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Modeling of Optimizing Multi-Hole Drilling Toolpath Distance with Multiple Tool Dimensions

MODELING OF OPTIMIZING MULTI-HOLE DRILLING TOOLPATH DISTANCE WITH MULTIPLE TOOL DIMENSIONS

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ABSTRACT

Multi-hole Drilling with Multiple Tool dimensions (MDMT) is a crucial technique in today's industry, allowing manufacturers to satisfy the increasing demand for precise and high-quality components while adopting the latest technological advancements and environmental standards. This paper introduces and validates a computational model for MDMT, offering numerous advantages over conventional drilling methods, including enhanced efficiency, accuracy, cost-effectiveness, and flexibility. The computational model was developed for the MDMT problem using the Travelling Salesman Problem (TSP) concept to measure the total toolpath distance. The Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) are applied to solving 12 cases of MDMT problems with varying numbers of holes, classified as small, medium, and large, using MATLAB software R2022b.Note that the algorithms were evaluated based on their solution quality, with lower fitness values indicating better performance. Overall, GA performed the best across most hole configurations, achieving the optimal fitness value in 5 out of 12 cases (small, medium, and large), ACO performed better in 4 out of 12 cases (small and medium) and PSO performed better in 3 out of 12 cases (medium and large). The research emphasizes the potential of multi-dimensional tools for accomplishing intricate drilling tasks. Other than that, this paper contributes to the existing literature on MDMT and highlights the importance of multi-dimensional tools in modern manufacturing. Future research could optimize the proposed computational model for various materials and drilling scenarios in MDMT.

Keywords: Multi-hole drilling; Multiple tool dimensions; Metaheuristics

1. INTRODUCTION

Multi-hole Drilling with Multiple Tool dimensions (MDMT), commonly referred to as MDMT, is a process of drilling multiple holes in a workpiece using more than one tool. MDMT is an important process in modern manufacturing. Furthermore, it offers numerous benefits, including increased efficiency, accuracy, cost savings, and flexibility. It is widely utilized in aerospace, automotive, and medical device manufacturing industries. This approach has several important advantages over conventional drilling methods. Note that the benefits include increased efficiency, improved accuracy, cost savings and greater flexibility.

Using multiple tools, the drilling process can be completed much faster than with a single tool. This can save time and increase productivity, which can be particularly beneficial for large-scale production operations [1]. Besides, using multiple tools allows for greater precision in drilling, as each tool can be specialized for a specific task, reducing errors, and improving the finished product's overall quality. Using multiple tools may require additional equipment and resources. However, it can increase efficiency and accuracy, resulting in significant cost savings over time [2]. This makes multi-hole drilling a cost-effective option for many industries. Different tools can be used to create holes of different shapes and sizes, benefiting a wide range of applications.

MDMT offers many advantages, but there are also some limitations to the existing methods. One of the main limitations is that most current research has focused on using traditional two-dimensional tools, which may not be suitable for more complex drilling tasks. This limitation arises since traditional drilling tools are limited in their ability to drill in multiple dimensions, such as at different angles or in non-linear paths [3]. Consequently, certain drilling tasks may require multiple tool changes or manual intervention, leading to potential errors and reduced overall efficiency.

The MDMT problem has been the subject of considerable research in recent years, with numerous studies investigating the benefits and limitations of this approach. Zhang 2012 [4] investigated the MDMT problem to reduce the time it takes to produce Printed Circuit Boards (PCBs) and reduce the machining cost. Note that minimizing tool switches and travel duration is critical to the MDMT problem. On the other hand, Liu et al. (2013) [5] handled the MDMT problem by modeling the problem using the Precedence Constrains Travelling Salesman Problem (PCTSP) and solving it using the Ant Colony Optimization (ACO) algorithm. This is to obtain the shortest path of the drilling process to save auxiliary time and boost machining productivity.

Mitic and Nedic (2022) [6] have published their research on MDMT problems to decrease airtime and tool-change times in the metalworking industry. A mathematical model is offered using the case study's typical geometry, and a Genetic Algorithm (GA) is employed to build and optimize the toolpath. Meanwhile, M Dalavi et al. (2016) [7] applied the Particle Swarm Optimization (PSO) algorithm to identify the optimum sequence of hole-making operations to minimize overall processing costs in the MDMT problem. They applied the PSO algorithm to investigate the possibility of this algorithm solving the complex problem of MDMT.

In another work, M. Dalavi et al. (2022) [8] published their research on MDMT problems to minimize tool travel time for hole-drilling operations using a new nature-inspired optimization algorithm, which is the modified Shuffled Frog Leaping Algorithm (SFLA). Alternatively, Kucukoglu et al. (2019) [9] have published their research on MDMT problems to minimize the total idle and unnecessary times of the tools for internal operations. To solve the problem, a recent optimization algorithm called Satin Bowerbird Optimizer (SBO) is utilized, successfully finding the optimal solution.

The above studies have significantly contributed, having most employed the TSP approach. In TSP with a set of cities, a salesman needs to randomly visit each city only once and return to the beginning city with the minimum total distance traveled. The well-established algorithms such as ACO, PSO, and GA are still dominating the optimization algorithms used to optimize toolpaths and will be used in this research. Note that ACO is a metaheuristic inspired by ants searching for food, where artificial ants construct solutions based on probabilistic decision-making and pheromone levels. Meanwhile, PSO mimics birds flocking or fish schooling, where particles adjust their positions in the solution space based on their best position and neighbors' best positions. Moreover, GA is a popular evolutionary optimization algorithm based on natural selection and genetics, generating new candidate solutions encoded as chromosomes. GA is widely used for solving TSP and other optimization problems due to its ability to handle complex and high-dimensional search spaces.

The existing literature suggests that MDMT is a promising approach for improving the efficiency and accuracy of drilling processes [10]. However, further research is needed to fully understand this approach's capabilities and limitations and develop new techniques and tools to enhance its effectiveness. The paper aims to present and validate a computational model for MDMT. This model aims to enhance the drilling process's efficiency and overcome existing methods' limitations.

The structure of the paper will consist of several sections. The first section will introduce the background of the research, the problem statement, the literature review, and the research objective. Subsequently, the second section will describe the concept of MDMT, including its benefits and limitations. The third section will present the methodology of this research, which includes modeling initialization, model development, model validation, and computational experiments. The fourth will present the model's results, including comparisons with experimental data where available. The final section will summarize the key findings, conclusions, and suggestions for future research.

2. MULTI-HOLE DRILLING WITH MULTIPLE TOOL DIMENSIONS (MDMT)

MDMT refers to a drilling process in which multiple holes are drilled in a workpiece using more than one tool, each with a different dimension. The tools used in this process can vary in size, shape, and orientation, allowing for greater flexibility and precision in the drilling process. Here, the benefits of MDMT include improved efficiency, accuracy, and versatility. The drilling process can be completed more quickly and precisely using different tool with different dimensions than a single tool. Additionally, different tools can be used to create holes with different shapes and sizes, allowing for greater flexibility in the drilling process.

The process of MDMT can be optimized using computational models. These models can consider factors such as the workpiece's geometry, the drilling tools' properties, and the desired hole pattern. Correspondingly, engineers can use a computational model to identify the optimal combination of tools and drilling parameters to achieve the desired results. In this paper, the computational model, which is a mathematical model, was developed for the MDMT problem using the TSP concept. The TSP approach was chosen due to the similarity to the MDMT problem based on literature review. Moreover, most reviewed papers modeled their problems using the TSP approach. TSP model can be expressed and formulated using integer programming as indicated in Eq. (1):

$$F(x) = \sum_{i}^{n}\sum_{j}^{n} X_{ij}D_{ij} \tag{1}$$

subjected to:

$$\sum_{i=1}^{n} X_{ij} = 1, j = 1, \ldots., n \quad , \quad \sum_{j=1}^{n} X_{ij} = 1, i = 1, \ldots., n$$

where

n = *total holes number*
Dij = *distance from point i to j*
$$X_{ij} = \begin{cases} 1 & if\ salesmen\ travels\ from\ i\ to\ j \\ 0 & otherwise \end{cases}$$

3. METHODOLOGY

This research has been performed by following the flowchart displayed in Figure 1. They can be classified into four steps, MDMT Modeling Initialization, MDMT Model Development, MDMT Model Validation, and MDMT Computational Experiment.

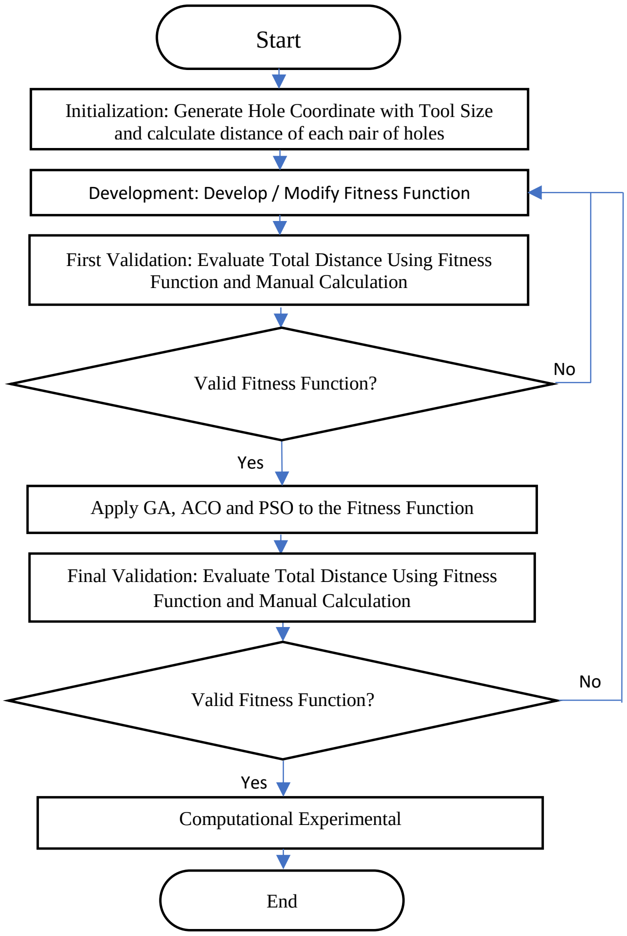

Figure 1: Flowchart of the modeling

3.1 MDMT Modelling Initialization

To model the MDMT problem using the TSP concept, the first step is to define the set of holes that need to be drilled. The coordinates of each hole are randomly created using

MATLAB software. Figure 2 and Table 1 demonstrate the sample of hole locations, holes coordinate, and tool sizes generated from MATLAB software, respectively. Consequently, the distance between each pair of holes is calculated using the Euclidean Distance formula, $D_{ij} = \sqrt{(|x_i - x_j|\hat{}2 + |y_i - y_j|\hat{}2)}$.

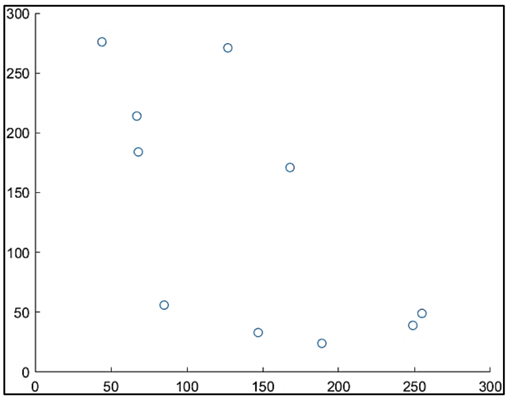

Figure 2: Hole location on a 2D plane.

Table 1: Coordinate and tool size.

No	Coor-x	Coor-y	Tool Type
1	44	276	3
2	147	33	1
3	249	39	3
4	255	49	3
5	85	56	3
6	68	184	3
7	168	171	3
8	189	24	2
9	127	271	1
10	67	214	2

3.2 MDMT Model Development

The fitness function was developed to determine the optimal total distance as an optimal fitness value. Subsequently, the fitness function is a user-defined function that takes one or more input variables representing a candidate solution. It returns a scalar value that represents the fitness or quality of the solution. In MDMT problems, the input variable is the number of holes, holes coordinate, tool size and toolpath (from the optimization algorithm). Below is the fitness function used to find the total toolpath distance.

```
function total_distance = Fitness(x)
n = 10;
data = [    44      276     3
            147     33      1
            249     39      3
            255     49      3
            85      56      3
            68      184     3
            168     171     3
            189     24      2
            127     271     1
            67      214     2];
x2 = [x;1:n];
x3 = sortrows(x2')';
hole_path = x3(2,:);
total_distance = 0;
i = 1;
hole2 = data(hole_path(i), :);
hole1 = [0,0,0];
distance1 = norm(hole2(1:2));
for i=2:n
   hole2 = data(hole_path(i), :);
   hole1 = data(hole_path(i-1), :);
   if i == 1 || hole2(3) ~= data(hole_path(i-1), 3)
      distance = norm(hole1(1:2)) + norm(hole2(1:2));
   else
      distance = norm(hole2(1:2) - data(hole_path(i-1), 1:2));
   end
total_distance = total_distance + distance;
end
hole_last = (data(hole_path(n), :));
total_distance = distance1 + total_distance + norm(hole_last(1:2));
end
```

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3.3 MDMT Model Validation

The MDMT model validation will be conducted by first verifying the accuracy of the fitness function output against manual calculations. This involves feeding in a path of holes and tool sizes into the fitness function and comparing the output with manual calculations of total toolpath distance. If the fitness function output matches the manual calculations, the fitness function accurately represents the MDMT process. Figure 3 illustrates the testing for fitness function verification. The path for ten holes for first verifying is 2 1 3 6 4 5 10 7 9 8 with coordinate and tool sizes for these ten holes, as displayed in Figure 2. After applying it to the fitness function, the fitness value is 3.5362×10^3, matching the manual calculations. Table 2 indicates the distance matrix, and Table 3 provides the manual calculation.

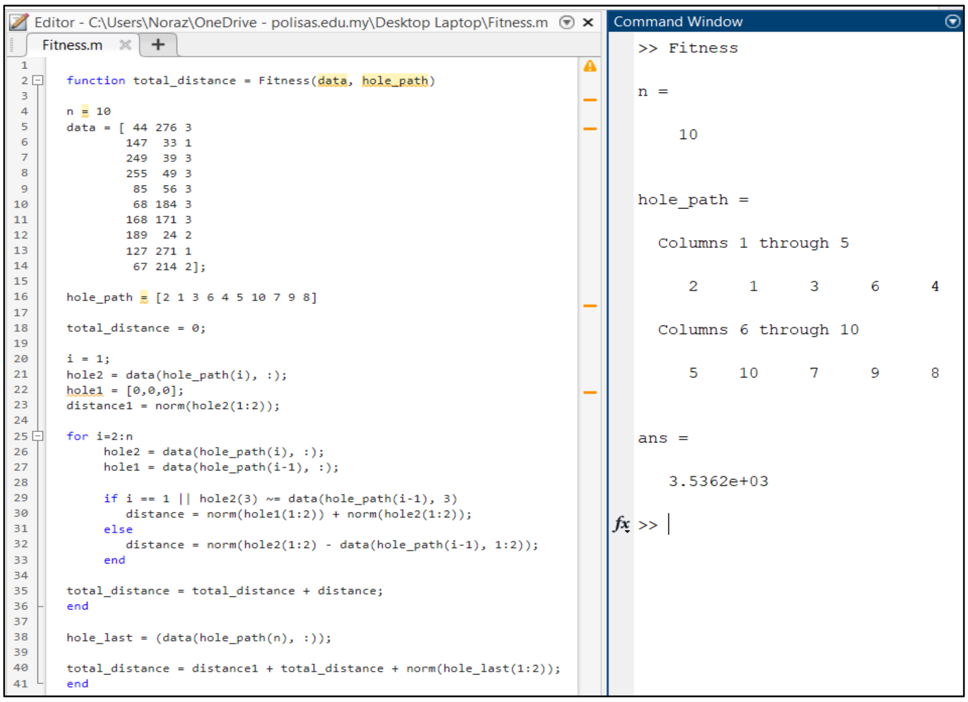

Figure 3: First fitness function validation.

Table 2: Distance matrix.

no	0	1	2	3	4	5	6	7	8	9	10
0	NaN	279.5	150.7	252.0	259.7	101.8	196.2	239.7	190.5	299.3	224.2
1	279.5	NaN	263.9	313.4	309.9	223.8	95.1	162.5	290.7	83.2	66.1
2	150.7	263.9	NaN	102.2	109.2	66.1	170.4	139.6	43.0	238.8	197.9
3	252.0	313.4	102.2	NaN	11.7	164.9	231.9	154.9	61.8	262.1	252.5
4	259.7	309.9	109.2	11.7	NaN	170.1	230.6	149.8	70.6	256.3	250.1
5	101.8	223.8	66.1	164.9	170.1	NaN	129.1	141.8	108.8	219.1	159.0
6	196.2	95.1	170.4	231.9	230.6	129.1	NaN	100.8	200.6	105.1	30.0
7	239.7	162.5	139.6	154.9	149.8	141.8	100.8	NaN	148.5	108.1	109.8
8	190.5	290.7	43.0	61.8	70.6	108.8	200.6	148.5	NaN	254.7	225.8
9	299.3	83.2	238.8	262.1	256.3	219.1	105.1	108.1	254.7	NaN	82.8
10	224.2	66.1	197.9	252.5	250.1	159.0	30.0	109.8	225.8	82.8	NaN

Table 3: Manual calculation.

No	Path	Tool	Movement	Distance	No	Path	Tool	Movement	Distance
1	2	1	0 to 2	150.7	10	Tool change		10 to 0	224.2
2	Tool change		2 to 0	150.7	11	7	3	0 to 7	239.7
3	1	3	0 to 1	279.5	12	Tool change		7 to 0	239.7
4	3	3	1 to 3	313.4	13	9	1	0 to 9	299.3
5	6	3	3 to 6	231.9	14	Tool change		9 to 0	299.3
6	4	3	6 to 4	230.6	15	8	2	0 to 8	190.5
7	5	3	4 to 5	170.1	16	End		8 to 0	190.5
8	Tool change		5 to 0	101.8					
9	10	2	0 to 10	224.2				Total Distance	3536.2

Once the model is verified, the output from the optimization will be compared with manual calculations of total distance and toolpath to further verify the results. The optimization will be conducted on ten holes problems. Table 4 summarizes the ACO, PSO, and GA output for the ten holes, while Table 5 provides the manual calculation.

Table 4: Total distance and toolpath from the ACO, PSO and GA.

Algorithm	Total Distance	Tool Path									
ACO	2211.236	2	9	5	3	4	7	1	6	8	10
PSO	2211.236	6	1	7	4	3	5	10	8	2	9
GA	2211.236	2	9	8	10	5	3	4	7	1	6

Table 5: Manual calculation based on toolpath from the ACO algorithm.

No	Path	Tool	Movement	Distance	No	Path	Tool	Movement	Distance
1	2	1	0 to 2	150.7	8	1	3	7 to 1	162.5
2	9	1	2 to 9	238.8	9	6	3	1 to 6	95.1
3	Tool change		9 to 0	299.3	10	Tool change		6 to 0	196.2
4	5	3	0 to 5	101.8	11	8	2	0 to 8	190.5
5	3	3	5 to 3	164.9	12	10	2	8 to 10	225.8
6	4	3	3 to 4	11.7	13	End		10 to 0	224.2
7	7	3	4 to 7	149.8				Total Distance	2211.2

3.4 MDMT Computational Experiment

Once the model is verified, the next step is to optimize the fitness function using standard metaheuristics ACO, PSO, and GA. The optimization will be conducted on four problems of varying sizes (small, medium, and large), with each algorithm run 3-5 times to ensure the best results are obtained. Note that the required output from the optimization includes the best cost or fitness, best toolpath, and convergence.

From the literature review, the range number of holes for the drilling path was approximately between 50 and 150. Therefore, the problems were classed into small (*n*= *1-50*), medium (*n*= *51-100*), and large (*n* =*101-150*) [11]. Four studies were in each category, each using a different hole and tool combination. Here, 20, 30, 40, and 50 holes problems were employed in the small category, with 3, 4, 5, and 6 tools being applied in each problem. The medium category included problems with 70, 80, 90, and 100 holes using 3, 4, 5, and 6 tools. Finally, problems with 120, 130, 140, and 150 holes using 3, 4, 5, and 6 tools made up the large group. The population size for all algorithms was set to 30, with a maximum iteration of 500.

4. RESULT AND DISCUSSION

Table 6 represents the output data recorded from optimization, including the minimum, average, and standard deviation of fitness values. The tables provide the results of three algorithms (ACO, PSO, and GA) for solving a problem.

Table 6: Minimum, average, and standard deviation of fitness value.

Problem Size	Minimum Fitness			Average Fitness			Standard Deviation		
	ACO	PSO	GA	ACO	PSO	GA	ACO	PSO	GA
20 Holes	**2904.03**	3447.90	2905.83	2997.70	4200.85	3639.99	116.4726	420.9509	446.5357
30 Holes	**3894.28**	5137.58	4205.79	4588.71	6176.15	5446.22	752.3539	642.7958	469.6297
40 Holes	**7142.82**	7941.21	7701.03	8850.88	9348.02	8469.83	1360.598	784.9465	421.7967
50 Holes	13215.72	11126.44	**10480.43**	15782.12	12801.90	12734.58	1137.577	926.7445	854.2105
70 Holes	**10214.00**	10912.82	11041.24	15144.58	12956.56	12757.87	2848.927	1079.98	868.9615
80 Holes	17082.79	15887.04	**15409.59**	21561.79	18222.24	17181.90	2012.683	1141.539	1060.888
90 Holes	26066.80	**19153.52**	19492.44	27508.59	21295.40	20868.14	715.1115	1339.752	818.447
100 Holes	31697.14	24654.69	**24124.42**	33416.44	27223.94	26458.84	701.108	1517.017	1092.526
120 Holes	26461.18	23503.09	**23144.35**	32723.15	25737.90	26287.67	2068.976	1441.396	1552.378
130 Holes	40032.51	**29023.44**	29439.50	41431.53	33243.71	32598.90	811.8819	1846.671	1208.887
140 Holes	45246.10	**32538.39**	34345.32	46592.62	36134.23	37187.46	838.4603	1603.686	1636.198
150 Holes	52274.73	41488.43	**39838.12**	53178.97	43994.04	43514.20	521.2095	1831.422	1547.605

The algorithms were evaluated based on their solution quality, with lower fitness values indicating better performance. Overall, GA performed the best across most hole configurations, achieving the optimal fitness value in 5 out of 12 cases (small, medium, and large). In comparison, ACO performed better for 4 out of 12 cases (small and medium), and PSO performed better for 3 out of 12 cases (medium and large).

A Standard Competition Ranking (SCR) approach was further used for a better and more understandable display of the optimization outcomes. The best algorithm was given rank 1 in this manner based on minimum fitness. Meanwhile, the worst algorithm was given rank 3. Based on Table 7, ACO has the highest first-ranking values compared to PSO and GA for small categories of MDMT problems, the same as the finding of Abidin et al. (2018). Correspondingly, GA has the highest first-ranking values compared to ACO and PSO for medium and large categories. GA appeared to handle the increase in complexity overall, as it consistently achieved the lowest scores across the range of hole configurations.

Table 7: Standard Competition Ranking (SCR) for minimum fitness.

Category	Ranking	Algorithm		
		ACO	PSO	GA
Small	Rank 1	3	0	1
	Rank 2	0	1	3
	Rank 3	1	3	0
Medium	Rank 1	1	1	2
	Rank 2	0	3	1
	Rank 3	3	0	1
Large	Rank 1	0	2	2
	Rank 2	0	2	2
	Rank 3	4	0	0

Figure 4 displays the average and standard deviation of fitness value. The standard deviation value is close to the average fitness value, meaning the data holes are tightly clustered around the mean or average fitness value. In other words, there is little variation or spread in the data. Thus, a small standard deviation indicates that the data holes are close together and more consistent.

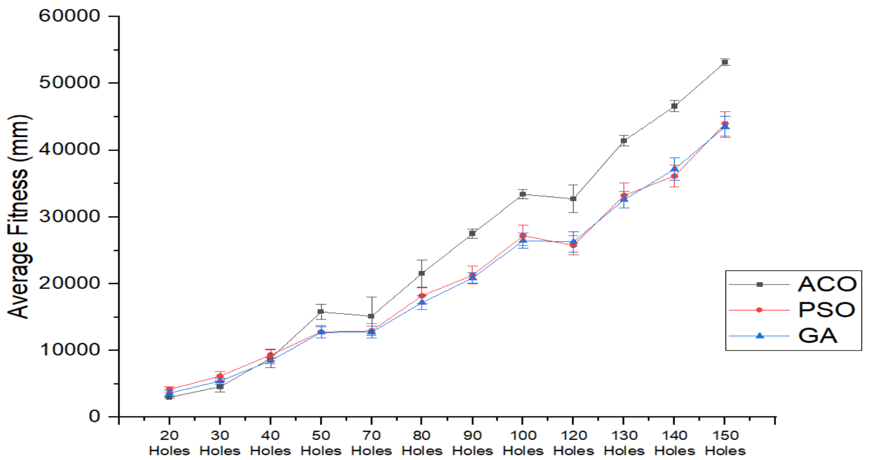

Figure 4: Average and standard deviation of fitness value.

5. CONCLUSION

The fitness function in MDMT is an important tool for optimizing the drilling process. By minimizing the total distance of the toolpath, engineers can identify the most efficient and effective combination of tools and drilling parameters to achieve the desired results. Based on the verification process, the fitness function performs well with optimal fitness values and suggests the model's effectiveness in improving the drilling process's efficiency. The computational model developed has been confirmed to be accurate by verifying its output with manual calculations, and both methods produce the same results. It proves that the objective of this research was successfully achieved, concluding that the valid model can be used in further investigation and studies. Based on computational experiment results, the GA demonstrated good performance for optimization on MDMT problems compared to PSO and ACO. Regarding recommendations for future research, the paper could suggest several avenues for further investigation. For instance, future research could explore how the proposed computational model could be optimized for different materials and drilling scenarios. This could involve testing the model with different materials, such as composites, plastics, and metals, to determine its effectiveness in each case. Additionally, researchers could investigate how the model could be adjusted for different drilling scenarios, such as varying hole sizes, depths, and angles, and how it could be integrated with other drilling technologies, such as laser drilling or waterjet cutting. Moreover, the impact of different tool geometries, such as helical or diamond-shaped, on the drilling process could also be explored. Finally, the research could also explore how the proposed model could be implemented in real-world manufacturing environments and how it could be integrated with existing manufacturing systems to enhance productivity, accuracy, and efficiency.

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