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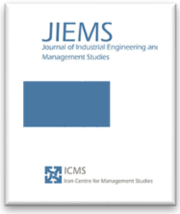

Integrated Simulation and Multi-Objective Optimization for Enhanced Efficiency and Cost Reduction in Open-Pit Mining Haulage Operations

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Abstract

The relentless pursuit of efficiency in open-pit mining, driven by escalating operational costs and stringent environmental mandates, places the optimization of haulage systems at the forefront of mining research. This study addresses the complex dispatching challenge within the shovel-truck system at the Sarcheshmeh open-pit copper mine (Kerman Province, Iran) to simultaneously maximize monthly throughput and minimize transportation costs. We introduce a robust simulation-optimization framework where a Discrete-Event Simulation (DES) model, developed in Arena, is tightly coupled with two leading evolutionary multi-objective optimization algorithms: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Fast Pareto Genetic Algo-rithm (FastPGA). This integration facilitates the exploration of the high-dimensional, non-convex Pareto front to identify a set of near-optimal fleet compositions (number of shovels and trucks). Experimental validations demonstrate significant operational improvements: the derived optimal solutions lead to a quantifiable reduction of up to 10% in average monthly transportation costs and an increase of up to 11% in average monthly material throughput. These findings offer critical managerial insights, establish-ing a data-driven blueprint for mining operators to adopt advanced meta-heuristic optimization techniques to enhance operation-al sustainability and economic performance in dynamic pit environments.

Keywords: Simulation, Multi-objective optimization, NSGA-II, FastPGA, Pareto optimality, Sarcheshmeh open-pit mine

Paper Type: Original Research

1. Introduction

Mining has been regarded as one of the most expensive and complicated industries for many years. Among all parts of the mining industry, the haulage system plays a key role, which is because of its considerable share in the operational costs of the transportation system. In the rapidly evolving field of open-pit mining, the optimiza-tion of haulage systems has emerged as a critical area of focus for enhancing operational efficiency and reducing costs (Ghasemi et al., 2025). As mining operations face increasing pressure to maximize productivity while min-imizing environmental impact, the need for innovative approaches to optimize these complex systems has never been more urgent. This research introduces a novel approach that leverages multi-objective optimization simula-tion to address the dual challenges of efficiency and cost reduction in open-pit mining haulage systems (Jahangiri et al., 2023). The haulage process, which involves the transportation of extracted materials from the pit to pro-cessing facilities, is often characterized by high operational costs and logistical complexities. Traditional methods of optimization have typically focused on single-objective criteria, such as minimizing costs or maximizing throughput. However, these approaches often overlook the intricate trade-offs between multiple objectives that are inherent in mining operations (Samiefard et al., 2025). By employing a multi-objective optimization frame-work, this research aims to provide a comprehensive solution that balances the competing demands of cost effi-ciency, operational performance, and sustainability (Abolghasemian et al., 2022). Through the integration of advanced simulation techniques and optimization algorithms, this study seeks to model the dynamic interactions within haulage systems, enabling a more nuanced understanding of how various factors influence overall per-formance (Hemmati et al., 2024). The proposed approach not only enhances decision-making capabilities but also empowers mining operators to implement strategies that align with both economic and environmental goals. As the mining industry continues to evolve in response to technological advancements and regulatory pressures, this research contributes to the growing body of knowledge on sustainable mining practices. By demonstrating the effectiveness of multi-objective optimization simulation in open-pit mining haulage systems, this study aims to pave the way for future innovations that can drive efficiency, reduce costs, and promote responsible resource extraction (Abolghasemian et al., 2020). According to the above-mentioned, the purpose of this research is to analyze the performance of the haulage system in Sarcheshmeh copper mine located in the Kerman Province of Iran and determine the optimal number of equipment (trucks and shovels) in order to maximize throughput and minimize the total cost of transportation. My system contains several stochastic parameters and is too complex to be modeled analytically. It is not possible to mathematically model all aspects of the problem, and many signifi-cant issues, including a variety of jobs, crushers, trucks, and shovels, and the placement of waste dumps, are ignored in analytical models. Also, mathematical models assume that most parameters like processing and transportation times, failure rates and repair times in a real haulage system are deterministic. As the level of complexity of the operation increases, simulation is determined as a powerful tool for system analysis. Thus, a discrete event simulation model is developed to study and analyze the behavior of the haulage system in Sar-cheshmeh copper mine using Arena simulation software. We provide two multi-objective methods to solve the optimization problem. These methods are then compared with the result of the Arena optimizing package, OptQuest. The first multi-objective method is the Non-Dominated Sorting Genetic Algorithm (NSGA-II) which was provided by Deb et al. (2003) and the second one is the Fast Pareto Genetic Algorithm (FastPGA) which was introduced by Eskandari and Geiger (2007). This paper is organized as follows. In Section 2, a review of related works is given, and Section 3 presents the problem description in the Sarcheshmeh copper mine and the haulage system. The simulation model, verification, and validation of the model are described in Section 4. Section 5 pre-sented the proposed framework and the optimization algorithms. In Section 6, the experimental results are pre-sented to compare the modified algorithms. Finally, the conclusions and proposal for future research are pre-sented in Section 7.

2. Literature Review

For research that analytically models a haulage system in mines, Himebaugh (1980) designed an automated dispatching system to determine the optimal truck assignment that maximizes productivity. Hodson and Barker (1985) improved this system for the assignments to be done in a two-step process. First, each shovel was guaranteed to load a certain number of trucks, and then the distribution of trucks was regulated according to the shovel loading time. White and Olson (1992) improved the previously developed model by Hodson and Barker (1985). They used dynamic programming to assign trucks to shovels to minimize the queue of waiting trucks and their idle time. In all of these studies, mathematical methods like queuing theory were used. A few efforts have been made to optimize a part of the haulage system. Huband et al. (2006) applied evolutionary algorithms in a simulation model of a case study to increase total earnings over the life period of the mining project. Feng and Wu (2006) used an integrated fast messy genetic algorithm and CYCLONE simulation technique to find the optimal dispatching schedule. Fioroni et al. (2008) used simultaneous simulation and optimization processes to achieve a feasible and reliable solution for a short-term mining plan. Qing et al. (2008) proposed an algorithm to improve labor productivity and the production scheduling efficiency in the truck/shovel system. Ercelebi and Bascetin (2009) used closed queuing network theory for the allocation of trucks to shovels. Syberfeldt et al. (2010) pro-posed a method based on an evolutionary algorithm for simulation-based multi-objective optimization of manu-facturing problems. Grewal et al. (2010) utilized simulation-based optimization to evaluate and compare two inventory replenishment strategies. A discrete-event simulation model of a simplified supply chain scenario was developed. Syberfeldt et al. (2010) proposed a method based on an evolutionary algorithm for simulation-based multi-objective optimization of manufacturing problems. Grewal et al. (2010) utilized simulation-based optimiza-tion to evaluate and compare two inventory replenishment strategies. A discrete-event simulation model of a simplified supply chain scenario was developed. Li et al. (2011) proposed simulation-based optimization to solve the hybrid flow shop scheduling problem. Subtil et al. (2011) proposed an algorithm for optimization of haulage systems in open-pit mines. This algorithm is a multi-stage method, with a multi-criterion approach that makes use of linear programming, discrete event simulation and specific heuristics for allocation. Li et al. (2011) pro-posed simulation-based optimization to solve the hybrid flow shop scheduling problem. Napalkova and Merkuryeva (2012) presented a simulation-based optimization method in supply chain management. They de-veloped a two-phase optimization method based on a hybrid combination of compromise programming, evolu-tionary computation and response surface-based methods. Napalkova and Merkuryeva (2012) presented a simu-lation-based optimization method in supply chain management. They developed a two-phase optimization method based on a hybrid combination of compromise programming, evolutionary computation and response surface-based methods. Mena et al. (2013) developed a simulation-optimization method to maximize the overall productivity of the fleet by taking into account the truck and shovel reliability and maintenance aspects. First, they presented an optimization model of a real open-pit mine. Second, they used Arena simulation software to evaluate the operation behavior in the real system. Vasquez (2014) focused on the optimization of the haulage system. Drilling exploration data from a mine located in the state of Arizona were used to build a block model and to design an open-pit and an Arena-based simulation was used to generate operating cycles that represent actual operations. Salimi et al. (2014) proposed the usage of NSGA-II as the optimization engine integrated with discrete event simulation to model the bridge construction processes. Syberfelt et al. (2015) presented an evolu-tionary multi-objective simulation-optimization system for personnel scheduling. Zeinali et al. (2015) presented a simulation-based optimization using Meta model to reducing patient waiting time in the emergency department. Abolghasemian et al. (2020) presented a two-phase simulation-based optimization for the haulage system in open pit mine. In the first phase, The OptQuest for Arena software package was used to solve the optimization problem to provide an optimal production quantity. In the second phase, the haulage system problem in the open-pit was modeled by bi-objective optimization programming by means of a meta-modeling approach. In another study, Abolghasemian et al. (2022) presented a simulation based multi objective for haulage systems in an open-pit mine using Meta modeling approach. For this purpose, a multi-objective optimization in the extrac-tion system of a copper open-pit mine complex is presented by the mod-ified-NBI optimization method and re-gression meta-model. For this purpose, two objective functions of maximizing the amount of total extraction, which is the sum of the extraction of sulfide, oxide, low-grade ores, and waste in this mine, and minimizing the transport time of haulage according to the limitation of its storage capacity, transport equipment, and budget, are considered. Jahangiri et al. (2023) presented a simulation-based optimization using a regression model to reduce patient waiting time in the emergency department in COVID-19 conditions. Abolghasemian et al. (2024) explored the application of analytical-based simulation modeling in the context of short-term and long-term planning in open-pit mining. For this purpose, a two-level hierarchical framework based on simulation is pre-sented for production planning and material loading machines in Iran's largest open-pit copper mine.

3. Problem description

In this section, we describe the problem definition, basic assumptions and input data considerations to better understand the problem.

3.1. Sarcheshmeh copper complex

Sarcheshmeh copper complex is located in the Kerman Province, southeast of Iran. Sarcheshmeh is a large opencast copper mine, considered to be the second-largest copper deposit worldwide. It is located at 65 kilometers southwest of Kerman city and 50 kilometers south of Rafsanjan. The average altitude of the region is about 2600 m the highest spot is approximately 3000m.

3.2. Haulage system

The Geology and Canalization departments are the initial segments of the ore production process, which undertake collecting, analyzing, and updating information on digging and excavation. Gathered data is processed by mine software like MingSight and DataMine to estimate the deposit. The results are given to the mining engineering department to develop excavation plans. In the excavation planning department, medium-term excavation designs are planned. The operational department is responsible for the implementation of excavation plans. After excavation, the type of minerals should be identified. The extracted deposits can be categorized into four groups:

1. Sulfide ore (grade of copper greater than 0.7%)
2. Oxide ore (grade of copper between 0.25% and 0.7%)
3. Low-grade ore (grade of copper between 0.15% and 0.25%)
4. Waste (grade of copper less than 0.15%)

The proportion of the amount of these rocks to the whole amount is 45%, 5%, 44% and 6%, respectively. Based on the different kinds of ore, a transportation strategy and the way of storing ores would be chosen. The first kind of mineral substance, sulfide ore, is transferred to a crusher station. There is a crusher machine with a capacity of 60000 tons per day. Then, the substance is moved to harp copper storage with a capacity of 150000 tons. After harping, the substance is stored in a soft copper storage. Oxide ore, low-grade ore and waste are transferred to their dumping station. The conceptual model of the haulage system at Sarcheshmeh copper complex is demonstrated in Figure 1.

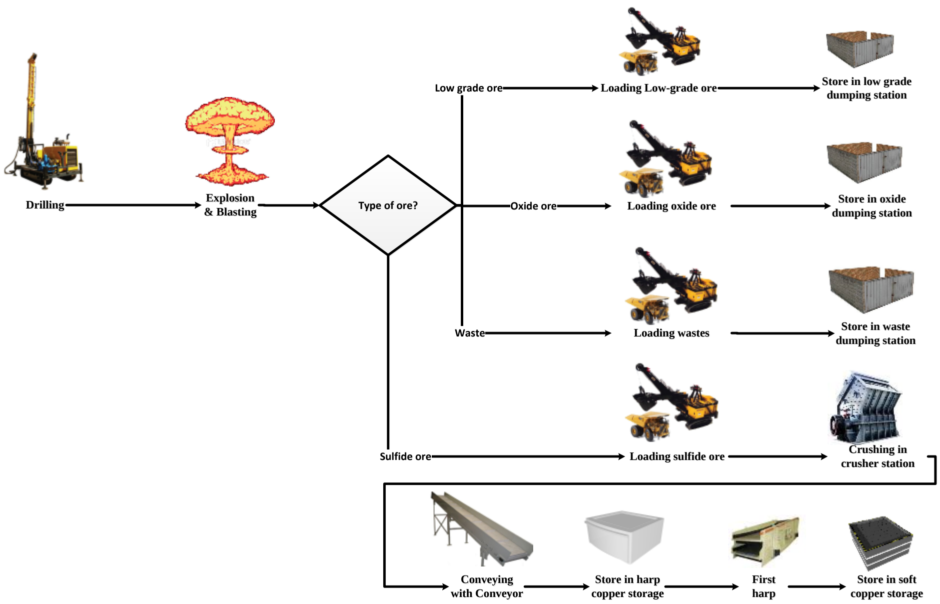

Figure 1. The conceptual model of haulage system at Sarcheshmeh copper mine

In order to transport ores, several shovels are assigned to the loading station. A shovel is a set of excavators that are used to load hard rocks, mostly used in open-pit mines. The mineral substance is loaded on a truck by a shovel, and when the truck is filled, it is taken to a dump. The way of assigning trucks and shovels is different on each working day. The main purpose of this research is to determine the optimal number of haulage system equipment in order to maximize the mineral monthly production, especially sulfide and oxide ore and minimize transportation costs.

3.3. Assumptions and input data

Important assumptions considered in the modeling of the haulage system are as follows:

- All paths in the haulage system are considered as a two-way road.
- Each shovel can serve only one truck at a time.
- Queue discipline for shovels and trucks is FIFO.
- All trucks start operation at the loading area near the shovel places.
- The existing haulage system in Sarcheshmeh copper complex is a non-dispatching one, which means that each truck is responsible for the transportation of only one mineral type, and it is not possible to change its path.
- Preventive maintenance time is the same for all trucks and shovels.
- There is no idle time of system between working shifts.
- Since the number of paths between the loading dump and unloading dump varies, the average distances are assumed to be the distance.

Table 1. The specification of available trucks and shovels

Equipment	35-Ton Truck	100-Ton Truck	120-Ton Truck	150-Ton Truck	240-Ton Truck	Shovel 4m3	Shovel 9.5m3	Shovel 15.5m3	Shovel 17m3
Quantity	5	15	10	10	2	6	4	4	1

The input data for this study was collected by the Engineering Department. The data was classified into two categories, including truck-shovel data and system data. The specifications of available trucks and shovels at Sarcheshmeh are mentioned in Table 1. Trucks, which are used to transfer oxide ore and wastes, vary between 35 tons and 100 tons. Moreover, 120 tons to 240 tons trucks are used to move sulfide and low-grade ore. It is possible to assign each shovel to every kind of ore. The hourly operating cost of shovels and trucks is shown in Tables 2 and 3, respectively. For each process mentioned in Figure 2, sufficient data were collected. Then, suitable probability distributions were defined using the Input Analyzer package existing in the Arena simulation software. Some of the results of input modeling for collected data are shown in Table 4. Due to confidentiality, it is not possible to reveal the real values of some input data, so some data points are disguised in the simulation modeling and analysis.

Table 2. Hourly operating cost of shovels ($)

Shovel	Depreciation	Overhead	Repair		Maintenance		Electricity	Lubricants	Other	Total
			spare parts	salary	spare parts	salary				
4m3	62	2	4	1	7	1	6	4	5	93
9.5m3	85	3	6	1	9	2	9	6	6	126
15.5m3	111	4	8	2	12	2	13	8	7	165
17m3	156	5	11	2	16	3	12	11	8	225

Table 3. Hourly operating cost of trucks ($)

Truck	Depreciation	Overhead	Repair		Maintenance		Gas	Lubricants	Other	Total
			spare parts	salary	spare parts	salary				
35-Ton	11	0	1	0	2	1	0	3	4	22
100-Ton	21	1	2	1	5	1	1	5	9	45
120-Ton	32	1	4	1	7	1	1	8	15	69
150-Ton	30	1	4	1	7	1	1	8	16	67
240-Ton	43	2	5	1	10	2	2	11	43	118

Table 4. Results of Input data modeling

Data	Distribution
Distance between loading sulfide ore and crusher station (Km)	EXPO (2.5)
Distance between loading oxide ore and dumping station (Km)	UNIFORM(2.41,4)
Distance between loading Low-grade ore and dumping station (Km)	EXPO(3.1)
Distance between loading wastes and dumping station (Km)	UNIFORM(3.44,4.21)
Loading Time on Trucks (Minute)	2.4+1.2*BETA(1.69,1.79)
Velocity of empty-truck (Km/hour)	34+10*BETA(1.23,1.02)
Velocity of full-truck (Km/hour)	12+11*BETA(1.01,0.863)
Preventive Maintenance Time for all trucks and shovels (working hour)	125

4. Simulation model

In this section, we explain the development of the simulation model, verification, validation and the simulation results.

4.1. Model development

Sarcheshmeh copper mine system contains several stochastic parameters such as cycle times, loading and transportation times. By having a representative probabilistic distribution of each stochastic element in this system, analyzing and optimizing such a real-world situation can be done by using a simulation approach with a very high degree of accuracy. In this research, we used Arena simulation software to model the haulage system at Sarcheshmeh copper mine.

4.2. Verification and validation

Verification is the task of answering the question, “Did we build the model right?” To monitor the logic of the model more carefully, the animation feature of Arena is used (Figure 2).

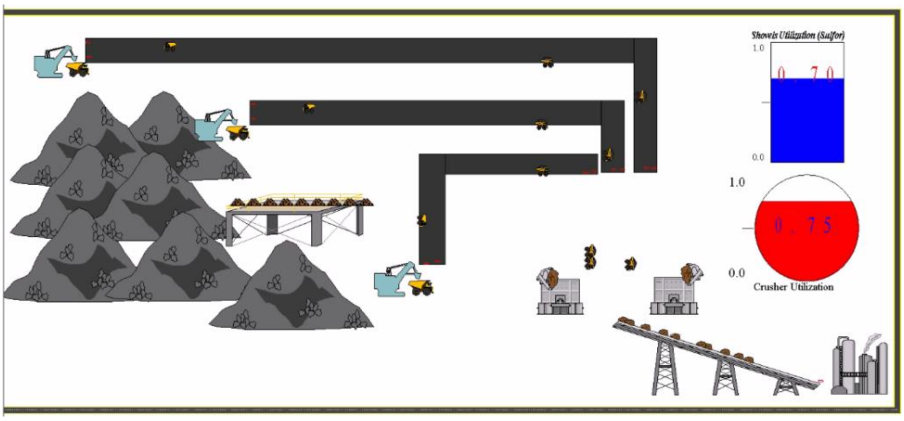

Figure 2. Animation of the haulage system at Sarcheshmeh copper mine in Arena software

Validation is the task of answering the question, "Did we build the right model?" The most common method for checking model validation is comparing the output data from the simulation with the actual data from the current system using statistical analyses (Montgomery and Runger, 2003). We compared real data on monthly sulfide throughput with simulation results using a paired t-test. The t-statistic test determines whether the difference between the means of the two series of values (real data and simulation results) is meaningful.

4.3. Simulation results

The output results of the simulation model, which show the existing situation of the system, are shown in Table 5. Average waiting time and average number of trucks in crushers queue are almost high. It means that crushers station is a common bottleneck in the shovel-truck system. Also, the length of trucks queue for loading sulfide and low-grade ores is somewhat long.

Table 5. Results of the simulation model for the current situation.

Performance measure	Mean ± Half width
Monthly throughput of sulfide ore (tons)	2,366,764±3,532
Monthly throughput of oxide ore (ton)	283,140± 14,748
Monthly throughput of low-grade ore (ton)	2,733,765± 34,345
Monthly throughput of waste (ton)	394,233± 15,770
Total cost ($)	601,779 ± 7,703
Average utilization of trucks	0.748 ± 0.012
Average utilization of shovels	0.962 ± 0.011
Average utilization of the crusher	0.98 ± 0.0162
Average number of trucks in the crusher's queue	5.2 ± 0.062
Average number of trucks in the queue of loading sulfide dump	3.42 ± 0.051
Average number of trucks in the queue of loading the oxide dump	1.84 ± 0.027
Average number of trucks in queue of loading low-grade dump	2.75 ± 0.041
Average number of trucks in queue of loading waste dump	1.26 ± 0.018
Average waiting time in crusher's queue (minutes)	18.62 ± 0.428
Average waiting time in queue of loading sulfide dump (minutes)	10.47 ± 0.218
Average waiting time in queue of loading oxide dump (minutes)	5.86 ± 0.104
Average waiting time in queue of loading low-grade dump (minutes)	8.6 ± 0.182
Average waiting time in queue of loading waste dump (minutes)	5.27 ± 0.11

5. Optimization algorithms

To solve our stochastic problem, two well-known multi-objective algorithms, NSGA-II and FastPGA have been chosen. These two methods are integrated with a simulation model to find the best value of decision variables.

5.1. NSGA-II

The NSGA-II algorithm is provided by Deb et al. (2003). It is a kind of genetic algorithm that uses a diverse procedure to avoid local convergence. In this algorithm, firstly, a set of possible solutions called a population is generated. The population of solutions evolves from one generation to the next through the use of two types of genetic operators: crossover and mutation. The genetic operators are applied to generate new offspring. Then the new population is selected out of the individuals of the current population and newly generated offspring. Ranking and crowding distance are two criteria for selecting the best individuals. The algorithm first ranks the different solutions in non-dominated fronts, and then keeps only the individuals that have a minimum distance between each other in order to maintain diversity in the front. This trend continues until the stopping criteria are satisfied.

5.2. FastPGA

The FastPGA algorithm was introduced by Eskandari and Geiger (2007). FastPGA utilizes a genetic algorithm with a new solution ranking strategy. Also, a regulation operator is introduced to dynamically adapt the popula-tion size of the genetic algorithm as needed up to a user-specified maximum population size. The new ranking strategy is based on the classification of candidate solutions into two different categories (ranks) according to solution dominance. Firstly, all non-dominated solutions are identified as the first rank. Secondly, all dominated solutions are identified as the second rank. The fitness of the non-dominated solutions in the first rank is calcu-lated by comparing each non-dominated solution with others and assigning a fitness value. These values are computed using the crowding distance approach. The fitness value of each dominated solution is equal to the summation of the strength values of all solutions. It dominates minus the summation of the strength values of all solutions by which it is dominated.

6. Proposed Framework

The simulation optimization of Sarcheshmeh copper mine consists of two related modules, the optimization module and the simulation module. As the number of equipment needs to be optimized, the setup of inputs, such as initial parameters and population, is done in the optimization module. Then the optimization module transfers the input variable to the simulation module through data transfer. The simulation module applies initial parameters and input variables and run the simulation. The results of the simulation are returned to the optimization module. The optimization algorithm searches for optimal solutions and creates a new population based on the results obtained by the simulation module. This trend continues until the stopping criteria is satisfied. Figure 3 shows the framework of the software used in the simulation-optimization. In order to implement the optimization algorithm, MATLAB software is applied. The simulation module is used to evaluate the solutions obtained by the optimization module. Arena is used to develop a simulation model. In order to integrate simulation module and the optimization module, an integrated environment is required. Microsoft Excel and Microsoft Visual Basic are used as the interface of optimization software and simulation software, respectively.

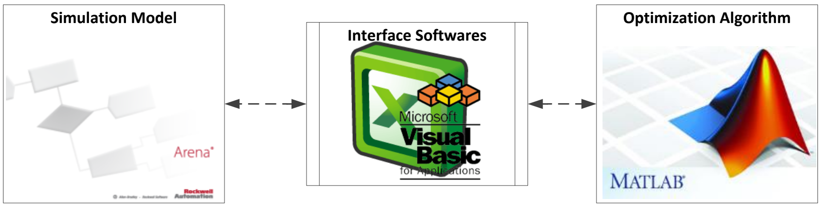

Figure 3. Framework of simulation-based optimization software

7. Experimental results

In this section, the computational results of FastPGA and NSGA-II are presented. For both FastPGA and NSGA-II, all of the parameters are summarized in Table 6. In this way, the number of evaluated solutions in each run of the two algorithms is equal.

Table 6. Parameter settings for FastPGA algorithm and the NSGA-II algorithm.

Algorithm parameter	NSGA-II	FastPGA
Population size	40	-
Initial population size	-	40
Maximum population size	-	40
Number of solution evaluations at each generation	40	10
Crossover probability	1.0	
Mutation probability	1.0	
Crossover type	Simulation binary crossover	
Mutation type	Polynomial mutation	
Selection scheme	Binary tournament	

We also used the OptQuest package existing in Arena Software to find a near-optimal solution. As OptQuest is designed for single-objective problems, we considered the constraint method to solve this multi-objective problem. The average monthly cost is considered as the original objective and the average monthly throughput is used as the constraint of the optimization problem. The ε parameter for monthly throughput is set in different levels and for each level, the OptQuest optimizer is run. The number of solutions evaluated by OptQuest optimizer is equal to the proposed algorithms. Figure 4 presents the results of OptQuest for four levels of throughput constraint: 2 (a), 2.5 (b), 3 (c) and 3.5 (d) million tons per month. Figure 5 shows the comparison of the performance trade-off curves obtained from the proposed methods and near-optimal solutions found by OptQuest for different levels of average monthly throughput. It is seen that there is a significant difference between the performance of FastPGA, NSGA-II and OptQuest for this real application, where each solution evaluation is computationally expensive. The average computational time for proposed algorithms and OptQuest are approximately 25-hours and 18-hours, respectively. The set of near-optimal solutions found by OptQuest are dominated by the Pareto solutions found by both proposed algorithms. As it is shown, FastPGA performs better than NSGA-II and all obtained Pareto solutions yielded by NSGA-II at the end of the search are dominated by the Pareto solutions of FastPGA.

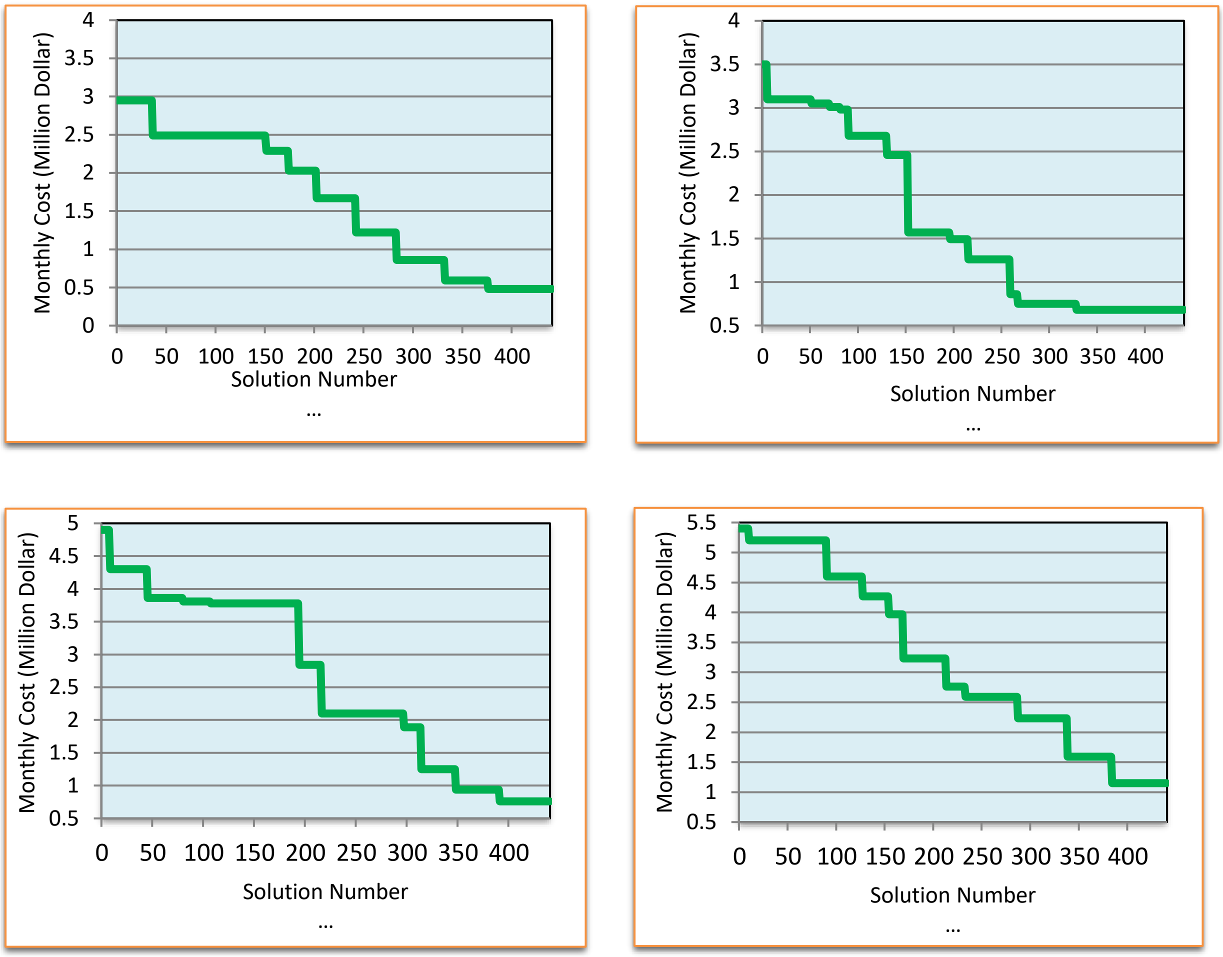

Figure 4. The optimization results obtained from OptQuest package for four different levels of monthly throughput, 2 (a), 2.5 (b), 3 (c) and 3.5 (d) million ton.

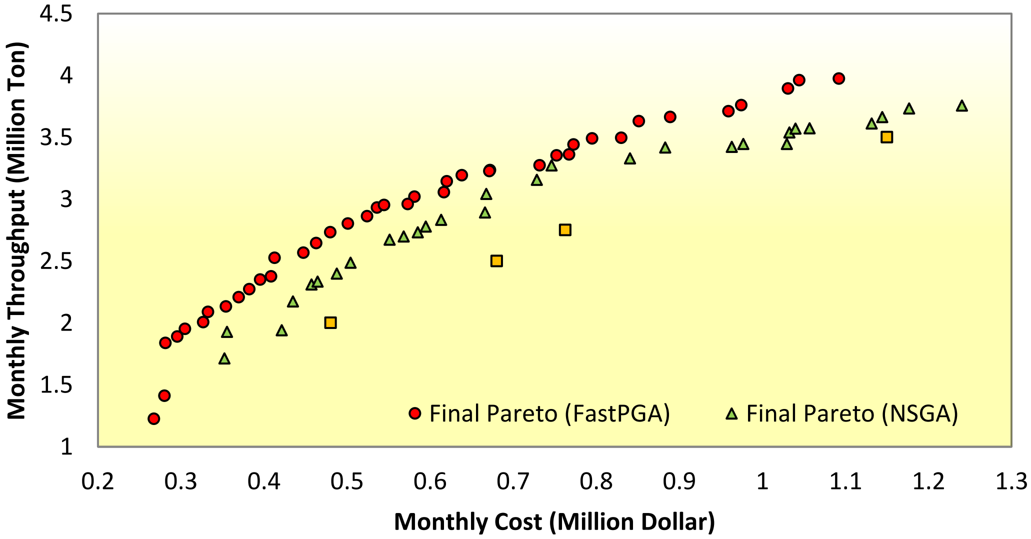

Figure 5. Comparison between the results of FastPGA, NSGA-II and OptQuest

According to final solutions, we found if optimized results are applied, the monthly cost will decrease approximately 10% and the monthly production will increase about 11%.

8. Conclusions

Haulage systems are responsible for transporting mined materials from the extraction site to processing facilities, and they significantly contribute to the overall operational costs of mining. Factors such as equipment selection, route planning, and scheduling play a crucial role in determining the efficiency and cost-effectiveness of these systems. Traditional optimization methods have often focused on single-objective criteria, such as minimizing transportation costs or maximizing throughput. However, these approaches frequently fail to account for the complex interplay between multiple objectives, leading to suboptimal solutions that do not fully address the challenges faced by modern mining operations. Recent advancements in computational techniques and simulation modeling have opened new avenues for addressing these challenges. Multi-objective optimization, which considers multiple conflicting objectives simultaneously, offers a more holistic approach to optimizing haulage systems. By incorporating various performance metrics—such as cost, time, and environmental impact—this methodology enables mining operators to make informed decisions that balance competing demands. Moreover, the integration of simulation techniques allows for the modeling of dynamic and stochastic elements within haulage systems, providing valuable insights into system behavior under varying conditions. This capability is particularly important in open-pit mining, where factors such as equipment availability, weather conditions, and material variability can significantly influence operational performance. In light of these developments, this research seeks to explore a novel approach that harnesses the power of multi-objective optimization simulation to enhance the efficiency and cost-effectiveness of open-pit mining haulage systems. By addressing the limitations of traditional optimization methods and leveraging advanced computational techniques, this study aims to contribute to the ongoing efforts to improve operational performance while promoting sustainable mining practices. Ultimately, the findings of this research are expected to provide valuable guidance for mining operators seeking to navigate the complexities of modern mining environments and achieve their economic and environmental objectives. This paper considers a simulation-based multi-objective optimization approach of a haulage system at Sarcheshmeh copper mine in Iran. The main purpose of this research is to determine the optimal number of equipment of haulage system in order to maximize the mineral monthly production and minimize transportation costs. The concept of multi-objective Pareto-optimization is considered in the proposed methods. Also, simulation as a handy tool is applied to optimize the behavior of the system and cope with the stochastic parameters in the real world. FastPGA and NSGA-II algorithms are modified to solve our complicated problem with a simulation model. In this simulation-based optimization approach, the process of finding the best solutions for the problem is first done by an optimization algorithm, and then the performance of the system is evaluated with the output of the simulation model. The experimental results show that the FastPGA provides better solutions than NSGA-II and the performance of the current system is improved. The findings from this research on a novel approach to increasing efficiency and reducing costs through multi-objective optimization simulation in open-pit mining haulage systems offer several critical managerial insights that can significantly enhance decision-making and operational performance within the industry. By adopting a multi-objective optimization framework, managers can make more informed decisions that consider various conflicting objectives, such as minimizing costs while maximizing throughput and minimizing environmental impact. This holistic approach enables a more comprehensive understanding of how different operational strategies can affect overall performance, leading to better resource allocation and strategic planning. The integration of simulation techniques allows managers to visualize and analyze the dynamic interactions within haulage systems. This capability enables the identification of bottlenecks and inefficiencies, facilitating targeted interventions that can streamline operations. By optimizing equipment utilization, route planning, and scheduling, mining companies can significantly enhance their operational efficiency and reduce unnecessary costs. The stochastic nature of mining operations means that conditions can change rapidly due to factors such as equipment breakdowns, weather variations, or fluctuations in material quality. The proposed optimization simulation approach equips managers with the tools to adapt to these changes effectively. By simulating various scenarios, managers can develop contingency plans and make real-time adjustments to their operations, ensuring resilience and continuity. As environmental regulations become increasingly stringent, mining companies must prioritize sustainable practices. The multi-objective optimization approach not only focuses on economic factors but also incorporates environmental considerations. By optimizing haulage systems with sustainability in mind, managers can ensure compliance with regulations while also enhancing the company's reputation and stakeholder relations. Implementing advanced optimization and simulation techniques fosters a data-driven culture within the organization. Managers are encouraged to leverage data analytics for continuous improvement, driving innovation and operational excellence. This cultural shift can lead to more proactive decision-making and a greater emphasis on performance metrics, ultimately benefiting the organization's bottom line. The insights gained from the optimization simulations can guide strategic investment decisions regarding equipment procurement, technology upgrades, and infrastructure development. By understanding the potential return on investment for various operational strategies, managers can prioritize initiatives that align with the company's long-term goals and financial objectives. Therefore, the managerial insights derived from this research underscore the importance of adopting innovative approaches to optimize haulage systems in open-pit mining. By embracing multi-objective optimization simulation, managers can enhance operational efficiency, reduce costs, and promote sustainable practices, positioning their organizations for success in a competitive and evolving industry landscape. Using dispatching mode in shovel-truck simulation-optimization and developing a model which dealt with the whole system can be the subjects for future research.

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