovel-truck systems in an open-pit mine considering carbon emission, a case study. *International Journal of Management Science and Engineering Management,* 18(2), 88-103.

[20]. Xu, H., Liu, F., Liao, J., & Liu, T. (2023). Research on selection and matching of truck-shovel in oversized open-pit mines. *Applied Sciences*, 13(6), 3851.

[21]. Alshibani, A., Elmaghraby, B., Bubshait, A., Ghaithan, A. M., Mohammed, A., & Hassanain, M. A. (2024). Advancing sustainability: An integrated decision support framework for fleet selection in open pit mining construction. *Results in Engineering*, 23, 102501.

[22]. Bazzazi, A. A., Osanloo, M., & Karimi, B. (2011). Deriving preference order of open pit mines equipment through MADM methods: Application of modified VIKOR method. *Expert Systems with Applications,* 38(3), 2550-2556.

[23]. Mirhosseyni, S. H. L., & Webb, P. (2009). A hybrid fuzzy knowledge-based expert system and genetic algorithm for efficient selection and assignment of

material handling equipment. *Expert Systems with Applications*, 36(9), 11875-11887.

[24]. Lashgari, A., Yazdani–Chamzini, A., Fouladgar, M. M., Zavadskas, E. K., Shafiee, S., & Abbate, N. (2012). Equipment selection using fuzzy multi criteria decision making model: key study of Gole Gohar iron min. *Engineering economics*, 23(2), 125-136.

[25]. Bandopadhyay, S., & Venkatasubramanian, P. (1987). Expert systems as decision aid in surface mine equipment selection. *International Journal of Surface Mining, Reclamation and Environment*, 1(2), 159-165.

[26]. Suglo, R. S., & Al-Hassan, S. (2007). Use of simulation techniques in determining the fleet requirements of an open pit mine. *Ghana Mining Journal*, 9.

[27]. Dindarloo, S. R., Osanloo, M., & Frimpong, S. (2015). 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*, 115(3), 209-219.

[28]. Ozdemir, B., & Kumral, M. (2019). Simulation-based optimization of truck-shovel material handling systems in multi-pit surface mines. *Simulation Modelling Practice and Theory*, 95, 36-48.

[29]. Ortiz, C. E. A., Curi, A., & Campos, P. H. (2014). The use of simulation in fleet selection and equipment sizing in mining. In Mine Planning and Equipment Selection: *Proceedings of the 22nd MPES Conference, Dresden, Germany*, 14th–19th October 2013 (pp. 869-877). Springer International Publishing.

[30]. Mohtasham, M., Mirzaei-Nasirabad, H., Askari-Nasab, H., & Alizadeh, B. (2022). 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*, 36(7), 461-491.

[31]. Ghaziania, H. H., Monjezi, M., Mousavi, A., Dehghani, H., & Bakhtavar, E. (2021). Design of loading and transportation fleet in open-pit mines using simulation approach and metaheuristic algorithms. *Journal of Mining and Environment,* 12(4), 1177-1188.

انجمن مهندسی معدن ایران
نشریه مهندسی معدن و محیط زیست
نشانی نشریه: www.jme.shahroodut.ac.ir
دانشگاه صنعتی شاهرود

توسعه‌ی ضریب تطابق برای بهینه‌سازی بهره‌وری ناوگان باربری در عملیات معدن‌کاری روباز

مهرناز محتشم*

گروه مهندسی معدن، دانشکده فنی و مهندسی، دانشگاه محقق اردبیلی، اردبیل

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۰۶/۰۴

تاریخ داوری: ۲۰۲۵/۰۶/۲۵

تاریخ پذیرش: ۲۰۲۵/۰۹/۰۹

DOI: 10.22044/jme.2025.16360.3188

کلمات کلیدی

سیستم باربری
انتخاب تجهیزات
توسعه فاکتور تطابق
بهبود بهره‌وری ناوگان
معدن‌کاری روباز

چکیده

در معادن روباز، تجهیزات حمل‌ونقل بخش قابل توجهی از کل هزینه‌های عملیاتی را تشکیل می‌دهند. بنابراین بهینه‌سازی عملکرد ناوگان برای کاهش هزینه‌ها و بهبود بهره‌وری بسیار مهم است. در این سیستم، تجهیزات بارگیری نقش کلیدی ایفا می‌کنند، زیرا کارآیی کامیون به شدت به عملکرد لودر بستگی دارد. ضریب تطابق، معیاری که سازگاری بین لودرها و کامیون‌ها را ارزیابی می‌کند، معمولاً برای افزایش کارآیی ناوگان استفاده می‌شود. با این حال، بسیاری از رویکردهای موجود، شرایط عملی معدن‌کاری مانند زمان توقف تجهیزات، زمان دقیق چرخه کامیون و خردایش ناشی از انفجار مواد را در نظر نمی‌گیرند. این موارد می‌تواند منجر به ارزیابی‌های نادرست عملکرد ناوگان و هزینه‌های عملیاتی بالاتر شود. این مطالعه یک ضریب تطابق بهبود یافته را پیشنهاد می‌کند که متغیرهای حیاتی را در بر می‌گیرد. این روش زمان توقف تجهیزات، تخمین زمان چرخه کامیون بر اساس مسیرهای سفر و خردایش مواد را در نظر می‌گیرد. در ساختار این مدل، ناوگان همگن و ناهمگن لحاظ شده است و ضریب کارآیی عملیاتی هر دستگاه برای انعکاس دقیق‌تر شرایط واقعی در نظر گرفته شده است. این مدل با استفاده از داده‌های معدن مس سونگون آزمایش شد. مقادیر ضریب تطابق هم با در نظر گرفتن زمان توقف تجهیزات و هم بدون در نظر گرفتن آن محاسبه شدند و ظرفیت لودرها با توجه به توزیع اندازه مواد منفجر شده تنظیم شدند. نتایج نشان داد که در عملیات ناوگان ناهمگن، ضریب تطابق با در نظر گرفتن کارآیی عملیاتی از ۰/۷۴ به ۰/۸۵ افزایش یافت. همچنین، تجزیه و تحلیل زیرسیستم‌ها مقادیر ضریب تطابق زیر ۱ را نشان داد که نشان‌دهنده نیاز به کامیون‌های بیش‌تری است. در مجموع، مدل توسعه یافته امکان استفاده کارآمدتر از تجهیزات را فراهم می‌کند، زمان بیکاری لودر را کاهش می‌دهد و باعث صرفه‌جویی چشمگیر در هزینه‌های عملیاتی می‌شود.

نویسنده مسئول مکاتبات: *m_mohtasham@uma.ac.ir* (م. محتشم)