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Optimizing the exploratory drilling rig route based on the multi-objective multiple traveling salesman problem

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ABSTRACT

Exploratory drilling is one of the most important and costly stages of mineral exploration procedures, so the continuation of mining activities depends on the gathered data during this stage. Due to the importance of cost and time-saving in the performance of mineral exploration projects, the effective parameters for reducing the cost and time of drilling activities should be investigated and optimized. Road construction and the sequence of the drilling boreholes by drilling rigs are among these parameters. The main objectives of this research were to optimize the overall road construction cost and the difference in length drilled by each drilling rig. The problem has been modeled as a Multi-Objective Multiple Traveling Salesman Problem (MOmTSP) and solved by the Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Finally; the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method has been used to find the optimal solution among the solutions obtained by the NSGA-II.

Keywords: *Exploratory drilling, Multi-objective multiple traveling salesman problem, Non-dominated sorting genetic algorithm-II, Optimization, Technique for order preference by similarity to ideal solution.*

1. Introduction

Estimation of the grade, thickness, and other characteristics of a deposit is one of the most important stages of mineral exploration, and the possibility of economic extraction could be examined based on its results. The reliable estimation of the characteristics is based on the gathered data from exploratory drill holes [1,2]. Therefore; exploratory drilling is one of the most important stages of mineral exploration procedures [3]. It is also the most expensive stage due to the high cost of drilling compared to other exploration activities [4]. Therefore; major optimization studies in exploratory activities are related to the exploratory drilling stage.

Three different trends could be found in the literature on exploratory drilling optimization: 1) Optimization of technical and engineering factors of the drilling, including bit type, geometry of bit, thrust, weight on bit, rotational speed, low frequency, and flushing rate [3,5,6], 2) optimization of drilling pattern [7–10], and 3) optimization of drilling rigs route [11–14]. Most of the previous research has focused on the first two trends, and little research has been done on the third trend. As expected, the investigations that have been done in the optimization of drilling rigs route are related to petroleum reservoirs. Due to different drilling conditions in mineral resources and mines rather than petroleum reservoirs, it is necessary to define the optimization problem of drilling rigs route differently from the models presented in petroleum reservoirs.

Exploratory drilling cost could be modeled and predicted simplified as a sum of two components of drilling rig relocation cost and drilling cost. The relocation cost could be calculated from the sum of the cost of transporting the drilling rigs into the area and the relocation cost between drilling points. Drilling rigs are usually the first heavy mining equipment that appears on the mining sites. Hence; until then, the road did not provide adequate access for heavy machinery traffic, and the cost of building a suitable road to the area will be added to the cost of transporting the drilling rigs. Since; there is mostly no road between the drilling points, a proper road must be created between them before moving the machine from one borehole to another [4]. Such a road must have suitable conditions for heavy machinery traffic on it. Hence; the relocation cost between two points is related to the cost of building a road between them. If the number of boreholes is more than 10, more than one drilling rig is available, and optimization of the drilling rigs route between boreholes will optimize the relocation cost. Also; in such conditions, designing the route that all drilling rigs have similar drilling lengths has a significant impact on optimizing drilling time. Therefore, in this paper, a multiple Traveling Salesman Problem (mTSP) is used to optimize the drilling rig's route between boreholes to optimize the cost and time of drilling.

The Traveling Salesman Problem (TSP) is one of the most popular and most well-known problems in combinatorial optimization problems that are used to model many real-world problems. The goal of TSP is to find the shortest route for a salesman to move from a depot, passing between a set of cities in which each city is visited only once and back to the depot. The mTSP is a generalization of the TSP in which m salesmen ($1 < m < n$) are used in the solution. In the case of mTSP, with a fixed start and endpoint in which all salesmen move from one starting point (depot), then all other cities are visited and each city is visited exactly once, and finally, all salesmen return to the starting point, the goal is to find a tour for all salesmen so that the overall distance traveled by salesmen are minimized [15,16]. The mTSP belongs to the class of NP-hard problems that could be approximately solved by heuristic optimization algorithms, such as genetic algorithms (GAs) [17–19].

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Since the issue of access road construction is of great importance in drilling exploratory boreholes, the optimal route with the shortest length should be determined to reduce the construction cost. In other words; an optimal task sequence for the drilling rigs must be planned firstly to ensure that it will be taken the least cost for the access road construction. Since; the purpose of the mTSP is a minimization the overall distance traveled by all salesmen, hence, some salesmen tend to travel more than others [20]. It means that, in the optimum drilling rigs route, one of the drilling rigs will drill more boreholes than the others and return later than them to the starting point. It will increase the drilling time and considerable differences in the drilling lengths and financial incomes of different drilling rigs. Therefore; the optimum route is not operational. In addition; since the drilling speed per meter of a borehole is much lower than the speed of the drilling rig moving on the ground, hence, in solving the drilling problem of exploratory boreholes using the mTSP, balancing the total drilling length by different drilling rigs, especially when the length of the boreholes is very different from each other, is more essential and operational than balancing the path traveled by different drilling rigs. Hence; a multi-objective function has been defined based on minimizing both the overall distance traveled and the difference between the total length drilled by different drilling rigs to solve this limitation. Therefore; the problem has been defined as a MOmTSP. In literature, some successful applications of the MOmTSP in solving engineering problems, such as task assignment of multiple vehicles [21] and routing and scheduling of courier service [22], have been reported. This type of problem could be solved by meta-heuristic optimization methods, such as Strength Pareto Evolutionary Algorithm II (SPEA2) [20], NSGA-II [23,24], Multi-Objective Particle Swarm Optimization (MOPSO) [25], and Multi-Objective Ant Colony Systems (MOACSs) [26] methods. Due to its advantages of good robustness, high computational efficiency, and diversity, the NSGA-II method is one of the most popular and widespread elitist multi-objective that has been introduced to solve multi-objective optimization problems. Recently; some research has been done on the application of NSGA-II in the optimization of mine engineering problems such as production process [27,28], stope layout designing and production scheduling [29], and flotation process [30] problems.

In this paper, to validate the proposed model, a data set of 49 exploratory boreholes from the Dareh-Zar copper porphyry deposit has been used as a case study. Then; NSGA-II was used to solve the problem.

The remainder of the paper is organized as follows. In section 2, the problem is defined. The mathematical models are formulated in Section 3. Sections 4 and 5 give an overview of the GA and NSGA-II, respectively. Section 6 presents the discussions and the obtained results. Finally, Section 7 presents the conclusion.

2. Problem definition

Since, in the case of mTSP, the goal is to find the shortest route traveled by all salesmen, depending on the distribution of the cities, it may create an imbalance between the distances traveled by different salesmen. Therefore; reducing the difference in the distances traveled between salesmen should also be considered a second goal in the mTSP.

Also, since the drilling time per meter of a borehole by a drilling rig is much longer than the traveling time by the drilling rig on the ground, hence, to prevent the increase in total drilling time, balancing the lengths drilled by different drilling rigs is much more important than balancing the distances traveled on the ground by them. Therefore; in this research, two objectives have been considered, including 1) minimizing the overall distance traveled by drilling rigs and 2) minimizing the difference in the lengths drilled between drilling rigs. It causes the drilling rigs to return to the starting point with a small-time difference from each other. Therefore; this reduces the stopping time of the drilling rigs at the endpoint relative to each other.

3. Problem Formulation

As mentioned before, the problem of drilling rigs' routes between boreholes could be formulated as a MOmTSP. In this section, we present definitions and parameters, decision variables, objective formulation, and constraints.

3.1. Definitions and parameters

The following definitions are used in the formulation of objectives and constraints:

- n the number of boreholes
- m the number of drilling rigs
- d_{ijk} distance traveled between borehole i and j by drilling rig k
- L_i length of the borehole i

3.2. Decision variables

The drilling rig route is defined as a route between the boreholes, based on which a drilling rig drills the boreholes in a specific order. If several drilling rigs are available, a separate route should be designed for each, according to which each borehole is placed solely in the route of one drilling rig. The variable x_{ijk} is a binary variable which means if drilling rig k passes from borehole i to borehole j, then x_{ijk} is equal to 1 and otherwise equal to 0. It was stated as follows.

$$x_{ijk} \in \{0,1\} \qquad i,j=1,\ldots,n,\ i \neq j,\ \ k=1,\ldots,m \tag{1}$$

Finally, according to the objectives of the problem, a sequence of x_{ijk} is determined for each of the drilling rigs.

3.3. Objective formulations

If we only seek to minimize the overall distance traveled by the drilling rigs, this will cause some drilling rigs to transport longer than other drilling rigs. So; the standard deviation of the lengths drilled by drilling rigs to balance the lengths drilled by them could be defined as a second objective function. Therefore; in this project, two objectives function have been defined: 1) minimizing the overall distance transported by drilling rigs (Eq.2) and 2) minimizing the difference in lengths drilled between drilling rigs (Eq.3).

$$\min\ Z_1=\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} d_{ij}x_{ijk} \tag{2}$$

$$\min\ Z_2=\mathrm{std}\Big(\sum_{j=0}^{n}\sum_{i=0}^{n} L_j x_{ijk}\Big) \tag{3}$$

3.4. Constraints

To ensure that exactly m salesmen leave and return the depot node, two constraints have been defined as follows respectively:

$$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{0jk}=m \tag{4}$$

$$\sum_{k=1}^{m}\sum_{i=1}^{n} x_{i0k}=m \tag{5}$$

Each borehole should be in the route of one drilling rig and should not be repeated in the routes. Therefore; to ensure that a drilling rig arrives at each borehole once (Eq.6) and ensure that a drilling rig leaves each borehole once (Eq.7), the following constraints have been considered.

$$\sum_{k=1}^{m}\sum_{i=1}^{n} x_{ijk}=1; \qquad j=2,\ldots,n \tag{6}$$

$$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{ijk}=1; \qquad i=2,\ldots,n \tag{7}$$

Sub-tour is the path created between the middle cities and is not connected to the depot. To remove the sub-tours generation on the final solution, the following constraint has been added to the problem as follows,

$$\sum_{i\in S}\sum_{j\notin S} x_{ijk} \geq 1; \quad \forall k=1,\dots,m,\ \forall S\subseteq\{0,1,2,\dots,n\} \tag{8}$$

4. Genetic Algorithm

Since the GA was proposed by John Holland in the early 1970s [31], it has quickly attracted the attention of researchers around the world and has been used to solve a variety of problems, including order-based problems like the TSP and mTSP.

In problem-solving using a GA, first, an initial population (parent, main population), which represents a possible solution to the problem, is created; then crossover and mutation operators are applied to the population, and a population of offspring (children) is created. Each of the initial population and the children population is evaluated using the fitness function. Then; using different scenarios, as much as the initial population, suitable members are separated from the initial population and the offspring population, and they are introduced as the main population of the next generation. This process will continue until the termination conditions, including pre-specified fitness value, are reached, no significant improvement occurs in the population for a given number of iterations, a set amount of computing time, or Number Function Evaluation (NFE) passes, are met.

When a genetic algorithm is implemented to solve a TSP and mTSP, each city is considered a gene, and each path/solution is considered a chromosome. A solution/ chromosome to the mTSP can be expressed in a variety of ways, including one-chromosome [17], two-chromosome [32], and two-part chromosome [16] techniques. The advantages of using a two-part chromosome in solving mTSP problems result in a smaller search space; as a result, it increases the computational speed and, in many cases, produces better solutions than one-chromosome and two-chromosome techniques [16,33]. As the name implies, a two-part chromosome comprises two parts. The first part includes a permutation of the n cities, and the next part has m genes. The numbers assigned to each gene in the second part indicate the number of cities assigned to each salesman and should be such that their sum equals the number of cities.

For example, Figure 1 shows a two-part chromosome that includes nine cities and three salesmen. The number of cities assigned to each salesman is 2, 4, and 3, respectively. According to the first part of the chromosome and the cities assigned to each of the salesmen, the first salesman passes through cities 3 and 9, respectively, the second salesman passes through cities 2, 4, 1, and 7, and finally, the third salesman passes through cities 6, 8 and 5, respectively. If we show the depot with 0, the movement path of each salesman will be as follows:

Salesman 1: 0→3→9→0
Salesman 2: 0→2→4→1→7→0
Salesman 3: 0→6→8→5→0

3	9	2	4	1	7	6	8	5	2	4	3
Salesman 1		Salesman 2				Salesman 3					

Figure. 1. Two-Part chromosome representation for nine cities with three salesmen.

4.1. Crossover

The crossover operator in GA is used on more than one selected parent to create one or more offspring. The probability of applying a crossover operator in a genetic algorithm is determined by p_c, which is called the crossover probability. Since in a TSP, the parents are in the form of a permutation of the n cities, the children of the crossover operator must also be in the form of a permutation of the n cities. Four well-known crossover operators, which include Single-Point Crossover (SPX), Two-Point Crossover (TPX) [34], Order Crossover (OX) [35], and Partially Mapped Crossover (PMX) [36] were used in this project.

4.2. Mutation

When we use only the crossover operator in the GA, the algorithm may converge the local minimum, which is so-called premature convergence. The mutation operator in a GA, through random changes of individuals, provides variation in the GA population [37] hence enabling GA to discover forgotten areas in the search space and, as a result, preventing the algorithm from getting stuck in the local minimum [16, 38–40]. Therefore; the mutation operator is one of the critical factors in the GA. The probability of applying a mutation operator in a GA is determined by p_m, which is called mutation probability.

In permutation problems, genes could not be considered independently. In other words, in the mutation operator, the chromosome is altered until the result of the mutation is also in the form of a permutation sequence [41].

Swap Mutation [42], Insertion Mutation [43], Simple Inversion mutation [31], Inversion mutation [44, 45], and Displacement mutation [46], which are employed in this project, are the five most common forms of mutation used for permutation problems that provide previously unprecedented variations to the population by making random changes on individuals.

5. Non-dominated Sorting Genetic Algorithm (NSGA-II)

NSGA-II is one of the most popular multi-objective optimization algorithms based on population, which evolves along the solution space to find well convergent and a set of non-dominated solutions. It is said solution x dominates solution y if and only if solution x is not worse than solution y for all the objectives and solution x is strictly better than solution y for at least one objective [23].

To solve multi-objective problems using NSGA-II, first, the parent population, which is called P_t with size N, is generated randomly by an initialization procedure. For each solution p in the population; the number of solutions that dominate the solution p is calculated (domination count). Also; a set of solutions that the solution p dominates (s_p) is obtained. All solutions which are not dominated by any other solution in the population; in other words, their domination count is equal to zero are put in the first Pareto front. To obtain the second front, set s_p of each solution p on the first Pareto front is examined, and the domination count of each member q of s_p reduce by one. Finally; each member q whose domination count equals zero is put in the second front. This process continues until all fronts are identified. Furthermore; for each point in each Pareto front, the average distance of two points on either side of the point along each of the objectives is calculated; this quantity is called Crowding Distance (CD) [47]. Then; crossover and mutation operators are applied to the parent population, and an offspring population is obtained is called Q_t. If the probability of applying the crossover operator is equal to p_c and the probability of applying the mutation operator is equal to p_m, then the size of the offspring population will be equal to $(N \times p_c) + (N \times p_m)$. Then; the parent population and the offspring population combine to obtain a population R_t that the size of R_t equal to $N + (N\times p_c) + (N \times p_m)$. The new population is classified according to the non-dominated sorting approach by considering the concept of dominance and is also classified according to the CD Sorting procedure on each Pareto front. To select N better members of a population as the main population of the next generation, members who have a better rank are chosen, or if they have the same rank, members are selected who have a higher CD. The flowchart of NSGA-II is shown in Figure 2.

6. Case study and Results

The data set used in this study includes information on 49 boreholes (including Longitud, Latitude, Elevation, and depth of drilling) and a Digital Elevation Model (DEM) map of the study area. The distribution of boreholes on the DEM map is presented in Figure 3. The length of the path between the two boreholes was obtained by using the map of the topography slope so that the slope of the path between the two boreholes, as much as possible, should not exceed 10 degrees. For example, the paths between borehole No. 1 and the other points are shown in Figure 3.

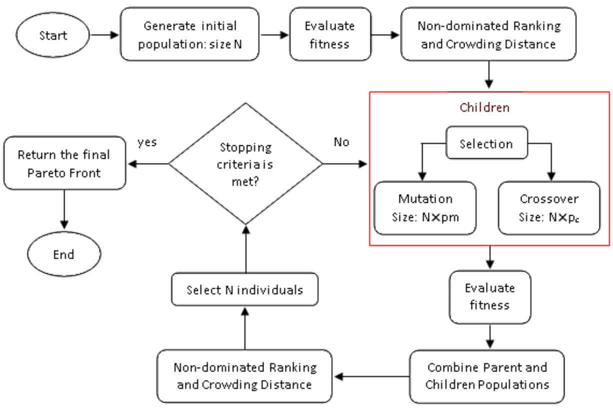

Figure 2. Flowchart of NSGA-II.

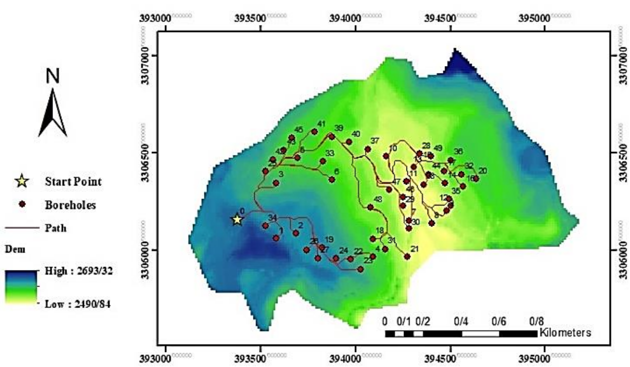

Figure 3. Distribution of boreholes on DEM map and the paths between borehole No. 1 and other points.

The number of drilling rigs (salesmen) in this project was considered three, and the NSGA-II algorithm was implemented to solve this problem.

To solve this problem, the NSGA-II with SPX, TPX, OX, and PMX operators, also, swap, insertion, simple inversion, inversion, and displacement mutation operators have been used. For all problems, we use a population of size 100, a crossover probability of 0.75, a mutation probability of 0.6, and a maximum number of generations of 2000. Solution time in solving the problem using NSGA-II with different forms of crossover and mutation operators was obtained between 18- 21 minutes (Table 1). In Table 1, it can be seen that the minimum solution time is related to the PMX and insertion mutation method, and the maximum solution time is associated with the OX and simple inversion mutation method.

By keeping the crossover operator constant, different mutation operators were compared. Figure 4 shows the non-dominant solutions for the dual objectives' overall distance and standard deviation using the SPX (Figure 4. a), TPX (Figure 4. b), OX (Figure 4. c), and PMX (Figure 4.d) operators. As shown in figure 4, it is clear that the simple inversion mutation operator has the best performance and the swap mutation operator has the worst performance. It could be because a simple inversion mutation divides the chromosome into three parts. All the links within a part are preserved and only two links between the parts are broken while in the other mutation operators, a large number of links are broken.

Also, by keeping the simple inversion mutation operator constant, the different crossover operators were compared with each other. As shown in Figure 5, the TPX and PMX operators show better performance than the other two crossover operators.

In the next step, all the non-dominant solutions obtained using different crossover and mutation operators, which included 714 solutions, were used to get the final non-dominant solutions. Finally; 52

Table 1. Solution time with different forms of crossover and mutation operators.

Method (Crossover- Mutation)	second	minute
OX- Displacement	1140.095849	19.00159748
OX- Insertion	1119.009876	18.6501646
OX- Inversion	1130.884069	18.84806782
OX- Simple Inversion	1267.727206	21.12878677
OX- Swap	1117.981665	18.63302775
PMX- Displacement	1254.421078	20.90701797
PMX- Insertion	1111.424067	18.52373445
PMX- Inversion	1114.209258	18.5701543
PMX- Simple Inversion	1240.752571	20.67920952
PMX-Swap	1159.782146	19.32970243
SPX- Displacement	1159.585815	19.32643025
SPX- Insertion	1141.389136	19.02315227
SPX- Inversion	1157.496324	19.2916054
SPX- Simple Inversion	1137.037451	18.95062418
SPX-Swap	1138.910945	18.98184908
TPX- Displacement	1230.977434	20.51629057
TPX- Insertion	1132.807332	18.8801222
TPX- Inversion	1140.507993	19.00846655
TPX- Simple Inversion	1122.822069	18.71370115
TPX- Swap	1142.035835	19.03393058

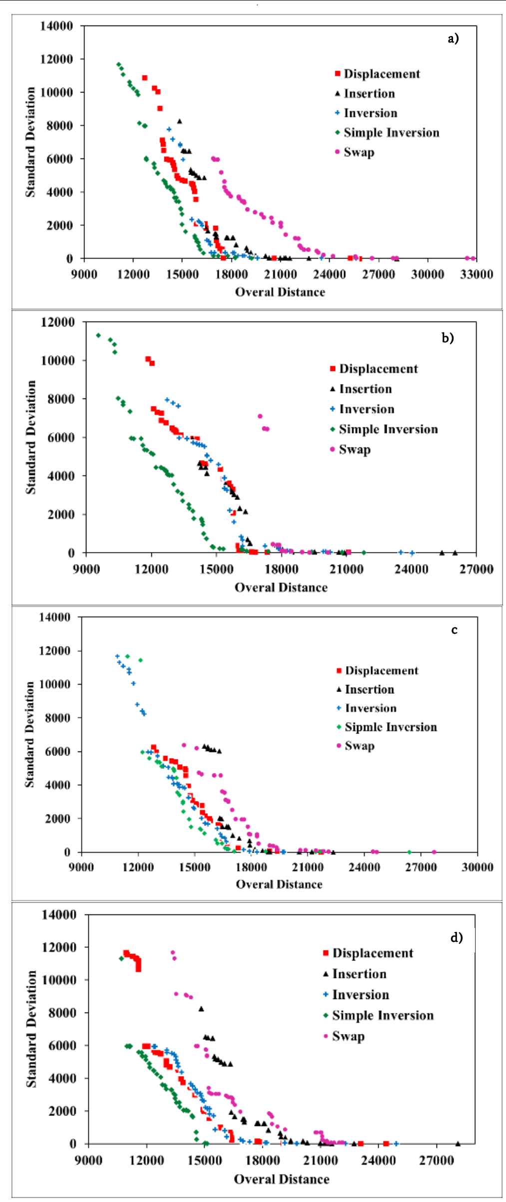

Figure 4. Non-dominated solutions with different mutations and a: SPX, b: TPX, c: OX, and d: PMX.

non-dominant solutions were obtained, which are shown in Table 2. Among these solutions, 23, 27, and 2 solutions are related to the PMX, TPX, and OX operators, respectively. Also; 1, 2, 1, and 48 solutions are related to the swap, displacement, inversion, and simple inversion mutation operators, respectively. According to the obtained result, it can be said that PMX and TPX operators and simple inversion mutation have a more significant role in creating the final non-dominant solutions.

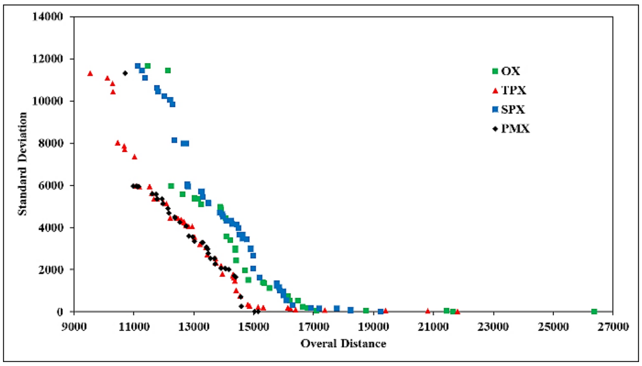

Figure 5. Non-dominated solutions with simple inversion mutation and different crossover.

As shown in Table 2, some solutions have a low overall distance, which increases the standard deviation of lengths drilled by drilling rigs. For example, the minimum overall distance obtained is 9542.5 meters, and the standard deviation of this overall distance is 11303.8, which is the highest standard deviation among the available answers. Also; the lowest value of standard deviation is equal to 5.4, and the overall distance of this standard deviation is 24642.7 meters, which is the highest overall distance among the available answers.

In many cases, objectives in the non-dominant solutions conflict with each other, and an optimal solution for one objective is usually not optimal for other objectives. Therefore; the optimal solution should be selected according to the specific interests of each project. Multi-Criteria Decision Making (MCDM) methods provide tools to help choose the best solution from the available solutions. The TOPSIS approach is one of the MCDM methods developed by Hwang and Yoon [48], and its purpose is to find a solution that has the shortest distance from the Positive Ideal Solution (PIS) and the maximum distance from the Negative Ideal Solution (NIS). The PIS is defined as the vector of the best values obtained from each criterion, and the NIS is defined as the vector of the worst values obtained from each criterion.

To find the best answer among the available solutions, the TOPSIS method was used. As mentioned above, reducing the standard deviation of the lengths drilled by drilling rigs is more important than reducing the overall distance traveled by the drilling rigs; from this, the weight assigned in the TOPSIS method to the objective function of standard deviation was considered 0.85 and the weight assigned to the objective function of overall distance was considered 0.15. These values were assigned based on the expert's experiences and the trial-and-error method. The result of the TOPSIS method is shown as a sequence of drilling boreholes in Figure 6. In the solution obtained using the TOPSIS method, the value of the overall distance traveled and the value of the standard deviation of the lengths drilled by the drilling rigs are equal to 15037.6 and 28.7 meters, respectively.

Table 2. Final non-dominated solutions.

Solution	Overal Distance (m)	Standard Deviation (m)	Crossover	Mutation	Solution	Overal Distance (m)	Standard Deviation (m)	Crossover	mutation
1	24642.7	5.4	OX	Swap	27	9542.5	11303.8	TPX	Simple Inversion
2	21711.9	9.2	OX	Displacement	28	10307.6	10434.8	TPX	Simple Inversion
3	24402.8	6.3	PMX	Displacement	29	10455.8	8028.5	TPX	Simple Inversion
4	15144.5	10.3	PMX	Simple Inversion	30	10698.4	7686.5	TPX	Simple Inversion
5	10978.0	5953.7	PMX	Simple Inversion	31	10110.3	11083.3	TPX	Simple Inversion
6	14587.1	260.7	PMX	Simple Inversion	32	14412.0	1010.1	TPX	Simple Inversion
7	11155.4	5948.7	PMX	Simple Inversion	33	10284.9	10828.5	TPX	Simple Inversion
8	11973.0	5124.5	PMX	Simple Inversion	34	11603.8	5607.6	TPX	Simple Inversion
9	12828.2	3596.1	PMX	Simple Inversion	35	13408.5	3068.5	TPX	Simple Inversion
10	15037.6	28.7	PMX	Simple Inversion	36	14364.3	1469.8	TPX	Simple Inversion
11	13544.9	2521.2	PMX	Simple Inversion	37	13447.4	2715.8	TPX	Simple Inversion
12	13707.1	2272.6	PMX	Simple Inversion	38	13952.6	1788.0	TPX	Simple Inversion
13	12139.6	4908.1	PMX	Simple Inversion	39	13207.9	3212.6	TPX	Simple Inversion
14	12741.8	4066.5	PMX	Simple Inversion	40	10679.8	7850.2	TPX	Simple Inversion
15	14576.7	712.7	PMX	Simple Inversion	41	14541.6	752.2	TPX	Simple Inversion
16	13026.5	3337.1	PMX	Simple Inversion	42	12214.4	4450.7	TPX	Simple Inversion
17	12170.4	4670.3	PMX	Simple Inversion	43	13904.9	2185.7	TPX	Simple Inversion
18	13910.8	2056.5	PMX	Simple Inversion	44	11790.3	5349.9	TPX	Simple Inversion
19	12955.6	3547.9	PMX	Simple Inversion	45	11668.1	5354.1	TPX	Simple Inversion
20	12538.1	4246.0	PMX	Simple Inversion	46	14309.8	1780.6	TPX	Simple Inversion
21	11607.0	5585.1	PMX	Simple Inversion	47	12678.9	4234.7	TPX	Simple Inversion
22	11090.7	5951.3	PMX	Simple Inversion	48	14340.9	1630.0	TPX	Simple Inversion
23	11774.7	5352.4	PMX	Simple Inversion	49	12467.9	4427.9	TPX	Simple Inversion
24	11109.8	5949.0	PMX	Simple Inversion	50	12732.0	4077.9	TPX	Simple Inversion
25	11784.6	5351.2	PMX	Simple Inversion	51	12427.0	4450.3	TPX	Simple Inversion
26	24031.0	6.3	TPX	Inversion	52	14312.9	1721.7	TPX	Simple Inversion

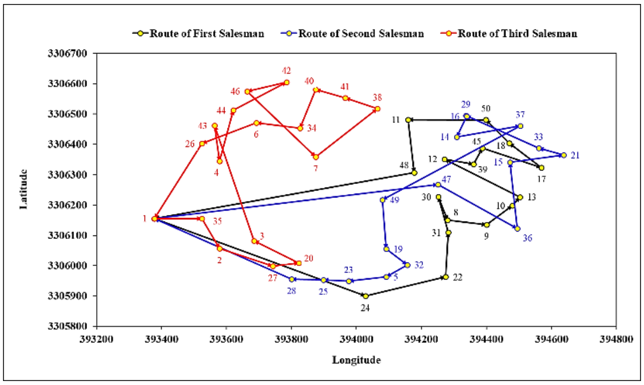

Figure 6. the path of the three drilling rigs.

Although, if only the purpose of solving the problem was finding the minimum overall distance in mTSP using the GA, a completely different path with less overall distance was obtained. Since; the problem under consideration is a bi-objective problem, and according to the weights assigned in the TOPSIS method to each of the objectives, the objective of finding the minimum overall distance is less important than the standard deviation. Therefore; the obtained solution, due to the low amount of standard deviation, is an acceptable path.

7. Conclusion

The purpose of this paper is to find the optimal drilling route to access different boreholes in exploratory drilling sites. It will reduce the costs associated with access road construction, the standard deviation of lengths drilled by drilling rigs, and drilling time. This problem was modeled as a MOmTSP, and the NSGA-II was used to solve it. 20 scenarios have been defined based on available crossover and mutation operators to solve this problem with NSGA-II. All the non-dominant solutions obtained using the 20 different scenarios were used to get the final non-dominant solutions. Then, final non-dominant solutions were obtained that PMX and TPX operators and simple inversion mutation have a more significant role in creating these solutions. Since the objectives in this problem conflict, the TOPSIS approach, as an MCDM method, was used to find the best solution among the solutions. Due to the greater importance of standard deviation relative to the overall distance, weights 0.85 and 0.15 were considered for their objective functions, respectively. The optimal solution obtained using the TOPSIS method has an overall distance traveled by the drilling rigs equal to 15,037.6 meters and a standard deviation equal to 28.7 meters. Although; the final path does not have the best value for the overall distance, according to the intended goals for the problem, it is an optimal solution for this problem.

The multi-objective problem could be solved by classic and evolutionary methods. This research is designed based on the evolutionary method. The comparison between the efficiency of a classic method (like the weighted sum method) and other evolutionary methods (such as MOACSs) with NSGA-II will be considered in future studies.

REFERENCES

[1] Chou, D. (1982) Optimizing exploratory drilling locations.

[2] Scheck, D.E. and Chou, D.-R. (1983) Optimum locations for exploratory drill holes. International Journal of Mining Engineering, Springer. 1, 343–55.

[3] Liao, X., Khandelwal, M., Yang, H., Koopialipoor, M. and Murlidhar, B.R. (2020) Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques. Engineering with Computers, Springer. 36, 499–510.

[4] Moon, C.J., Whateley, M.K.G. and Evans, A.M. (2006) Introduction to mineral exploration. Blackwell publishing.

[5] Irawan, S., Rahman, A. and Tunio, S. (2012) Optimization of weight on bit during drilling operation based on rate of penetration model. Research Journal of Applied Sciences, Engineering and Technology, 4, 1690–5.

[6] Derdour, F.Z., Kezzar, M. and Khochemane, L. (2018) Optimization of penetration rate in rotary percussive drilling using two techniques: Taguchi analysis and response surface methodology (RMS). Powder Technology, Elsevier. 339, 846–53.

[7] Drew, L.J. (1967) Grid-drilling exploration and its application to the search for petroleum. Economic Geology, Society of Economic Geologists. 62, 698–710.

[8] Drew, L.J. (1979) Pattern drilling exploration: Optimum pattern types and hole spacings when searching for elliptical shaped targets. Journal of the International Association for Mathematical Geology, Kluwer Academic Publishers-Plenum Publishers. 11, 223–54. https://doi.org/10.1007/BF01028966

[9] Griffiths, J.C. and Drew, L.J. (1966) Grid spacing and success ratios in exploration for natural resources: The Pennsylvania State Univ. Min Ind Expmt Stat, Special Publ.

[10] Soltani, S., Hezarkhani, A., Tercan, A.E. and Karimi, B. (2011) Use of genetic algorithm in optimally locating additional drill holes. Journal of Mining Science, Springer. 47, 62–72.

[11] Lamas, L.F., Botechia, V.E., Schiozer, D.J. and Delshad, M. (2017) Optimization for drilling schedule of wells in the development of heavy oil reservoirs. Brazilian Journal of Petroleum and Gas, 11.

[12] Wang, L. and Oliver, D.S. (2019) Efficient Optimization of Well-Drilling Sequence with Learned Heuristics. SPE Journal, OnePetro. 24, 2111–34.

[13] Kulachenko, I. and Kononova, P. (2020) A matheuristic for the drilling rig routing problem. International Conference on Mathematical Optimization Theory and Operations Research, Springer. p. 343–58.

[14] Kulachenko, I.N. and Kononova, P.A. (2021) A hybrid algorithm for the drilling rig routing problem. Journal of Applied and Industrial Mathematics, Springer. 15, 261–76.

[15] Bektas, T. (2006) The multiple traveling salesman problem: an overview of formulations and solution procedures. Omega, Elsevier. 34, 209–19.

[16] Carter, A.E. and Ragsdale, C.T. (2006) A new approach to solving the multiple traveling salesperson problem using genetic algorithms. European Journal of Operational Research, Elsevier. 175, 246–57.

[17] Tang, L., Liu, J., Rong, A. and Yang, Z. (2000) A multiple traveling salesman problem model for hot rolling scheduling in Shanghai Baoshan Iron & Steel Complex. European Journal of Operational Research, Elsevier. 124, 267–82.

[18] Király, A. and Abonyi, J. (2010) A novel approach to solve multiple traveling salesmen problem by genetic algorithm. Computational Intelligence in Engineering, Springer. p. 141–51.

[19] Singh, A. (2016) A review on algorithms used to solve multiple travelling salesman problem. International Research Journal of Engineering and Technology (IRJET), 3, 598–603.

[20] Alves, R.M.F. and Lopes, C.R. (2015) Using genetic algorithms to minimize the distance and balance the routes for the multiple traveling salesman problem. 2015 IEEE Congress on Evolutionary Computation (CEC), IEEE. p. 3171–8.

[21] Xu, Z., Li, Y. and Feng, X. (2008) Constrained multi-objective task assignment for UUVs using multiple ant colonies system. 2008 ISECS International Colloquium on Computing, Communication, Control, and Management, IEEE. p. 462–6.

[22] Chang, T.-S. and Yen, H.-M. (2012) City-courier routing and scheduling problems. European Journal of Operational Research, Elsevier. 223, 489–98.

[23] Bolaños, R., Echeverry, M. and Escobar, J. (2015) A multiobjective non-dominated sorting genetic algorithm (NSGA-II) for the Multiple Traveling Salesman Problem. Decision Science Letters, 4, 559–68.

[24] Shuai, Y., Yunfeng, S. and Kai, Z. (2019) An effective method for solving multiple travelling salesman problem based on NSGA-II. Systems Science & Control Engineering, Taylor & Francis. 7, 108–16.

[25] Wei, C., Ji, Z. and Cai, B. (2020) Particle swarm optimization for cooperative multi-robot task allocation: a multi-objective approach. IEEE Robotics and Automation Letters, IEEE. 5, 2530–7.

[26] Necula, R., Breaban, M. and Raschip, M. (2015) Tackling the bi-criteria facet of multiple traveling salesman problem with ant colony systems. 2015 IEEE 27th International Conference on Tools with Artificial Intelligence (ICTAI), IEEE. p. 873–80.

[27] Wang, X., Gu, X., Liu, Z., Wang, Q., Xu, X. and Zheng, M. (2018) Production process optimization of metal mines considering economic benefit and resource efficiency using an NSGA-II model. Processes, Multidisciplinary Digital Publishing Institute. 6, 228.

[28] Gu, X., Wang, X., Liu, Z., Zha, W., Xu, X. and Zheng, M. (2020) A multi-objective optimization model using improved NSGA-II for optimizing metal mines production process. IEEE Access, IEEE. 8, 28847–58.

[29] Foroughi, S., Hamidi, J.K., Monjezi, M. and Nehring, M. (2019) The integrated optimization of underground stope layout designing and production scheduling incorporating a non-dominated sorting genetic algorithm (NSGA-II). Resources Policy, Elsevier. 63, 101408.

[30] Zhang, W., Yuan, Q., Jia, S., Li, Z.S. and Yin, X. (2021) Multi-Objective Optimization of Froth Flotation Process: An Application in Gold Ore. Sustainability, Multidisciplinary Digital Publishing Institute. 13, 8314.

[31] Holland, J.H. (1975) Adaptation in Natural and Artificial Systems.

[32] Malmborg, C.J. (1996) A genetic algorithm for service level based vehicle scheduling. European Journal of Operational Research, Elsevier. 93, 121–34.

[33] Singamsetty, P. and Thenepalle, J. (2021) An efficient genetic algorithm for solving open multiple travelling salesman problem with load balancing constraint. Decision Science Letters, 10, 525–34.

[34] De Jong, K.A. (1975) An analysis of the behavior of a class of genetic adaptive systems. University of Michigan.

[35] Davis, L. (1985) Applying adaptive algorithms to epistatic domains. IJCAI, p. 162–4.

[36] Goldberg, D.E. and Lingle, R. (1985) Alleles, loci, and the traveling salesman problem. Proceedings of an International Conference on Genetic Algorithms and Their Applications, Carnegie-Mellon University Pittsburgh, PA. p. 154–9.

[37] Yang, S. (2002) Adaptive non-uniform mutation based on statistics for genetic algorithms. ACM.

[38] Albayrak, M. and Allahverdi, N. (2011) Development a new mutation operator to solve the traveling salesman problem by aid of genetic algorithms. Expert Systems with Applications, 38, 1313–20. https://doi.org/10.1016/j.eswa.2010.07.006

[39] Abdoun, O., Abouchabaka, J. and Tajani, C. (2012) Analyzing the Performance of Mutation Operators to Solve the Travelling Salesman Problem.

[40] Deep, K. and Mebrahtu, H. (2011) Combined mutation operators of genetic algorithm for the travelling salesman problem. International Journal of Combinatorial Optimization Problems and Informatics, International Journal of Combinatorial Optimization Problems and Informatics. 2, 1–23.

[41] Eiben, A.E. and Smith, J.E. (2003) Introduction to evolutionary computing. Springer.

[42] Oliver, I.M., Smith, D.J. and Holland, J.R.C. (1987) A study of permutation crossover operators on the TSP, genetic algorithms and their applications. Proceedings of the Second International Conference on Genetic Algorithms, p. 224–30.

[43] Fogel, D.B. (1988) An evolutionary approach to the traveling salesman problem. Biological Cybernetics, Springer. 60, 139–44.

[44] Fogel, D.B. (1990) A parallel processing approach to a multiple travelling salesman problem using evolutionary programming. Proceedings of the Fourth Annual Symposium on Parallel Processing, Fullerton, CA. p. 318–26.

[45] Fogel, D.B. (1993) Applying evolutionary programming to selected traveling salesman problems. Cybernetics and Systems, Taylor & Francis. 24, 27–36.

[46] Michalewicz, Z. (1992) Genetic Algorithms + Data Structures = Evolution Programs. Springer Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-02830-8

[47] Deb, K., Agrawal, S., Pratap, A. and Meyarivan, T. (2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. International Conference on Parallel Problem Solving from Nature, Springer. p. 849–58.

[48] Hwang, C.-L. and Yoon, K. (1981) Multiple Attribute Decision Making. Springer Berlin Heidelberg, Berlin, Heidelberg. 186. https://doi.org/10.1007/978-3-642-48318-9