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Simulation-Based on Multi-Objective Optimization in Complex System: A Meta-Modeling Approach

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Abstract

This research investigates simulation-based Multi-Objective Optimization (MOO) in complex systems. The main goal of this research is to develop a metamodeling approach that can simultaneously simulate multiple conflicting objectives in complex systems. This research seeks to identify and analyze the challenges in optimizing complex systems and provide solutions to improve the performance and efficiency of these systems. By using meta models, an attempt is made to reduce computational time and increase the accuracy of optimization results.

In this paper, MOO in the mining system of a copper mining complex is presented using the NBI optimization method and regression meta model. For this purpose, two objective functions are considered: maximizing the total extraction amount, which includes the sum of sulfide, oxide, low-grade ore and waste extractions in the mine, and minimizing the transportation travel time, subject to the constraints of storage capacity, transportation equipment and budget. The Central Composite Design (CCD) method is used to construct the Design of Experiments (DOE) for the design variables.

Firstly, the design variables include the number of 120-ton, 240-ton, 35-ton and 100-ton trucks are considered. The amount of objectives in each design combination is considered as the response surface. The appropriate meta model to maximize the total extraction rate and minimize the transportation travel time, two modified nonlinear regression functions are determined. The accuracy of the models for selection is examined using PRESS and R^2 statistics. Also, the most common PRESS error is used to validate the meta models. Then, the MOO problem is solved using the modified NBI method. Finally, the Pareto solutions using this approach are presented and discussed.

This study investigates simulation-based MOO in complex systems and develops a metamodeling approach. The results show that the use of meta models can significantly reduce computational time and increase the accuracy of optimization results. By simulating multiple conflicting objectives simultaneously, this study identifies and analyzes the challenges in optimizing complex systems and provides effective solutions to improve the performance of these systems. In addition, the models developed in this study can help in optimal decision-making in various engineering and management fields and can be used as an efficient tool in solving complex problems. Ultimately, this study will not only contribute to a better understanding of optimization processes in complex systems, but will also pave the way for future research in this area.

Keywords: Meta model, Modified NBI method, Multi-objective optimization, Design of experiment, Central composite design, Simulation.

1 | Introduction

Mines have long been recognized as one of the most expensive and complex industries, with numerous studies focusing on various aspects such as geology, drilling planning, and operational processes [1]. Effective exploitation of mines is crucial for economic growth, as each ton of copper ore can be valued at nearly

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$100,000 [2]. However, the presence of uncertain parameters complicates traditional modeling techniques. Simulation models serve as powerful tools for creating flexible models without many assumptions, increasingly used to enhance system performance in a competitive market [3], [4]. Multi-Objective Optimization (MOO), which involves evaluating multiple objectives, is common in engineering design but requires extensive simulation runs, each demanding significant computation time [5]. Despite this, the investment in computational time is justified for finding optimal solutions [6], [7]. Although research on simulation-based MOO is limited, various studies have demonstrated its effectiveness using evolutionary algorithms to improve manufacturing processes, personnel planning, and machining operations [5]. Meta-models, which establish relationships between input variables and responses, are essential for optimizing complex models [8], [9]. Different meta-modeling techniques, such as Response Surface Methodology (RSM) and artificial neural networks, have been developed, but no single method has proven superior [10], [11]. Simulation-based optimization is categorized into common optimization and hierarchical optimization, each addressing different levels of complexity in problem-solving [12]. Recent studies have shown promising results in increasing productivity and efficiency in various applications, including mining and manufacturing, through simulation-based approaches [13–15]. Meta-models establish relationships between input variables and response levels to forecast simulation calculations [13]. These are mathematical estimation models designed for simulation purposes [5]. Various meta-modeling techniques, including RSM, Kriging, and artificial neural networks, have been developed to tackle optimization problems [16–18]. While studies have compared surrogate models based on accuracy, efficiency, and stability, no single method has emerged as superior, with the choice of meta-model often being arbitrary [19]. Typically, low-order polynomials are employed in related studies, where unknown coefficients are determined by minimizing residual errors between fitted values and the objective function [20]. The response surface method, a collection of statistical and mathematical techniques, optimizes probabilistic functions like simulation models and has gained traction in engineering for product design and development [12], [21].

Therefore, the tendency to use meta models in MOO is very important. Because, in engineering problems, generally more than one goal is considered, and considering that the goal functions conflict with each other, there is no optimal solution for them, but instead, a set called Pareto solutions. It seems that MOO based on a meta model is an effective approach both in MOO and in the design of complex products, whose main goal is to determine a suitable functional relationship between input and output in the system. Therefore, in this paper, for the simulation-based optimization framework, an estimated function is substituted for the complex simulation model.

In the following, the paper is organized as follows. In Section 2, presented literature review for identification research gap. In Section 3, the definitions, concepts, and details of the modified NBI MOO method are simulation model, formulated problem structure and the meta modeling method are explained. Statistical analysis, optimization of the mathematical model, and the comparison of the obtained results are presented in Section 4. Finally, Section 5 contains conclusions and some suggestions for future research studies.

2 | Literature Review

MOO is a compelling area of research within optimization methods, particularly regarding the application of interactive techniques. However, there has been limited research in the literature focusing on MOO through the simulation of interactive algorithms, despite the prevalence of various evolutionary algorithms. For instance, Syberfeldt et al. [14] introduced an evolutionary algorithm-based approach for simulation-driven MOO aimed at enhancing cell manufacturing at VOLVO in Sweden. Their findings indicated that utilizing simulation alongside evolutionary algorithms could boost cell usage and minimize delays. In another study, Syberfeldt et al. [22] explored simulation-based MOO for the personnel planning system at the Swedish post office, aiming to establish optimal work schedules that reduce working hours and administrative burdens, employing the NSGA-II algorithm for this purpose. The results demonstrated the algorithm's ease of implementation in optimization tasks. Moussavi et al. [23] tackled an integer multi-objective programming challenge to create an ergonomic work cycle within a truck assembly production system, focusing on balancing worker workloads and shortening production cycle times. Their model, developed using Goal Programming and solved with the Gurobi algorithm, proved effective in achieving both objectives. Amouzgar et al. [13] presented a robust framework for MOO in metal cutting machining processes, targeting the minimization of tool-chip temperature and wear depth while maximizing the removal rate. Their study employed knowledge discovery and data weighting techniques to analyze non-dominated solutions through data mining, enhancing understanding of the metal cutting process. Das and Pratihar [24] proposed a method to improve the accuracy of solutions derived from MOO evaluation algorithms. This involved obtaining a set of Pareto points through a weighted multi-objective evaluation algorithm, which was then utilized in a neural system to derive modified Pareto solutions, providing valuable insights for engineering analysis. Karmellos and Mavrotas [25] compared MOO frameworks for designing energy distribution systems under uncertainty, presenting two models to identify areas needing heating, cooling, and electricity while considering uncertain factors like energy prices and demand. Russell and Taghipour [26] introduced a novel solution method using MOO to address complex scheduling issues in low-volume production systems, modeling scheduling problems through integer multi-objective linear programming. Their models were validated in a real-world aerospace industry case study, confirming their reliability. Zhang et al. [27] applied MOO to determine concrete mix ratios under nonlinear constraints, proposing a machine learning-based optimization method using metaheuristic algorithms, which serves as a design guide for decision-making prior to construction. One effective strategy for rapid and precise estimation of complex and costly models is the simulation of meta-models or surrogate models.

Despite the growing interest in simulation-based MOO within complex systems, several research gaps remain unaddressed:

Limited integration of meta-modeling techniques: while meta-modeling approaches such as RSM, Kriging, and artificial neural networks have been explored, there is a lack of comprehensive studies that systematically compare these techniques in the context of simulation-based MOO. Further research is needed to identify which meta-modeling methods yield the most accurate and efficient results across various complex systems.

Insufficient exploration of interactive algorithms: although interactive algorithms have shown promise in MOO, there is a scarcity of research focusing on their application within simulation frameworks. Investigating how interactive algorithms can enhance the performance of simulation-based MOO could provide valuable insights and improve decision-making processes in complex systems.

Challenges in handling uncertainty: many existing studies do not adequately address the uncertainties inherent in complex systems. Future research should focus on developing robust meta-modeling techniques that can effectively incorporate and manage uncertainty, thereby improving the reliability of simulation-based MOO outcomes.

Scalability issues: current approaches often struggle with scalability when applied to large-scale complex systems. Research is needed to develop scalable meta-modeling strategies that can efficiently handle high-dimensional design spaces and large datasets without compromising accuracy.

Real-world applications and case studies: there is a need for more empirical studies that apply simulation-based MOO with meta-modeling approaches to real-world complex systems. Such studies would help validate theoretical models and demonstrate practical applications, enhancing the relevance of research findings.

Integration of machine learning techniques: the potential of machine learning to improve meta-modeling and simulation-based MOO remains largely untapped. Future research could explore how machine learning algorithms can be integrated into meta-modeling frameworks to enhance predictive capabilities and optimize performance.

Holistic framework development: a comprehensive framework that combines simulation, MOO, and meta-modeling techniques is lacking. Developing such a framework could facilitate a more systematic approach to tackling complex system challenges and enhance the overall effectiveness of optimization efforts.

By addressing these gaps, future research can contribute significantly to the field of simulation-based MOO, providing valuable tools and methodologies for managing complex systems effectively.

3 | Research Methodology

3.1 | Modified NBI Method

The modified NBI method aims to identify the Pareto frontier in MOO problems, utilizing a two-stage process. The first stage involves applying the modified CHIM instead of the original NBI algorithm, while the second stage manages the iterations to resolve the optimization problem. Normalization of objective functions is crucial, ensuring values range from zero to one, with users able to set upper limits if necessary. The quasi-Newton method is employed to find a relative minimum for the optimization challenges, differing from population-based methods like Genetic Algorithms (GA), which require multiple parameters and often yield inconsistent results. In contrast, the modified NBI method simplifies the process by focusing on a single parameter to generate Pareto points, ensuring consistent outcomes without the need for numerous iterations. The overall algorithm for this modified NBI optimization is also provided.

Input: number of significant digits

Number of initial points

Output: non-dominated set

<u>//Start//</u>

Step 1. Normalize objective functions.

Step 2. Generating Pareto point.

Step 3. Initiate objective function optimization.

Step 4. Accurate Pareto set.

Step 5. Fix objective function values.

Step 6. Remove Pareto dominated points.

Step 7. Optimal stage.

<u>//Finish//</u>

In the first stage, the objective functions are placed between the minimum value of zero and the maximum value of one. Therefore, we determine the objective functions in the interval $[\![0;1]\!]$. This causes the Pareto frontier to be placed inside a bounded box. In the second step, a V_m is selected for each pair in this step to generate the space of Pareto points. In the third step, the first optimization problem with the starting minimum point for $f_1;\ t = 1;\ \beta = 0$ starts. If at the end of optimization $t = 0;\ \beta = 1$, then go to *Step 4*. Because in this case, a Pareto point has been estimated. Otherwise, use $t + V_m$ and $\beta + V_m$ as starting points for the next optimization, and this step is repeated. In the fourth step, if the estimated Pareto set needs more accuracy, a smaller V_m is used to generate more Pareto points and we return to *Step 3*. Otherwise, we go to *Step 5*. In the fifth step, for $N > 2$, we use different values in $[\![0;1]\!]$ in order to construct the values of objective functions to determine the results of multiple objectives. Then we return to *Step 1* and determine the objective functions in the interval $[\![0;1]\!]$. If all combinations are determined, we stop. Otherwise, go to the *Step 6*. In the sixth step, based on the described filter [28], the set of inferior Pareto points is removed from the set of generated Pareto points. In the seventh step, choose a range for V_m for more precision of the generated Pareto set and repeat *Steps 2* to 6 for all V_m values in the range.

3.2 | Meta Modeling Approach

The key components of the proposed framework involve meta model-based optimization [29], which includes determining the structure of the meta model, designing experiments to refine the meta model, conducting simulation experiments, fitting the meta model, and validating its accuracy along with the optimization of the meta model within the problem context. The algorithm for identifying an appropriate meta model is illustrated below. This algorithm has been applied for MOO based on simulation, with the detailed steps provided in the following sections [2].

Objectives, variables and parameters input:

Output: meta model and a non-dominated set.

//Start//

Step1. Simulation model development.

Step 2. Design of experiment.

Step 3. Conduct simulation model experiment.

Step 4. Fit the meta model.

Step 5. Meta model validation.

Step 6. Apply optimization algorithm.

Step 7. Quality of results.

//Finish//

The algorithm begins with the development of a Discrete Event Simulation (DES) model. If the model is validated, the process moves forward; if not, modifications are made to achieve the necessary validity. Next, a suitable DOE is created. In the third step, the scenarios from the previous design are executed in the simulation model to identify the dependent variable. The fourth step involves selecting the optimal meta model and determining its unknown coefficients through statistical analysis. The fifth step assesses whether the constructed meta model can accurately predict system performance. If it lacks validity, adjustments are made either in the DOE or the type of meta model. In the sixth step, management constraints are applied to derive a set of non-dominant solutions for the MOO problem. Finally, the seventh step compares the results with the current situation to evaluate the level of improvement.

4 | Findings

4.1 | Picture of Problem

The Sarcheshmeh open-pit copper mine complex, situated in Kerman province in southeastern Iran, is recognized as the second largest copper deposit globally. It lies 65 kilometers southwest of Kerman city and 50 kilometers south of Rafsanjan, at an average altitude of approximately 2600 meters, with the highest point reaching around 3000 meters. The extracted ores are classified into four categories:

I. Sulfide ore (copper grade over 0.7%).

II. Oxide ore (copper grade between 0.25% and 0.7%).

III. Low-grade ore (copper grade between 0.15% and 0.25%).

IV. Waste (copper grade below 0.15%).

These categories account for 45%, 5%, 44%, and 6% of the total rock volume, respectively. The transportation and storage strategies are determined based on the type of ore. Sulfide ore is sent to a crusher station with a capacity of 60,000 Tons per day, followed by storage in a harp copper facility with a capacity of 150,000 Tons, and subsequently in a soft copper storage. Oxide ore, low-grade ore, and waste are directed to their respective dumping stations. The conceptual model of the haulage system at the Sarcheshmeh copper complex is illustrated in *Fig. 1*.

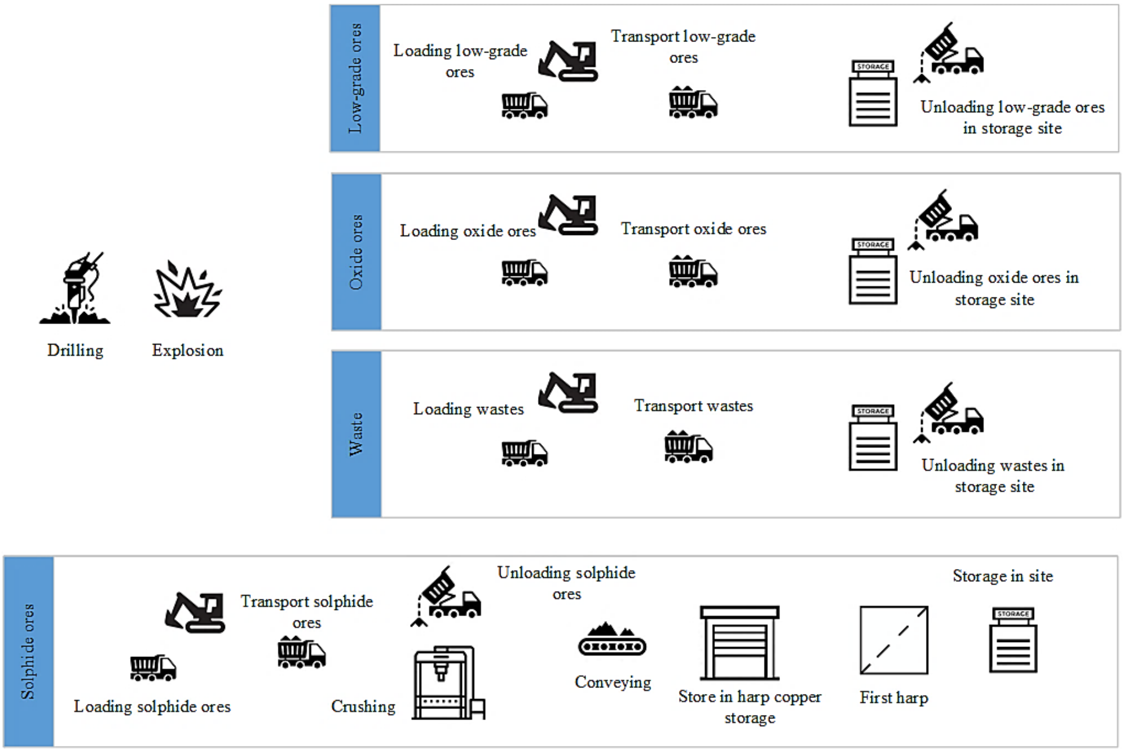

Fig. 1. The conceptual model of haulage system at Sarcheshmeh copper mine.

In order to transport ores, a number of Trucks are assigned to the loading station. The mineral substance is loaded on a truck by a shovel, and when the truck is filled, it is led to a dump. The main purpose of this research is determining the optimal number of haulage system equipment especially number of trucks in order to maximize sulfide ore and maximize loaded ores in the Trucks according to equipment and storage capacity and budget. The key resources in the Sarcheshmeh copper mine are as follow:

I. Truck 120 Tons (X_1).

II. Truck 240 Tons (X_2).

III. Truck 35 Tons (X_3).

IV. Truck 100 Tons (X_4).

Currently Sarcheshmeh open copper mine has nine Trucks 35 Tons, 36 Trucks 100 Tons, 20 Trucks 120 Tons and two Trucks 240 Tons. Trucks which are used to transfer oxide ore and wastes are varied 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 ores. The hourly operating cost of trucks are shown in *Table 1*.

Table 1. Hourly operating cost of trucks (cost unit) [30].

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

4.2|System Discrete Event Simulation Model

This paper examines the use of simulation modeling with Arena software® to analyze the haulage system at the Sarcheshmeh copper open-pit mine, as detailed by Eskandari et al. [30]. The developed model demonstrates no significant discrepancies in results at the 95% confidence level, indicating its accuracy. To execute the model, simulation parameters such as the duration and number of repetitions must be established. The haulage system operates 24 days a month, leading to a repetition length of one month. The number of repetitions is set at 10, based on the half-width of trucks, which is crucial for assessing system performance. A warm-up period is implemented to ensure system stability, with experiments revealing that performance reaches a steady state after four days. *Table 2* presents the lower, upper, and current bounds for truck operations. These configurations are incorporated into the model, which runs on a personal computer with an Intel Core i3 1.8 GHz CPU and 4GB of RAM.

Table 2. Number of trucks combination at each type.

Type	Combination (Lower Bound, Current, Upper Bound)
Truck 120 Tons	(12,20,28)
Truck 240 Tons	(3,4,5)
Truck 35 Tons	(9,15,25)
Truck 100 Tons	(25,36,45)

4.3|Haulage Multi-Objective Planning in the Sarcheshmeh Copper Mine Complex

Based on the previous information, the managers of the Sarcheshmeh copper mine complex tend to optimize the combination of key haulage resources based on two objective functions: maximizing the total extraction amount, which is the sum of the extraction amount of sulfide, oxide, low-grade ores, and waste in this mine, and minimizing the travel time of the haulage. find the relocation according to the storage capacity limit and the haulage and budget considered. The optimization problem is mathematically formulated as follows in *Eq. (1)*.

$$
\begin{aligned}
&\max \mathrm{f}_1\ (\mathrm{X}_1;\mathrm{X}_2;\mathrm{X}_3;\mathrm{X}_4),\\
&\min \mathrm{f}_2\ (\mathrm{X}_1;\mathrm{X}_2;\mathrm{X}_3;\mathrm{X}_4),\\
&\mathrm{s.t.}\\
&\sum_{i=1}^{4} c_i x_i \leq B,\\
&\sum_{i=1}^{4} c_i' x_i \leq C,\\
&L_i \leq x_i \leq U_i, \quad \text{for } i = 1;2;3;4,\\
&x_i \text{ integer.}
\end{aligned}
\tag{1}
$$

Eq. (1) is an integer MOO problem. The functions of this problem do not have an analytical mode and must be evaluated through simulation according to the framework presented in this paper. $c_i$is the cost of each truck. B is the total budget available. c_i' is the capacity of each key resource. C is the total storage capacity in the system. L_i and U_i are respectively the lower and upper bounds of resources in the mine complex.

4.4 | Numerical Results

This paper presents a framework for MOO of extraction rates and travel times for moving equipment in a copper mine using a meta modeling approach. The Central Composite Design (CCD) is employed for sampling and determining objective values. The primary goals are to maximize total extraction, which includes sulfide, oxide, low-grade rocks, and waste, while minimizing travel time for hauling, considering storage capacity, haulage, and budget constraints. The study focuses on key resources such as 120-ton, 240-ton, 35-ton, and 100-ton trucks, excluding other equipment like shovels, as they have minimal impact on the objectives or existing processes. This simplification reduces the design space. The approach begins with designing the operational process of the copper mining complex through a DES model. MOO is achieved using meta model-based simulation and DOE to analyze various scenarios. DOE serves as a valuable mathematical tool for statistical modeling and systematic problem analysis to optimize variables. The initial step in creating a meta model involves selecting input variables and their levels within system constraints, as detailed in *Table 2*.

Table 2. Predetermined parameters of experimental design.

Variable ID	Variable Name	Minimum	Maximum	$-\alpha$	$+\alpha$
X_1	Trucks 120 Tons	12	28	4	36
X_2	Trucks 240 Tons	3	5	2	6
X_3	Trucks 35 Tons	9	25	1	33
X_4	Trucks 100 Tons	25	45	15	55

These variables $(X_1; X_2; X_3;\ X_4)$ are independent variables that are used as the input value of the simulation model to make the dependent variables of the extraction rate of minerals and the duration of moving trucks. Distances $(X_1; X_2; X_3;\ X_4)$ is 17, 5, 21, 21, respectively, which is considered for each combination. By using a pseudo-regression model, instead of $17 \times 5 \times 21 \times 21 = 37485$ combinations for only one objective and 2×37485 for both objectives, all combinations of input variables can be shown. A CCD with 25 experiments for both objective is employed for this purpose. CCD is the most famous design of the response surface method. CCD consists of a two-stage fractional or full factorial design with central points to which several points called non-center points have been added. If the distance of the center of the design to the factorial points is considered to be ± 1 for each variable, the distance of the center of the design to the non-centered points will be $\pm\alpha$ where $|\alpha| > 1$. The reason for using this design is the proper estimation of curvature in the system model. Each combination in this plan is repeated 10 times and the average of each performance is determined as the dependent variable. Then, the best and most qualitative meta model is selected through statistical analysis.

The problem consists of two objectives: maximizing the extraction rate of mineral stones and minimizing the time of moving haulage in the mine. Both goals are calculated using simulation results. Before fitting, we must determine the accuracy of the functions for each objective. Using R^2 and P-Value statistics for candidate meta models, the best prediction function is selected for each of the objectives. The R^2statistic indicates the difference between the experimental and predicted values, the higher the value, the more significant it means that there is no significant difference between these two values. In *Table 4*, the validation of the candidate models for each objective has been examined.

Table 4. Accuracy model of responses for three candidate regression functions.

Response	Function	P-Value	R^2	Status
Total ores production	Linear model	0.0004	0.62	Significant
	Two factor interactions model	0.0249	0.69	Significant
	Modified model	0.0001	0.93	Significant > Selected
Total trucks travel time	Linear model	0.0003	0.63	Significant
	Two factor interactions model	0.0335	0.67	Significant
	Modified model	0.0001	0.94	Significant > Selected

The evaluation results of the model's accuracy, as shown in *Table 4*, indicate that the modified model is sufficiently accurate for predicting performance across both response surfaces. It is essential to estimate the coefficients of significant effects for both objectives to properly fit the model. Statistical analyses, including effect identification and estimated coefficients for total production and truck travel time in the copper mine complex, are detailed in *Table 5* and *Table 6*. The total ore production model has an F-Value of 3.24, suggesting significant agreement between experimental and predicted values. Similarly, the truck travel time model has an F-Value of 19.62, indicating its significance as well, with only a 0.01% chance that such a large F-Value could occur due to random noise. $\text{Prob} > \text{F}$ values below 0.05 confirm the significance of model terms, while $|t|$ values exceeding 1.96 also indicate significance. Although variables X2 and X4 are not meaningful in the first and second responses, respectively, they are included in the analysis because they are decision variables within the system, and their optimal values will be calculated in the future.

Table 5. Estimated effects and coefficients for the total ores production.

Term	Coefficient	S.E Coefficient	P-Value	t-Value
Intercept	0.47	0.035	0.0001	13.4285
X_1	0.15	0.033	0.0005	4.5454
X_2	0.058	0.033	0.1010	1.7575
X_3	0.20	0.033	0.0001	6.0606
X_4	0.053	0.019	0.0140	2.7894
X_1X_2	0.069	0.023	0.0105	3
X_1^2	0.041	0.019	0.0535	2.1578
X_2^2	0.055	0.019	0.0140	2.8947
$X_1X_2X_3$	-0.064	0.023	0.0160	-2.7826
$X_1^2X_2$	0.14	0.040	0.0038	3.15
$X_1^2X_3$	-0.18	0.040	0.0007	-4.5

Table 6. Estimated effects and coefficients for the trucks travel time.

Source	Coefficient	S.E Coefficient	P-Value	t-Value
Intercept	0.71	0.018	0.0001	39.4444
X_1	-0.082	0.015	0.0001	5.4666
X_2	0.23	0.026	0.0001	8.8461
X_3	-0.047	0.015	0.0075	-3.1333
X_4	0.008	0.015	0.5672	0.5333
X_1X_4	0.039	0.018	0.0503	2.1666
$X_1X_2X_3$	0.048	0.018	0.0205	-2.6666
$X_1X_2X_4$	-0.052	0.018	0.0139	-2.8888
$X_1^2X_2$	-0.12	0.032	0.0021	-6.6666
$X_1X_2X_3X_4$	0.073	0.018	0.0015	4.0555
X_2^4	-0.015	0.003	0.0008	-5
X_4^4	-0.007	0.003	0.0459	-2.3333

Based on the statistical analysis, the pseudo-model of the total amount of ore extraction and the total time of moving the trucks is formulated as follows *Eq. (2)* and *Eq. (3)*.

$$\begin{aligned} Y_1 = {} & 0.47 + 0.15X_1 + 0.058X_2 + 0.2X_3 + 0.053X_4 + 0.069X_1X_2 + 0.041X_1^2 + 0.055X_2^2 \\ & - 0.064X_1X_2X_3 + 0.14X_1^2X_2 - 0.18X_1^2X_3. \end{aligned} \tag{2}$$

$$\begin{aligned} Y_2 = {} & 0.71 - 0.082X_1 + 0.23X_2 - 0.047X_3 + 0.008X_4 + 0.039X_1X_4 - 0.048X_1X_2X_3 \\ & - 0.052X_1X_2X_4 - 0.12X_1^2X_2 + 0.073X_1X_2X_3X_4 - 0.015X_2^4 - 0.007X_4^4. \end{aligned} \tag{3}$$

The copper mine complex can use the above meta models to find the non-dominated solutions subject to given constraint when all functions are validating. Simulation validity measures how well the model represents the real world system [10]. To provide the validity of the meta models built in our paper we use most common PRESS error is root mean square PRESS denoted as $\text{RMSE}_{\text{PRESS}}$ Calculated by $\sqrt{\frac{\text{PRESS}}{n}}$ where, n is number of test points selected to evaluate the model. It is obvious that value of zero for RMSE is the optimal desired values [31]. In *Table 10*, the $\text{RMSE}_{\text{PRESS}}$value obtained for modified models and other considered models for each objective is shown. Therefore, we conclude that the modified models can be used as an abstraction model of the simulation model.

Table 7. Validation of the meta models.

Function	$\mathbf{RMSE_{PRESS}}$
Total ores production (Y_1)	$RMSE_{PRESS}^{Modified} = 0.16$
	$RMSE_{PRESS}^{Linear} = 0.2$
	$RMSE_{PRESS}^{2FI} = 0.26$
Total trucks travel time (Y_2)	$RMSE_{PRESS}^{Modified} = 0.11$
	$RMSE_{PRESS}^{Linear} = 0.17$
	$RMSE_{PRESS}^{2FI} = 0.24$

4.5 | Mathematical Optimization

Mathematical problem considered as follow *Eq. (4)*.

$$
\begin{aligned}
&\text{Maximize } (Y_1);\ T_{extraction}(\mathbf{x}),\\
&\text{Minimize } (Y_2);\ T_{Truck\ transportation}(\mathbf{x}),\\
&\text{s.t.}\\
&120x_1 + 24x_2 + 35x_3 + 100x_4 \leq 60000,\\
&12 \leq x_1 \leq 28,\\
&1 \leq x_2 \leq 5,\\
&5 \leq x_3 \leq 25,\\
&25 \leq x_4 \leq 45,\\
&x_i \text{ integer} \quad \text{for } i = 1;2;3;4.
\end{aligned}
\tag{4}
$$

In the Integer Nonlinear Multi-Objective Optimization (INMOO) problem is considered, Y_1 is the function of the total amount of ores extraction in the mine, and its equation is specified by the symbol $T_{extraction}$in the model. Y_2 is the function of the total transportation time of trucks, which is represented by the symbol $T_{Truck\ transportation}$. x is a vector of design variables that has four components x_1 number of trucks 120 Tons; x_2 number of trucks 240 Tons; x_3 number of trucks 35 Tons; x_4 the number of trucks is 100 Tons. Both functions were obtained using the analysis described earlier. The MOO problem has been coded and solved through the modified NBI method with two meta models with Maple software.

Two-Dimensional (2D) graphs have been used to show the Pareto frontier of both objectives, where each axis represents each objective. The Pareto frontier represents a surface covering all possible mass values.

In engineering applications, such as the case study presented in this paper, understanding the relationship between objective functions and non-dominated solutions is crucial. Analyzing the differences among non-dominated solutions and their impact on objective functions aids in comprehending MOO challenges. The modified NBI method algorithm is illustrated in *Fig. 2*, displaying the normalized values of both objective functions in a 2D space, with values ranging from zero to one. The optimization algorithm generates 43 non-dominant points, forming a complete set of Pareto points, as depicted in *Fig. 3*. The optimization phase commences with this non-dominant set, leading to the identification of the best non-dominated solutions, which constitute the Pareto set. The final Pareto set includes 19 out of 36 non-dominated solutions, represented in *Fig. 4*. *Fig. 5* compares the accuracy of the solutions derived from the built models to the current situation, indicating that the optimization method yields superior solutions. The red dot in *Fig. 5* marks the objective function values in the existing state. Consequently, designers or engineers can select optimal variable designs that meet their goals by utilizing the Pareto frontier and the non-dominated solution set.

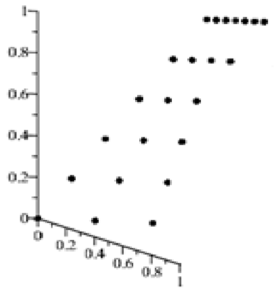

Fig. 2. 2D plot of normalized points of objective functions.

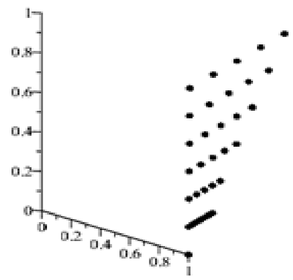

Fig. 3. All points of the generated Pareto set.

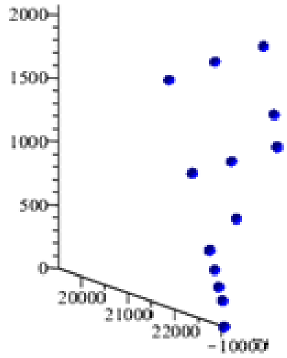

Fig. 4. The non-dominated final solutions.

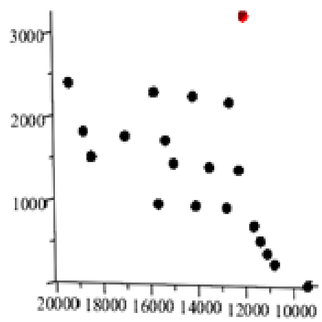

Fig. 5. Comparison of the current situation and the results obtained.

5 | Conclusion

This paper demonstrates that the modified NBI method and regression models are effective tools for MOO in physical systems, particularly in mining complexes. A control model for the extraction of sulfide, oxide, low-grade ores, and waste, as well as haulage transportation time, has been developed for the Sarcheshmeh copper mining complex in Iran. The paper illustrates how engineers and designers can easily select optimal variable designs that meet desired objectives by identifying the Pareto frontier and the set of non-dominated solutions. Utilizing MOO, RSM, DOE, simulation modeling, and the modified NBI mathematical method, the study investigates the effects of input variables and their interactions. RSM offers significant advantages, providing extensive information from a limited number of experiments, which saves time. Additionally, it effectively reveals the interactions between factors (input variables) on the response. The discrete event model considers the number of 120-ton, 240-ton, 35-ton, and 100-ton trucks, establishing their permissible levels. The modified NBI method identifies non-dominant points for maximizing ore extraction and minimizing haulage transportation, achieving high accuracy across all combinations compared to the current situation. Future research could apply multi-criteria decision-making methods, such as TOPSIS, to rank the final non-dominated sets in the mining complex.

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Data Availability

All data are included in the text.

Conflicts of Interest

The authors declare no conflict of interest.

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