Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 13, No. 4, Autumn 2020 *Print ISSN: 2008-7055*
pp. 705-732 *Online ISSN: 2345-3745*
Document Type: Research Paper *DOI: 10.22059/ijms.2020.294809.673898*

A Two-Phase Simulation-Based Optimization of Hauling System in Open-Pit Mine

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(Received: January 13, 2020; Revised: April 11, 2020; Accepted: May 9, 2020)

Abstract

One of the key issues in mining is the hauling system. Truck and shovels are the most widely used transportation equipment in mines. In this paper, a two-phase simulation-based optimization is presented to maximize utilization of hauling system in the largest Iranian open-pit copper 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 programing by means of meta-modeling approach. Meta-modeling approach could estimate the exact total production quantities, and solved the problem by determining the optimal value of shovels using the design of experiments. The efficient solution of the bi-objective problem was obtained using ε-constraint method. The results of the proposed approach were compared with the current situation, where the total production had increased by 21% (equivalent to 10K tons) through the proposed approach. Therefore, calculations in this mine show that how the proposed framework can improve the production and productivity of haulage system.

Keywords

Simulation-based optimization, Meta-modeling, Design of experiment, Multi-objective optimization.

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1. Introduction

Mining is a worldwide industry, and mineral resources comprise one of the most important and fundamental bases of the economy of each country. Todays, mining ores are considered as one of the sources of income generation in the world. The mining sector, as one of the substructures of the economy, plays a major role in supplying the raw materials of other industries, and the development of investment in this sector can lead to the acquisition of appropriate added value in many other parts of the economy of a country. Thus, the role of mines and resources in the economic growth of any country is indisputable. Undoubtedly, the proper utilization of mines in the country is considered as a positive and important factor in economic growth and development (Eskandari, Darabi, & Hosseinzadeh, 2013). However, mining projects in general and open-pit mines in particular have high operating costs. On average, 50% of operating costs are in open-pit mines and even 60% in big open mines include transportation costs and material hauling (Afrapoli & Askari-Nasab, 2019). Among all the operations of the materials management in the open-pit mines, hauling enjoys the highest operational costs (Curry, Ismay, & Jameson, 2014). Thus, optimal mining plans and proper fleet management have a significant impact on the operational efficiency of a mine. Generally, the common goal of managing mine systems is to optimize production and productivity based on real-time data. For this purpose, the multi-stage optimization approach is common. In this approach, the solution to each step is used in the next step, which is divided into three sub-issues, including the shortest route model, the optimization of truck and shovel assignment, and the optimization of truck dispatch time. The shortest route model determines the best route between the two points in a mine. In the optimization of the allocation of trucks and shovels, the resources are diverted to drilling operations based on truck loading. The issue of the allocation of trucks in mines is often considered as an allocation problem, or sometimes a transportation problem (Afrapoli & Askari-Nasab, 2019).

Planning in a mine is a very complex duty. It is known that traditional techniques are not suitable for the evaluation of complex system such as the open-pit mine (Dengiz, Tansel & Belgin, 2016), as mines have several stochastic characteristics. Therefore, simulation is an appropriate tool to overcome the complexities of systems, and is an easy way to understand system behavior (Abolghasemian, Eskandari, & Darabi, 2018). However, the important drawback of simulation is that it is computationally time consuming. Therefore, a mathematical model of the simulation model, a surrogate one called meta-model, is needed to replace the simulation model. Thus, in this paper, a two-phase simulation-based optimization is presented to maximize utilization and improve the productivity of hauling system in the largest Iranian open-pit copper mine. This proposed framework is a useful tool for reducing the variable space of a complex system. The main advantage of the proposed framework is that it can carry out production planning verification. To solve the existing problem with the proposed framework, it is necessary to develop an optimization program and a mathematical model. For this purpose, the optimization framework has been developed by OptQuest tools for Arena. OptQuest is a tool that is linked with simulation software such as the Arena and can perform simultaneous simulation and optimization for different scenarios (Zeinali, Mahootchi, & Sepehri 2015). Also, a mathematics model approximated by a surrogate model is called a Meta-Model because in simulation-based optimization problems, the objective function is stochastic with random characteristics and uncertain conditions. Therefore, objectives can be clearly specified when the simulationist run the simulation model with different scenario to find setting that fit objectives. Simulation-based optimization is an appropriate tool for achieving such goals Barton (2009).

The remainder of this paper is organized as follows. A literature review of important topics is provided in section 2, while the details of the case study are described in Section 3. In section 4, the two-phase simulation-based optimization is described. In addition, the experiments to demonstrate the utility of the two-phase simulation-based optimization are detailed in section 4. Finally, the conclusion is presented in Section 5.

2. Literature review

The two-phase simulation-based optimization presented in this paper is very similar to the hierarchical production planning (HPP) framework that has been part of many efforts to solve integrated programming and scheduling problems. Generally, in simulation-based optimization, the simulation model is considered as a black box. The output of each simulation is generated through an algorithm defined in the software to determine the best possible system response, subject to all aspects defined in the objective function and the constraints. The simulation-based optimization is the optimization of an objective function subject to the constraints, where both of them can evaluated through a stochastic simulation. Therefore, the simulation-based optimization is a concept for methods used to optimize stochastic simulation (Amaran, Sahinidis, Sharda, & Bury, 2017). A discrete-event simulation-based optimization is illustrated in Fig. 1. The results of the simulation replications provide an approximate of a performance measure. The estimate values are then reported into a control module. The control modules suggest filtration to create new parameters in the deterministic optimization model. The iterative process ends after a stopping criterion is met (Shishvan & benndorf, 2019). In this regard, Glover, Kelly, and Laguna (1996), Tekin and Sabuncuoglu (2004), and Amaran et al. (2017) discussed the introduction of the simulation-based optimization algorithms and applications. Simulation software packages employ optimization packages embedded in them to optimize the stochastic simulation model (Eskandari, Mahmoodi, Fallah, & Geiger, 2011). According to Law (2007), there are some optimization software packages such as AutoStat®, Extend Optimizer®, OptQuest®, SimRunner®, and Witness Optimizer® that use different search strategies. Moreover, Fu (2002) introduced software that can be used to optimize the simulation model. The OptQuest tool and Sim Runner software are the most popular simulation software used in this field. Jafferali, Venkateshwaran, and Son (2005) compared the performance of OptQuest and SimRunner in determining the optimal timing for manufacturing systems. They determined that OptQuest software would get the best near-optimum value. In addition, Eskandari et al. (2011) evaluated and compared two simulation-based optimization software packages, namely OptQuest and witness optimizer, to determine their performance based on the quality of the obtained solutions in a reasonable computational effort. Jerbi, Ammar, Krid, and Salah (2019) evaluated and compared Taguchi method and OptQuest to a flexible manufacturing system performance optimization context, based on simulation.

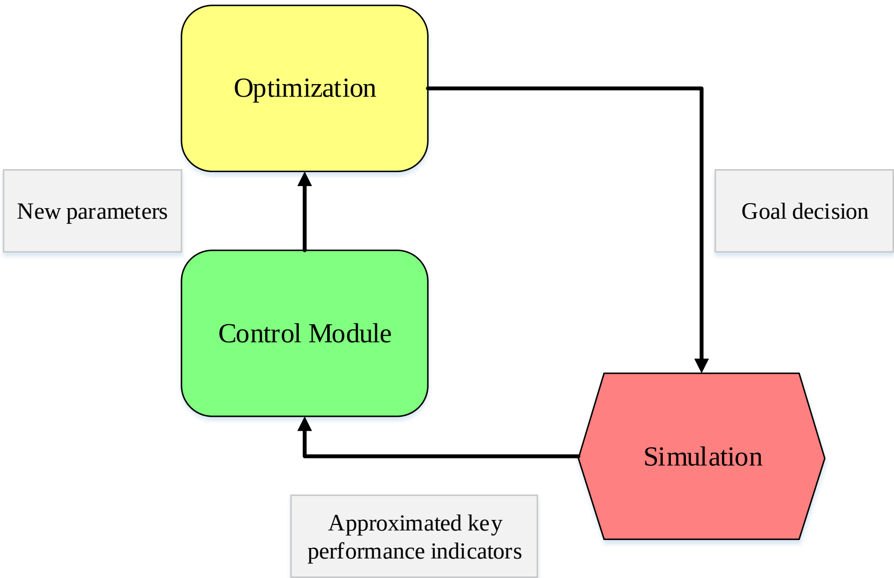

Fig. 1. Simulation-based optimization mechanism

Other studies conducted by the researchers in this area in recent years regarding the problem of production planning and hauling in mines are divided into two categories including one-stage and multi-stage methods (Nageshwaraniyer, Son, & Dessureault, 2013a). Thus, multi-stage methods are able to cover the production targets well. The multi-stage method divides the allocation problem into two sub-issues. The first one is the production problem that is at the forefront of attention, and the second is the loading of hauling. Among the published papers, a lot of attention has been paid to the heuristic methods for solving the problem of loading the truck dispatching. For example, He, He, Wei, Lu, and Huang (2010) described the manner of constructing the truck-dispatching model and the application of genetic algorithm (GA). Their results showed that using GA to optimize mine vehicle dispatching is feasible and effective. Subtil, Silva, and Alves (2011) proposed a multi-stage approach for dynamic truck dispatching in a real open-pit mine. In the first stage of this approach, they define the optimal number of trucks that maximize the total production by a robust linear programming. In the second stage, they present a dynamic dispatching heuristic to computational simulation and multi-criterion optimization techniques for decision making for truck dispatching. Results show that their proposed approach generates efficient dispatch decision for truck in a real case. Although, in small-scale problems exact methods are better than heuristic methods, they are considered as solutions to the problem of allocation because they are used for the desired measures such as maximizing production or minimizing equipment and some inactivity such as waiting time for trucks or the idle time of shovels. These methods do not provide an optimal solution such as an exact method for the problem, but provide a near-optimal solution (Zhang & Xia, 2015). Afrapoli and Askari-Nasab (2019) examined suchlike models and algorithms used in the mining system. Himebaugh (1980) designed the self-control system for optimal truck allocation to increase productivity. White, Arnold, and Clevenger (1982) introduced the first model of the network to dispatch a truck to shovel in a truck-shovel system for open pit mines. Hodson and Barker (1985) developed the model of White et al. (1982) in two stages. At the first stage, each load would load a given number of trucks. At the second stage, trucks would be assigned to specified regions. White, Olson, and Vohnout (1993) developed the Hodson and Barker (1985) model. They used dynamic programming to allocate truck to the route so that the length of the queue and the waiting time for loading and unloading time could be reduced. Sgurev et al. (1989) studied the control of the time of industrial trucks in open pits. Alarie and Gamacheh (2002) studied the existing solving methods for dispatching trucks in open pits. Barnes, King, and Johnson (1997) studied the analysis of open-pit mine systems using probabilistic techniques. Koenigsberg (1982) studied truck-shovel system for an open mine through the application of the queuing theory and mathematical programming. Mena, Zio, Kristjanpoller, and & Arata (2013) presented simulation-based optimization framework for allocating trucks by route based on their operating performance. In the problem of their study, equipment availability is a variable and maximizing the overall efficiency is the problem objective. Their results show that the simulation-based optimization provides an initial set of decision variables. In their framework, when events occur (e.g. failure of truck) during the simulation model run, the simulation-based optimization model provides a new set of variables to the simulation model. Nageshwaraniyer, Son, and Dessureault (2013b) considered a robust simulation-based optimization framework for a truck-shovel system in open-pit mine. Maximizing the value revenue obtained from the delivered trains to customers was the objective function problem. The response surface method (RSM) was applied to define the variance expression of the objective function problem under different parameter setting of the simulation model. Upadhyay and Askar-Nasab (2018) presented a simulation-based optimization framework to account for uncertainties in mining operations for robust short-term productions planning and proactive decision-making. This framework used a discrete event simulation (DES) model of mine operations that worked with a goal-programming based mine operational optimization tool to develop an uncertainty short-term schedule. This framework helped the planner to make a good decision to gain the mine operational and short-term objectives. Upadhyay, Tabesh, Badiozamani, and Askari-Nasab (2019) presented a simulation-based optimization framework to approximate the efficiency of truck-shovel system for open-pit mine in Alberta. Historical data were used to fit probability distributions for haulage cycle components and mine road network and long-term production schedule were the main inputs to the model. The developed model was sufficiently validated through implementing it on a real case. Ozdemir and Kumral (2019) provided a dual-level dispatch system to maximize the efficiency of the truck-shovel system. Shishvan and Benndorf (2019) discussed a matter of dispatching materials in a coalmine by involving a combination of simulation and solution to a transport problem. In Moniri-Morad, Pourgol, Aghababaei, and Sattarvand (2019), the truck allocation problem is analyzed using the simulation-based optimization. The Proposed model provides an integrated simultaneous structure between optimization and discrete-event simulation that could identify the bottleneck process. Minimizing the total number of trucks is considered as the objective function. Akhtari and Sowlati (2020), proposed the integrated hybrid model based on the optimization-simulation approach. The hybrid model is applied in Canada. The results show that the proposed model could affect the long-term investment decision.

Considering the review of the theoretical sources in the literature, the planning of hauling in the mine can be categorized into a probable planning category. In this case, given that it is very difficult to express the flow details in the actual mine in the problem, it is necessary to construct a system simulation model including decision variables for problem solving. In addition, in previous studies, the simulation-based optimization using the meta-model is not considered. Therefore, it is necessary to provide a simulation-based optimization framework to measure the hauling performance in the mine using surrogate model.

3. Case Study

Details of copper mining are described in this section.

3.1. Sarcheshmeh copper mine complex

Sarcheshmeh copper mine complex is located in Kerman province in the southwest of Iran. Sarcheshmeh has a big open mine, and it is considered the second largest copper mine in the world. The mine is located 65 kilometers southwest of Kerman city and 50 kilometers south of Rafsanjan city. The average altitude of the area is about 2600 meters; the highest point is about 3000 meters. In this mine, geology and canalization departments form the primary part of the ore extraction process, which consists of digging and excavation data collection, data analysis, and information updating related to the results of data processing provided to the engineering department to develop the excavation plans. In this section, mid-term plans are designed. The operational department is responsible for implementing excavation plans of the planning department. After excavation, the type of extracted minerals should be specified. In general, we classified the extracted minerals in four categories, namely sulfide ore with a copper grade of more than 0.7%, oxide ore with a copper grade between 0.25% and 0.7%, Low-grade ore with a copper grade between 0.15% and 0.25% and Waste with a copper grade of less than 0.15%. The ratio of extraction of various types of ores in this mine is 45%, 5%, 44%, and 6%, respectively. Based on the various types of ore, a transfer and storing ores strategy is selected for extractive ores. The first type of mineral is sulfide ore, which is first transported to a crusher station after loading. In this mine, there is a crusher machine with a capacity of 60,000 tons per day. Subsequently, the material is transported to a copper storage with 150,000 tons capacity. After harping, the substance is stored in a soft copper storage. Oxide ores, Low-grade ores, and wastes are transported to their dumping site. The conceptual model of the material handling system in the Sarcheshmeh copper mine is shown in Figure 2. In addition, the operating cost of each hour of Shovels is shown in Table 1, where U_i is the highest acceptable level for shovels, and L_i is the lowest acceptable level for shovels. Furthermore, current number columns represent the current number of shovels used in the mineral complex, and cost columns represent the hourly cost of each shovel. Sarcheshmeh copper mine complex management has considered limitations to maximize the amount of production and income mining as (1) the number of available shovels is limited, (2) the amount of sulfide ore loaded from extraction sources should be based on mine capacity, (3) the amount of sulfide ore, oxide, low grade, and extracted wastes should be based on the present demand, and (4) the total cost of present loading in the mine, which includes the costs of loading materials into trucks with shovels, should be minimized.

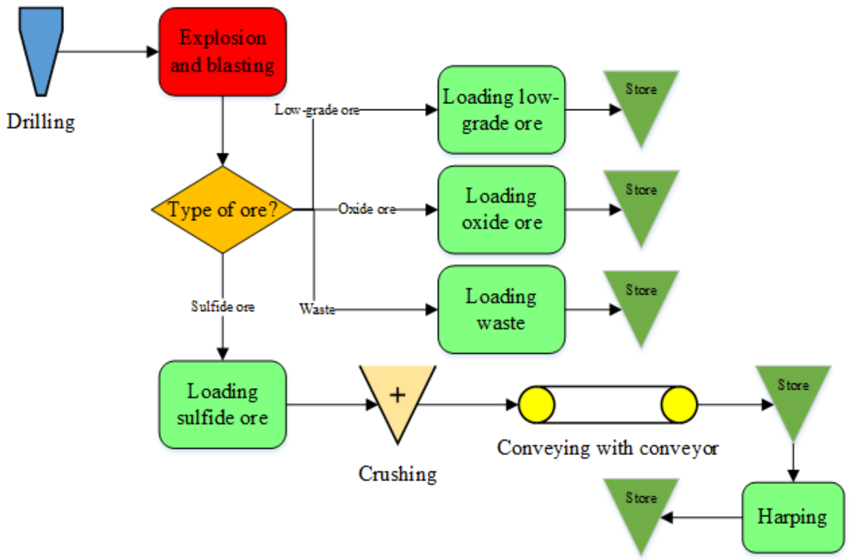

Fig. 2. The conceptual model in the Sarcheshmeh copper mining complex

Table 1. The specifications for the equipment needed for the truck to be moved (Eskandari et al., 2013)

Shovel types	U_i	L_i	Current numbers	Cost ($)
Shovel 1-4m^3	11	9	10	45
Shovel 2-9.5m^3	9	7	8	69
Shovel 3-15.5m^3	9	7	8	67
Shovel 4-17m^3	2	1	1	118

3.2. Symbolization

Table 2 indicates the symbols used for the variables and parameters used in the developed model.

Table 2. Symbols

Variables	Variables Descriptions
TP	Total productions (tons)
X_i	Number of shovel types $\boldsymbol{i}$, $\boldsymbol{i = 1, 2, 3, 4}$
TC_i	Total crusher input (tons)
S_{out}	Sulfide ore output (tons)
O_{out}	Oxide ore output (tons)
L_{out}	Low-grade ore output (tons)
W_{out}	Wastes output (tons)
Parameters	**Parameters Description**
C_i	Cost of shovel $\boldsymbol{i}$ ($), $\boldsymbol{i = 1, 2, 3, 4}$
B	Available budget ($)
C_c	Maximum crusher capacity (ton)
L_s, U_s	Minimum and maximum amount of sulfide Ore that can be excavated, respectively (tons)
L_o, U_o	Minimum and maximum amount of oxide ore that can be excavated, respectively (tons)
L_l, U_l	Minimum and maximum amount of low-grade ore that can be excavated, respectively (tons)
L_w, U_w	Minimum and maximum amount of wastes that can be excavated, respectively (tons)
Other factors	**Parameter Description**
Upper mine plan	Maximum amount of ore types that can be excavated
Lower mine plan	Minimum amount of ore types that can be excavated

4. Two-phase Simulation-Based Optimization Framework

Two-phase simulation-based optimization framework is described in this section to increase the revenue of the mine in each shift. In the first phase, the optimum production control of the current situation in the mine is presented. In addition, the value of near-optimum controlled variables in the simulation model is calculated based on the available demand and integrated capacity. Solving problem determines the value of decision variables in the limited capacity of the crushing station. The decision variables are the value of sulfide, oxide, low-grade, and waste ore production and the total crusher input. Figure 3 shows the first phase architecture.

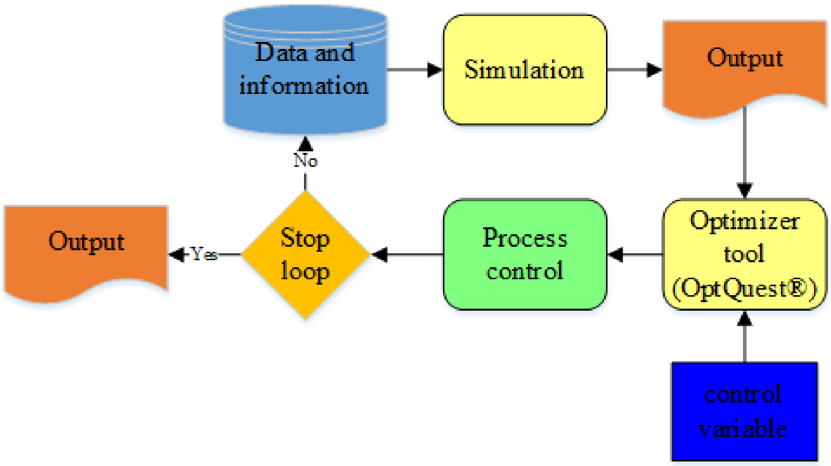

Fig. 3. First phase simulation-based optimization structure

After determining the optimal values obtained from first phase, the optimal production plan is set for the system. Then, in the second phase, a surrogate model based on the meta-modeling approach is developed to define the deterministic function. A meta-modeling optimization flowchart is shown in Figure 4. According to Barton and Meckesheimer (2006), a meta-modeling optimization has the following key elements.

Identifying a meta-model form: The identification of the meta-model form for the estimation of functions is carried out randomly or due to its popularity in the area with which the problem is associated (Chugh, Sindhya, Hsksnen, & Miettinen, 2019).

Designing the experiment: the meta-model form determines the design of the simulation experiment, which in turn determines the input combination of the simulation model (Kleijnen, 2016).

Fitting the meta-model and validation: First, we should run the simulation model to determine the response for fitting the meta-model. Second, from the data we obtain the approximate for the parameter value of the meta-model (e.g., least square estimate). Then we evaluate these estimates using mathematical and statistical criteria. Next, we should determine the meta-model validity measures with respect to the simulation model, first for the validity data set and then for the data set used for fitting the meta-model (Kleijnen & Sargent, 1997).

Optimization: there are many mathematical techniques for optimizing the decision variables of functions such as simplex, genetic algorithm, simulated annealing, and Tabu search.

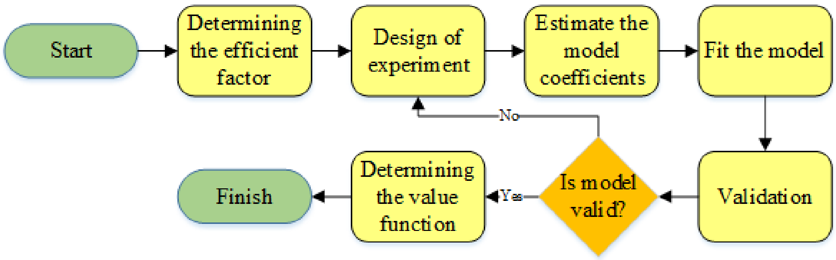

Fig. 4. Meta-modeling optimization structure

4.1. Simulation-Based Optimization in the First Phase

In this section, we discuss the optimization of production at Sarcheshmeh copper mine complex to increase revenue of the mine in each shift. For this purpose, the OptQuest optimization tool available in the Arena software was used at the first phase of the proposed framework. OptQuest is an innovative way to search for an optimized strategy that performs searches by estimating the output of the simulation model. OptQuest tool uses intelligent search methods such as scatter search, Tabu search, and neural network. Scatter search is the main search strategy and is applied to create a set of initial solutions and the best subset vectors to be the reference solutions. Then, the algorithm forms the linear combination of subsets of current reference points and creates new points. Next, the scatter search chooses a combination of the best solutions. Scatter search uses them as initial points, and the iterative process ends after a stopping criterion is met. Tabu search uses adaptive memory to prevent the search from reinvestigating solutions that have already been evaluated. Neural network is used to screen out non-dominated solutions and to function as a prediction model to approximate the objective function (Eskandari et al., 2011). Therefore, OptQuest provides a potential solution to the model developed in the Arena software. OptQuest carefully analyzes the simulation results and provides a potential new solution through the clever search that it performs (Afrapoli & Askari-Nasab, 2019). To use OptQuest, we should first define the structure of the optimization problem. In other words, the decision variables and the target function should be defined to increase the value of monthly production based on the plans and capacity of the mine by determining the optimal value for the decision-making variables in the extraction process at the Sarcheshmeh copper mine complex. In fact, more revenue can be obtained through more production. For this purpose, upper and lower limits of the decision variables are placed in OptQuest as predetermined parameters. In Table 3, these values are shown. Also, the general structure of the planning problem which is presented in Equations (1-7) is shown to maximize the monthly production of an integrated OptQuest product.

$$MaxTP = Total\,\mathrm{Pr}oduction \tag{1}$$

$$s.t \quad \sum_{i=1}^{4} \mathrm{Tc}_i \leq C_c \tag{2}$$

$$L_s \leq S_{out} \leq U_s \tag{3}$$

$$L_o \leq O_{out} \leq U_o \tag{4}$$

$$L_l \leq L_{out} \leq U_l \tag{5}$$

$$L_w \leq W_{out} \leq U_w \tag{6}$$

$$\mathrm{Tc}_i,\, S_{out},\, O_{out},\, L_{out},\, W_{out} \geq 0 \tag{7}$$

Table 3. Predetermined parameters in OptQuest optimization

Parameter	Upper mine plan	Lower mine plan	Unit
crusher capacity	60000	0	Tons
sulfide ore output	35000	20000	Tons
oxide ore output	20000	15000	Tons
low-grade ore output	3500	3000	Tons
wastes output	1500	0	Tons

Applying the specified settings and defining the problem, the model was implemented in OptQuest. The best simulation value in replication round 85 was obtained from among the 25 possible solutions that can be found in a set of defined equations. In this replication round, the production was 57799 tons, the low-grade ore was 3043 tons, oxide ore was 15336 tons, sulfide ore was 31254 tons, and the waste was 1196 tons. In addition, the amount of the optimum input to the crusher station was 57897 tons. The details of other solutions obtained in the problem are shown in Appendix A. All the values in Appendix A are rounded up. Figure 5 shows the total production per replication of the simulation.

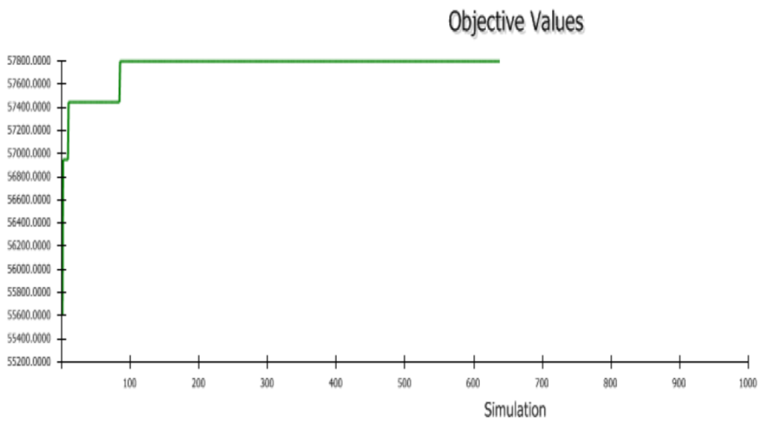

Fig. 5. Total production of the system in each replication of simulation

Table 4 indicates a comparison between the current and optimal production situations. Further, the optimal situation is balanced against the current situation. According to the obtained combination, the output increases by 10000 tons, which indicates a 21% increase in the revenues. Total revenue is calculated by multiplying the per ton price in total production. Copper per ton price is 6000 dollars[1].

Table 4. A comparison between the current and optimal production status

Status	Variables					TP	Total revenue ($)
	L_{out}	O_{out}	S_{out}	W_{out}	Tc_{in}		
Current	17422	6094	15121	9019	35000	47703	286218000
Optimum	3043	15336	31254	1196	57897	57799	346794000

4.2. Simulation-based optimization using meta-model at the second phase

A simulation model is an alternative for the real system, which is defined for a subset of input variables, and the simulation model response as a function of this subset. A meta-model is an abstract model of the subset of simulation input variables that can describe the real system function. In this paper, the construction of a meta-model was performed based on the mathematical method (Madu, 1990). The simulation model was made to determine the system outputs to get the variable response for different scenarios. The four factors are as follows:

X_1: Number of shovels type 1,
X_2: Number of shovels type 2,
X_3: Number of shovels type 3,
X_4: Number of shovels type 4,

The acceptable bounds for variables were $9 \leq X_1 \leq 11$، $7 \leq X_2 \leq 9$، $7 \leq X_3 \leq 9$ and $1 \leq X_4 \leq 2$. These factors were independent variables which were used as input variables in the simulation model to construct the amount of production as the dependent variable. All of the possible combinations of four independent variables and their output results were aggregated $3 \times 3 \times 3 \times 2 = 54$ and used to fit the meta-model. However, it takes a lot of time to collect such amount of data to estimate the regression equation, especially when the number of factors

1. https://www.tgju.org/basemetal

is high. Madu (1990) and Kleijnen and Standridge (1988) used a full factorial design to provide a valid meta-model overnight. The full factorial is a design of experiment consisted of two factors for each one, and since the response of such a design needs a $2{\times}2{\times}\ldots{\times}2 = 2^k$ experiment, it is called 2^{k}. When, there are k factors in an operation, this design needs the least number of runs. The level of each factor can be quantitative or qualitative. In this study, this design required 16 combinations, in which only the upper and lower bounds of each factor were used in the simulation for data gathering. First, the validation was done by comparing the simulation results and the data obtained from the actual system through the simulation model t-test (Dengiz, Bektas, & Ultanir, 2006). The confidence intervals of the simulation results can be calculated at 95% confidence level. These confidence intervals are used to compare the simulation model results with the data obtained from the actual system. In order to estimate the number of replications, the average half-width of each confidence interval for all replications is calculated by trial-and-error approach until that it is less than 5% of the average mean, and the length of running time of the simulation model is smooth (Zeinali et al., 2015). Therefore, each combination of factors was performed 10 times for 30 days to ensure that the accuracy of the error in estimating the average production rate was less than 0.05. In addition, the warm-up period was set for the simulation run to omit any bias at the process. To measure warm-up period steady-state analysis is necessary. To analyze the steady state of system performance, the batch mean method was used. According to this method, a single sufficiently long run was determined from the plots of performance measure and their correlogram across the simulation for various lags using the results of Analyzer of ARENA software. Dengiz and belgin's (2014) steady-state analysis indicates that the warm-up period of system is 4 days, which should be considered in the settings of the simulation model. A full factorial design based on two levels, four variables, and 10 replicates are shown in the design of experiment table in Appendix B. Furthermore, the main effects of the four factors, as well as the interaction between the factors in the regression model are shown in Equation (8).

$$TP = \beta_0 \sum \beta_i X_i + \sum\sum \beta_{ij} X_{ij} + \sum\sum\sum \beta_{ijk} X_{ijk} + \beta_{1234} X_1 X_2 X_3 X_4 + \varepsilon \tag{8}$$

Where TP is total production, β_0 is the constant value of the regression meta-model, β_i is the main effect of factors coefficient, β_{ij} is two factor interaction coefficient, β_{ijk} is three factor interaction coefficient, β_{1234} is four factor interaction coefficient, and ε is partial error at the regression model. The simulation results for $2^4 = 16$ is the compiled design point (see Appendix B), and the coefficients of β are estimated for the regression meta-model. The results of the experiment were statistically analyzed using the DX software, and are shown in Table. 5.

Table 5. Statistical analysis of regression meta-model

Sentence	Effect	Coefficient	Value F	P-values
Constant	47898	39382.25	5.52	0.01
X_1	-327.94	-1640.25	11.96	0.01
X_2	-44.69	2331.81	0.22	0.65
X_3	33.56	827.37	0.12	0.73
X_4	-185.94	8055.37	3.75	0.09
X_1X_3	240.19	240.19	6.25	0.04
X_1X_4	-203.06	-406.12	4.47	0.05
X_2X_3	-297.06	-297.06	9.57	0.01
X_3X_4	-273.06	-546.12	8.08	0.02

The first column in Table 5 indicates the main effects and all of the significant interactions. In the second column, the potential effect of sentences is shown. In addition, the effects coefficients are shown in the third column, and the probability values and P-values are shown in the last two columns, respectively. According to the results shown in Table 5, the statistical value obtained for the model is 5.52, which indicates that the model is significant. In fact, according to the F-values, only 1.82% of the model may be disturbed within the defined range. The P-values of the sentences under 0.05 in Table 5 are meaningful, and the P-values of the sentences greater than 0.1 indicates that the sentence is not meaningful. Although X_2 and X_3 are not meaningful, we used them for analysis in the model, because these variables are the system decision variables and we intended to calculate their optimal value in the future. The results of Auto-Select regression model in DX software fits the polynomial regression model as Equation (9).

$$TP = 39382.25 - 1640.25X_1 + 2331.81X_2 + 827.3X_3 + 8055.37X_4 + 240.19X_1X_3 - 406.12X_1X_4 - 297.06X_2X_3 - 546.12X_3X_4 \quad (9)$$

The statistical P-value for a meaningful model was set as 0.01. In the regression model, the interaction effects indicate the simultaneous effect of the corresponding variations of decision variables on the response level. The meta-model presented in Equation (9) is made using the real-world simulation model as evaluated in this paper. By clarifying this equation, we can obtain the best possible combination of the decision variables through optimizing the model under management constraints after its validation.

4.3. Meta-model validation

The simulation model validity shows how the model can reflect the behavior of the real system. The meta-model validity is accomplished through many methods that compare meta-model output and simulation output. In this paper, the Absolute Relative Error (ARE) method, $\mathrm{ARE}(\mathrm{SO}, \mathrm{MO}) = |(SO - \mathrm{MO})|/SO$, was used to accept the meta-model, in which SO is the simulation output and MO is a meta-model output (Madu, 1990). In order to ensure the validity of the meta-model, it is necessary for the meta-model and simulation model in the other five design points-other than the points of the design – to be executed randomly within the acceptable range, and then the results obtained from the simulation run are compared with the values obtained from the meta-model.

Table 6. Meta-model validation model

$\mathbf{X_1}$	$\mathbf{X_2}$	$\mathbf{X_3}$	$\mathbf{X_4}$	MO	SO	ARE
10	8	8	1	48081	47656 ± 329	0.008
9	8	7	2	48717	47433 ± 502	0.02
11	9	8	1	47912	48600 ± 427	0.01
10	7	8	2	47751	49201 ± 556	0.02
9	7	8	1	48251	49045 ± 484	0.01

The first four columns in Table 6 represent the random points selected for the factorsX_1, X_2, X_3, and X_4, respectively. The two other columns represent the values obtained from the meta-model and the simulation model. Subsequently, the absolute value of the relative error is calculated in the last column. The average ARE for meta-modeling is 1.3%. Therefore, the meta-model can determine well the values close to the optimal decision variables. Therefore, Equation (9) can be used in managerial decision-making. In future, the optimal combination of loading machines can be determined for the problem by imposing technological constraints.

4.4. Loading hauling problem

The optimal combination of loading machines to maximize the amount of cargo loaded by shovels on the trucks as well as the reduction of current transportation equipment costs based on management constraints and decision variables are done via the following equations (10-13)

$$\begin{aligned} TP = {} & 39382.25 - 1640.25X_1 + 2331.81X_2 + 827.3X_3 + 8055.37X_4 + \\ & 240.19X_1X_3 - 406.12X_1X_4 - 297.06X_2X_3 - 546.12X_3X_4 \end{aligned} \tag{10}$$

$$s.t \qquad \sum_{i=1}^{4} C_i X_i \leq B \tag{11}$$

$$L_i \leq X_i \leq U_i \qquad i = 1,2,3,4 \tag{12}$$

$$X_i \;\; integer \qquad i = 1,2,3,4 \tag{13}$$

Equation (10) demonstrates the target function that is determined based on the preceding steps. Equation (11) shows the highest cost for loading the ores by shovels, which guarantees that it does not exceed the cost of loading machinery from the budget level. In Equations (12), we consider the range defined for shovels. The problem obtained from equations (10-13) can be considered as the maximum total production loading machinery on trucks while the budget does not exceed the value of $\boldsymbol{B}$. In this case, the problem of the bi-objective optimization in equations (14-16) is as follows.

$$\max TP \tag{14}$$

$$\min \sum_{i=1}^{4} C_i X_i \tag{15}$$

$$s.t \qquad x \in X \tag{16}$$

Where $X = \{x \in R^4 | L_i \leq x_i \leq L_i, x_i \geq 0\ , i = 1,2,3,4\}$ is written in the equations (14-16) considering the upper bound B on the second objective function via the ε-constraint method. The ε-constraint method was used to solve this bi-objective problem. The ε-constraint method in this study was considered according to the stance of Pirouz and khorram (2016). Their method has two main advantages. One of the advantages of this method is its reduction of the search space to find the non-dominated points. Another advantage of this method is its shorter run time in comparison with original method. According to this method, we first solve the single-objective optimization problem for each goal. Next, we determine the step length. Then, we generate the suitable sets of the points, and finally we will solve the single-objective optimization and estimate the Pareto frontier. The structure of the function of the total cost of the loading machinery is shown as $C_T = \sum_{i=1}^{4} C_i X_i$. The cost function is considered as $C_1X_1 + C_2X_2 + C_3X_3 + C_4X_4$ in the model, where loading machinery at the Sarcheshmeh copper mine complex should be improved or maintained by determining the optimal value of the loading machinery.

The non-linear integer programming model is solved using the LINGO software, and the optimal combination of the loading machinery is obtained $X_1^* = 9, X_2^* = 8, X_3^* = 7, X_4^* = 2$. Furthermore, the meta-model value for the optimum combination $TP(X_1^*, X_2^*, X_3^*, X_4^*)$ is 48210 tons, which indicates an increase in the production from 47703 tons to 48210 tons.

5. Conclusions

Mining operations can be profitable by improving the configuration of the haulage system in a mine that has quite high operating costs. The purpose of this paper was to achieve the optimal production level through an efficient allocation of shovels. However, the problem was quite complex, because the mine had uncertain parameters (e.g. the loading time of the shovels). This paper considered the use of simulation-based optimization with OptQuest tool, the design of the experiment, a regression model, and a simulation model to evaluate the behavior of a real case and to identify the interaction between variables. This study presented a two-phase stage simulation-based optimization in a copper mine complex with the problem of determining the total production quantity and the optimum number of shovels to reach total production through meta-modeling. The purpose of the research project was to maximize total production in each shift of work by determining the optimal production plan for the types of integrated minerals at the first phase and solving the problem of the loading machinery to determine the number of shovels at the second phase. To this end, a simulation model that was described by (Eskandari, Darabi & Hosseinzadeh, 2013) in the ARENA software was applied. The OptQuest tool was used to solve the first phase problems and determine the optimal amount of minerals in the complex. In the second phase, using meta-modeling and design of experiment, a decision-making support system was designed based on an integrated simulation-optimization procedure to evaluate the performance of the mine's current situation in order to estimate the explicit form of the total production objective function. A near-optimum solution was obtained through the regression model that was able to estimate the optimal level of production. As a result, with the feasible configuration of the decision variables, the total production in the mine increased by 21%. Future studies are recommended to study a vehicle routing problem optimization in an open pit mine or to develop an evolutionary algorithm to multi-objective optimization for the second phase. Also, this method can be used for modeling in other sectors.

Acknowledgment

The authors would like to make special thanks to the two anonymous reviewers for their careful reading of our manuscript and their relevant and useful comments that helped us improve the paper.

Table of the best solutions

Simulation	Status	TP	L_{out}	O_{out}	S_{out}	W_{out}	Tc_{in}	X_1	X_2	X_3	X_4
85	Feasible	57799	3043	15336	31254	1196	57897	9	8	8	1
119	Feasible	57799	3043	15336	31254	1488	57897	9	8	8	1
147	Feasible	57799	3043	15336	31254	1465	57897	9	8	8	1
149	Feasible	57799	3043	15336	31254	1276	57897	9	8	8	1
150	Feasible	57799	3043	15336	31254	1500	57897	9	8	8	1
161	Feasible	57799	3043	15336	31254	1451	57897	9	8	8	1
162	Feasible	57799	3043	15336	31254	1308	57897	9	8	8	1
163	Feasible	57799	3043	15336	31254	1479	57897	9	8	8	1
164	Feasible	57799	3043	15336	31254	1496	57897	9	8	8	1
165	Feasible	57799	3043	15336	31254	2357	57897	9	8	8	1
166	Feasible	57799	3043	15336	31254	1298	57897	9	8	8	1
167	Feasible	57799	3043	15336	31254	1320	57897	9	8	8	1
168	Feasible	57799	3043	15336	31254	1270	57897	9	8	8	1
169	Feasible	57799	3043	15336	31254	1473	57897	9	8	8	1
170	Feasible	57799	3043	15336	31254	1401	57897	9	8	8	1
172	Feasible	57799	3043	15336	31254	1385	57897	9	8	8	1
183	Feasible	57799	3088	15336	30070	1364	53637	9	8	8	1
184	Feasible	57799	3016	15336	33483	1500	60000	9	8	8	1
185	Feasible	57799	3000	15330	35000	1500	60000	9	8	8	1
189	Feasible	57799	3021	15334	32725	1500	60000	9	8	8	1
214	Feasible	57799	3016	15333	33479	1500	60000	9	8	8	1
215	Feasible	57799	3023	15335	32321	1500	60000	9	8	8	1
216	Feasible	57799	3028	15335	31674	1500	60000	9	8	8	1
217	Feasible	57799	3004	15331	34592	1500	60000	9	8	8	1
218	Feasible	57799	3000	15330	32725	1500	60000	9	8	8	1

Design of experiments

Run	Factors				Replications (R_i)										$\overline{R_i}$
	X_1	X_2	X_3	X_4	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}	
1	9	9	9	2	47394±6038	46225±1750	47567±1493	47732±1055	48088±847	48135±709	47638±417	47643±364	47656±329	47630±295	47571
2	9	9	9	1	48282±3269	47861±1213	47509±886	47610±611	47899±574	48014±632	47975±586	47816±520	47543±497	47389±453	47786
3	11	9	7	2	47345±3796	47497±1773	47681±1124	47813±883	47507±735	47480±595	47435±523	47704±461	47774±407	48040±401	47628
4	11	7	7	1	48434±3546	46432±2282	47129±1362	47325±1027	47007±957	47056±805	47095±678	47285±596	47211±539	47181±531	47215
5	9	9	7	1	49022±4826	48978±1595	48055±1152	48206±804	48732±723	48917±647	48857±573	48883±504	48811±460	48578±449	48703
6	11	9	9	1	49830±8915	47671±3006	48277±1648	48138±1123	48598±910	48864±764	48833±662	48877±599	48907±533	48776±535	48678
7	9	7	7	1	48328±5494	47340±1593	48012±1017	47806±745	47446±754	47456±641	47841±588	47933±515	48310±549	48408±497	47888
8	11	9	9	2	44801±4958	45473±2160	46500±1464	45879±1091	46636±985	46957±818	46421±758	46660±991	46927±638	47007±587	46326
9	11	7	9	1	48486±2940	48231±899	48598±622	49101±575	48669±730	48566±630	48668±596	48568±553	48710±495	48804±453	48640
10	9	7	7	2	50104±1971	49522±935	48764±1209	48351±987	47920±903	47472±792	47661±676	47822±589	47817±521	47645±484	48308
11	9	7	9	1	49358±2748	49176±674	48584±406	47921±703	48170±592	48287±496	48292±426	48170±381	48441±373	48273±356	48460
12	9	7	9	2	47604±4239	47211±1050	48049±1265	48459±930	48357±715	48700±615	48775±514	48574±489	48344±459	48548±427	48262
13	11	9	7	1	47502±6113	47865±1676	47808±1105	47104±925	46848±779	47060±726	47268±634	47113±566	47233±591	47245±530	47305
14	11	9	7	2	47396±5976	47674±1944	48411±1184	47900±986	47834±788	47854±718	45397±702	48283±614	48218±558	48367±507	47733
15	11	7	7	2	48205±8985	46470±2618	46353±1531	46157±1212	46557±965	46965±851	47552±818	47801±728	47679±656	47654±595	47039
16	9	9	7	2	48353±2084	49041±1600	48681±902	48992±1538	49029±650	48943±725	48880±695	48914±621	48728±566	48758±531	48833

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