Optimizing the Electrical Wire Routing through Multiple Points using Multi-Objective Ant Colony Algorithms for Electrical Wire Routing (MOACS-EWR)

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Abstract— Ant colony optimization algorithm is a remarkable nature-inspired algorithm which produces outstanding optimization solutions. During the recent years these algorithms have been applied to various difficult combinatorial optimization problems and proved successes. In this paper, we present a novel approach of ant colony optimization algorithm to optimize the electrical wire routes through multiple points. In this study, **Multi-Objective Ant Colony Algorithms for Electrical Wire Routing (MOACS-EWR) is used to optimize multiple objectives: length of the path and the number of bends in the path. The study was done using two approaches with modifications to local pheromone updating rule. The results of the study shown that the proposed modifications are performed well in optimizing electrical wire routes through multiple points.**

Keywords— Ant colony optimization, electric cable routing, multi-point covering, multi-objective problem

I. Introduction

Nature-inspired algorithms offer solutions for complex problems in science and engineering. Inspiring by the foraging behavior of ants, Dorigo and Stutzle introduced the Ant Colony Optimization (ACO) algorithm in 1990s [1]. Ants are depositing pheromones when they are navigating from their nests to food sources. Ant Colony Optimization algorithm was developed by imitating this amazing behavior of ant colonies. ACO has been used for solving combinatorial optimization problems like Traveling Salesman Problem (TSP) and Job-Shop Scheduling Problem (JSSP) [2]. Recently there are many versions of ACO have been applied to challenging problems proved with valuable solutions [3].

Designing electrical wire layouts has become very complicated with the growth of the electrical requirements in building industries. Still the manual trial and error methods are commonly used in wiring [4]. Optimization is finding the best solution for a problem with regard to a single objective or multiple objectives. Optimization leads to numerous advantages over cost, time and quality. By optimizing the length of the electrical wire route, required amount of the wire can be reduced which will lead to reduce the complexity and the voltage drops of the circuits.

The aim of this study is to apply Multi-Objective Ant Colony Algorithms for Electrical Wire Routing (MOACS-EWR) in order to optimize wire route between a starting point and a target point while following an intermediate point. MOACS-EWR designed to optimized wire route considering multiple objectives: length and number of bends with avoiding obstacles.

Over the past few years several ACO algorithms were proposed to optimize the length considering single or multiple objectives. Ant colony algorithm for ship pipe route design (SPRD) in 3D space was introduced by Fan et al. [5]. They considered optimizing multiple objectives like length and number of bends with obstacle avoidance. They have modified the state transition rule to move ants from the starting point to the destination, and the initial pheromone values are zero. Initially, paths are built using only heuristic information. After generating the initial solution set, the objective function value is calculated, and the global pheromone rule for the initial best solution is applied. While the ants are constructing the tours, local pheromone rule is applied to the visited edges. The performance of the algorithm was compared with a genetic algorithm (GA) and adaptive genetic algorithm with simulated annealing (ASAGA). It was proved that the proposed algorithm is better in terms of performance and speed.

Alvarado et al. introduced an application of ACO algorithm to solve electrical distribution planning problems [4]. In this research, they improved the Ant Colony System (ACS) and modified three basic features. First, they have used a proportional pseudo-random transition rule to explore new paths with the use of the accumulated **knowledge of the problem to select the "best route." This is** followed by the application of global pheromone level revision rule to those branches belonging to the best networks found so far. Pheromone is deposited only in those branches that fit to the best network. This aims for direct search, which focuses the explorations toward the best one found to date. Finally, the local pheromone level revision rule is applied in which these levels are updated during the route generation process. They have used this methodology to a real-world energy distribution planning problem and gained satisfactory results.

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Christodoulou and Ellinas [6] reviewed the pipe routing using ACO to help for better management of water resources, water distribution systems and the optimized routing of pipe networks. They implemented a methodology to optimize the water-flow routing in pipe networks using ACO. The study considered the optimum path for minimum pipe lengths, minimization of the required number of valve operations of an active path, and keep a minimum pressure drop along the path. Initially, all pipe branches are deposited with a little amount of pheromone according to the distance of the branch. Then the ants start from the starting node and build tours pseudo-randomly until they reach to the end node or a dead end. A local pheromone updating is done to the visited nodes while the ants are building their tours. Finally, global pheromone updating is applied to the globally best path. The performance of the modified algorithm is compared against the traditional critical path method (CPM) and proved that the modified ACO produced better results.

Fernando and Kalganova proposed multi-colony ant systems for Multi-Hose Routing [7]. They proposed two versions of multi-colony ant systems based on AS (MCAS-MHR-1 and MCAS-MHR-2). These algorithms were applied to search for optimized paths for routing multiple hoses/pipes in parallel while avoiding the obstacles. In the first version, all colonies use a single pheromone matrix, and in the second version separate pheromone matrices are used for each colony. In the second version ants can smell the pheromones laid by individual ants in the other colonies when building the path. But in the first version all the pheromones laid by ants in different colonies are added at the edges as a single value. In both methods, pheromones are updated based on the quality of the shortest paths as well as the shared paths. The results show that there is no considerable difference between the two algorithms, however, the first one takes less computational time since that needs less computer memory than the second one.

Most of these methods were considered optimizing the route between two points and they didn't focus covering intermediate points in the route. In this study, our main aim is to optimize path between two points by following an intermediate point.

II. Electrical Cable Routing

Electrical cabling is a critical factor that needs vigilant addressing in building constructions. The entire system could seize if a single cable goes down. Hence, accurate designing of the cable structure is vital. Best optimized layouts of circuits improve the manageability by reducing the difficulties and the cost of the entire wiring system. Most probably, the wiring installations are done through trial-and-error methods by prior accumulated knowledge. Through the past decades, electrical requirements grew rapidly, making wiring designs more complicated for manual performance. Researchers have introduced several designs, techniques, and systems to design electrical plans for different types of applications such as construction machinery, aircraft, automobiles, spacecrafts, ships, and building industries.

Electrical wiring design must follow the recognized standards, IET (The Institution of Engineering and Technology), which is also known as BS7671, defined as the standard regulations for wiring. These regulations are essential to electrical engineers and installation designers for proper and secure electrical installations [8]. In this study, the standard mounting heights of electrical accessories were considered when designing the models of the grids (walls).

III. Multi-Objective Ant Colony Optimization Algorithm for Electrical Wire Routing (MOACS-EWR)

MOACS-EWR algorithm is derived from Ant Colony System (ACS) with several modifications to achieve optimized wire routes. First modification is done to the ACS state transition rule (equation 1). Normally, an ant k in point r selects the next point s based on either exploitation or exploration. This is selected using a random number q which is uniformly distributed in [0 1], and q_0 is a parameter ($0 \leq q_0 \leq 1$) in the algorithm. In this experiment q_0 is taken as 0.9, and if $q \leq q_0$, normal ACS exploitation rule is applied. Otherwise ants use biased exploration to select the next point. In this situation, the random proportion rule (equation 2) is used to calculate the probability of selecting the next point. In ACS, the heuristic information in the random proportion rule is taken by considering 1/distance (r, s) from the point r to the point s. However, in this study the heuristic information is modified to select 1/distance (s, t) from the next possible point (s) to the target point (t) to make the solution more feasible.

After calculating the probabilities of moving to the next possible cities, roulette wheel selection is applied to select the next city, by generating a random number between [0,1] and comparing it with the calculated probabilities. This encourages ants to explore more paths depending on their probabilities. The paths with high values of probability get higher chance to be selected.

In this algorithm, ants design the circuit by travelling from starting point to the ending point where the socket outlet is located. Initially, all ants in the colony placed in the starting point. Then each ant selects the next grid point to move according to the modified state transition rule explained as in equation 5 with roulette wheel selection. This selection is made according to the closest and the highest level of pheromone. Then the ants apply the local pheromone updating rule in equation 4 to update the pheromones in the visited edges of their constructing tour. When the ants who reached to the target point where the power socket is located, tour is completed. After all ants complete there tours the total length of their tours are calculated. Then the best path is selected and the pheromones of the edges of that path are updated with extra amount of pheromones according to the modified global updating rule in equation 6.

Global updating rule in equation 6 is the next modification to achieve the optimized path with minimum length, minimum number of bends and straight angles. This study uses weighted sum approach when designing the objective function to optimize multiple objectives. The pheromones are updated in the iteration best path according to the designed objective function which optimizes the length, the number of bends and the angles of the bends. Modifications are further explained in the next section. Heuristic functions are designed with considering the normalization of both continuous and discrete quantities.

A. An ant position on city r chooses the city s to move, by applying the state transition rule (pseudo-random-proportional rule) is given by equation (1)

$$s = \begin{cases} \arg\max_{u \epsilon J_k(r)} \left[[\tau(r,s)] \cdot [\eta(r,s)]^{\beta} \right] & \text{if } q \leq q_0 \text{ (exploitation)} \\ S & \text{otherwise (biased exploration)} \end{cases} \quad (1)$$

where $\tau(r,s)$ is the pheromone density of an edge (r,s), heuristic information $\eta(r,s)$ is the [1/distance $((s,t))$], reciprocal of distance from point s to the target point t. $J_k(r)$ is the set of cities that remains to be visited by ant k positioned on city r. β is a parameter which decides the relative importance of pheromones versus heuristic information $(\beta>0)$. q is a random number uniformly distributed in [0, 1], q_0 is a parameter ($0 \leq q_0 \leq 1$), and S is a random variable from the probability distribution given by the equation (2).

$$p_k(r,s) = \begin{cases} \dfrac{[\tau(r,s)] \cdot [\eta(r,s)]^{\beta}}{\sum_{u \epsilon J_k(r)} [\tau(r,u)] \cdot [\eta(r,u)]^{\beta}} & \text{if } s \; \epsilon J_k(r) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

B. Then the pheromones are updated in the edges of the best ant tour using the global updating rule given in equation (3).

$$\tau(r,s) \leftarrow (1-\alpha) \cdot \tau(r,s) + \alpha \cdot \Delta\tau(r,s) \quad (3)$$

where $0 < \alpha < 1$ is the pheromone decay parameter.

Objective function is modified to minimize the total length of the circuit (L_{gb}) and the number of bends (N_B) in the circuit.

$$\Delta\tau(r,s) = \begin{cases} (f_{(1)})^{-1} & \text{if } (r,s) \epsilon \text{ global} - \text{best} - \text{tour} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$f_1 = w_1 \left(\frac{L_{gb}}{2D}\right) + w_2 \left(\frac{N_B}{4}\right) \quad (5)$$

where $w_1 + w_2 = 1$, L_{gb} is the length of the global best tour, D is the diagonal length of the plot, N_B the number of bends in the global best tour, 4 is the maximum no of bends allowed before a circuit breaker is met.

w_1 and w_2 are the weighting factors associated with the length and the number of bends respectively. They should be selected according to the proportion of importance being given to one objective over the other. The sum of the weights is equal to one. This method was used to select the optimized path considering multiple objectives.
$w_1 = 0.6$, $w_2 = 0.4$ is the best weight combination obtained.

C. When ants move from one city to another city, local pheromone updating rule is applied as in equation (6).

$$\tau(r,s) \leftarrow (1-\rho) \cdot \tau(r,s) + \rho \cdot \Delta\tau(r,s) \quad (6)$$

where $0 < \rho < 1$ is a parameter and $\Delta\tau(r,s) = \tau_0$, τ_0 is the initial pheromone level.

Modification for Approach 2

$$\tau(r,s) \leftarrow (1-\rho) \cdot \tau(r,s) + \rho \cdot \Delta\tau(r,s) + w \quad (7)$$

$w = 100$, w is the additional amount of pheromone.

D. Roulette Wheel Selection

Using the roulette wheel selection, the probabilities calculated by the state transition rule in equation 1 to select the next city to move, is mapped into contiguous segments of a line span within [0, 1] such that each individual's segment is equally sized to its probability. A random number is generated and the individual whose segment spans the random number is selected.

IV. EXPERIMENTATION

Several points may need to connect through the path when laying a single wiring circuit. Hence, we have modified the MOACS-EWR algorithm and apply that to cover multiple points in a circuit. Development is done through two approaches. In this study, ants start their tour from the starting point and move towards the target. The intermediate point is covered while they build their tours. This study focuses on finding the optimized path by considering obstacle avoidance and covering the intermediate point. The implementation employs two approaches.

These approaches were tested using two models of walls (model 1 and model 2) with different set of starting, intermediate and target points. Following Figures 1and 2 of Model 1 is with 3 obstacles and 44 grid points. Each model is tested for two different intermediate points and same starting and target points. First combination is: starting point S (X_S, Y_S) is point 17 (19.5, 0.5), intermediate point M (X_M, Y_M) is point 21 (8.5, 4), target point E (X_E, Y_E) is point 3 (2.5, 0.5) as shown in Figure 1. Second combination is: starting point S (X_S, Y_S) is point 17 (19.5, 0.5), intermediate point M (X_M, Y_M) is point 31 (1.5, 9), target point E (X_E, Y_E) is point 3 (2.5, 0.5) in Figure 2.

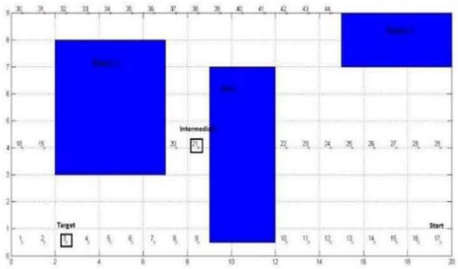

Fig 1: Model 1with three obstacles and starting point S (X_S, Y_S) is point 17 (19.5, 0.5), intermediate point M (X_M, Y_M) is point 21 (8.5, 4), and target point E (X_E, Y_E) is point 3 (2.5, 0.5)

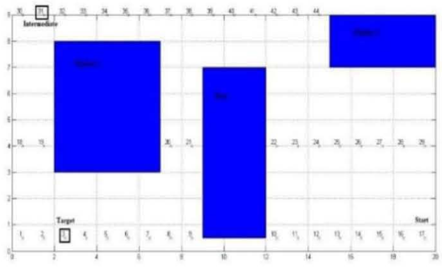

Fig 2: Model 1 with three obstacles and starting point S (X_S, Y_S) is point 17 (19.5, 0.5), intermediate point M (X_M, Y_M) is point 31 (1.5, 9), and target point E (X_E, Y_E) is point 3 (2.5, 0.5)

Following Figures 3 and 4 of Model 2 is with 4 obstacles and 44 grid points. Each model is tested for two different intermediate points and same starting and target points. First combination is: starting point S (X_S, Y_S) is point 44 (19.5, 9), intermediate point M (X_M, Y_M) is point 35 (8.5, 9), target point E (X_E, Y_E) is point 3 (2.5, 0.5). Second combination is: starting point S (X_S, Y_S) is point 44

(19.5, 9), intermediate point M (X_M, Y_M) is point 22 (10.5, 4), target point E (X_E, Y_E) is point 3 (2.5, 0.5).

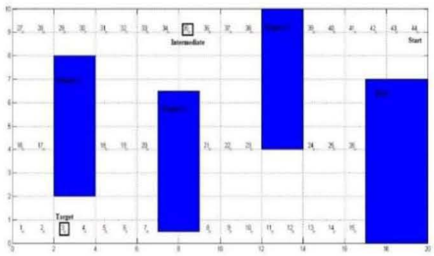

Fig 3: Model 2 with four obstacles and starting point S (X_S, Y_S) is point 44 (19.5, 9), intermediate point M (X_M, Y_M) is point 35 (8.5, 9), and target point E (X_E, Y_E) is point 3 (2.5, 0.5)

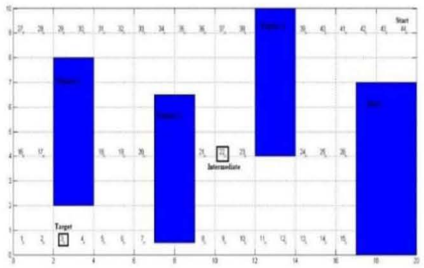

Fig 4: Model 2 with four obstacles and starting point S (X_S, Y_S) is point 44 (19.5, 9), intermediate point M (X_M, Y_M) is point 22 (10.5, 4), and target point E (X_E, Y_E) is point 3 (2.5, 0.5)

A. Approach 1 - Multi-objective ant colony optimization algorithm to cover multiple points in electrical wire routing (MCAS-MHR-1).

In this approach, ants design the circuit by travelling from starting point to the ending point where the socket outlet is located. Initially, all the ants in the colony placed in the starting point. Then each ant selects the next grid point to move according to the modified state transition rule explained as in equation 1 with roulette wheel selection. This is selected according to the closest and the highest level of pheromone. Then the ants apply local pheromone updating rule in equation 6 to update the pheromones in the visited edges of their constructing tour.

When the ants who reached to the target point where the power socket is located, tour is completed. After the ants completed their tours, only the paths which cover the intermediate point were selected. Out of these paths shortest path is selected. Then the pheromones of the edges of that path are updated with extra amount of pheromones according to the global updating rule in equation 3. This process is repeated until all iterations are completed. Finally, global best tour is selected. This tour is the optimized path between the staring, intermediate and target points.

B. Approach 2- Multi-Objective Ant Colony Optimization Algorithm to Cover Multiple Points in Electrical Wire Routing with modified local pheromone updating rule (MCAS-MHR-2).

In this approach, ants design the circuit by travelling from starting point to the ending point where the socket outlet is located. Initially all the ants in the colony placed in the starting point. Then each ant selects the next grid point to move according to the modified state transition rule explained as in equation 1 with roulette wheel selection. This is selected according to the closest and the highest level of pheromone. Then the ants apply local pheromone updating rule to update the pheromones in the visited edges while they construct the tour. In this approach, when the local pheromone updating is applied if the ants selected the intermediate point as the next point to move, the edge links to the intermediate point is updated with extra amount of foreign pheromones as in equation 7. Otherwise the local pheromone rule in equation 6 is applied.

When the ants reached to the target point where the power socket is located, the tour is completed. After the ants complete their tours, only the paths which cover the intermediate point are selected. Out of these paths shortest path is selected. Then the pheromones of the edges of that path are updated with extra amount of foreign pheromones according to the modified global updating rule in equation 3. This process is repeated until all iterations are completed. Finally, global best tour is selected. This tour is the optimized path between the starting, intermediate and target points. When ants are moving from one city to another, local pheromone updating rule is applied as in equation 6.

The parameter settings for the algorithm were:

The no of ants= 20, no of turns the algorithm is run is MAX_TURN= 1000, pheromone decay parameter ρ= 0.1, α= 0.1, β= 2, q_0= 0.9, D= 22, τ_0= $(n.L_{nn})^{-1}$ where L_{nn} is the tour length produce by the nearest neighbor heuristic and n is the number of cities. The heuristic distance $\eta(s,t)$, the [1/distance $((s,t))$] is the distance from point s to the target point (socket outlet).

The simulation was conducted on a PC with Intel Core i5-6200U processor (Processor speed= 2.4 GHz, Memory= 8 GB) in the Windows 10 Home operating system using MATLAB (Version R2012b). All the combinations of above two models were run through ten trails and the performance was recorded.

V. RESULTS AND DISCUSSION

The experimentation was carried through ten trails for each model. Each model was tested with two combinations of same starting and ending points with different intermediate points. These experimentations were carried out through approaches 1 and 2. Table 1 contains the results of the best routes of entire ten trails of model 1. For each approach, for both routes best distances, number of bends in the path and the time taken to design the routes were recorded.

When we compare the results of both approaches; lengths of the paths were slightly change and the approach 2 results the shortest lengths. When we consider the number of bends, there is a difference in both approaches as shown in table 2 and 4. Considering the number of bends approach 2 shows better results. Also, there is a significant difference in time in both approaches. It shows that the time taken in approach 2 is much less than the approach 1.

TABLE 1: BEST DISTANCES OF MODEL 1

	Approach 1			Approach 2		
Start, Intermediate and Target	Best Distance (Feet)	Number of Bends in the Best Path	Time (Seconds)	Best Distance (Feet)	Number of Bends in the Best Path	Time (Seconds)
17-21-3	26.98	4	42.12	26.69	4	10.36
17-31-3	32.23	3	30.68	30.51	3	7.69

Table 2 shows the average values of the ten trails of all the instances. For each approach average distance, number of bends and the time were recorded. According to the average results of model 1, approach 2 shows better results than the approach 1 for the distances and number of bends with a high speed. According to the results of Tables 1 and 2, approach 2 is better and faster than the approach 1.

TABLE 2: AVERAGE RESULTS OF MODEL 1

	Approach 1			Approach 2		
Start, Intermediate and Target	Average Distance (Feet)	Average Number of Bends	Average Time (Seconds)	Average Distance (Feet)	Average Number of Bends	Average Time (Seconds)
17-21-3	27.45	4	41.94	27.17	4	14.01
17-31-3	34.67	4	42.10	30.96	3	13.68

Following figures from 5-8 show the best routes given in all instances of both approaches of model 1.

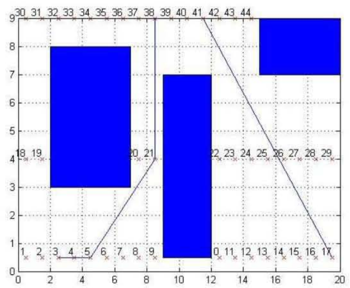

Fig 5 Model 1: Approach 1 - 3 obstacles best distance for 17-21-3 – Best path 17,41,38,21,5,3 Distance 26.98 feet, Number of bends 4

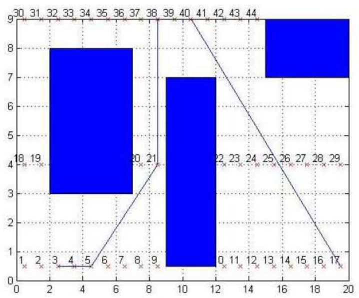

Fig 6 Model 1: Approach 2 - 3 obstacles best distance for 17-21-3 – Best path 17,40,38,21,5,3 Distance 26.69 feet, Number of bends 4

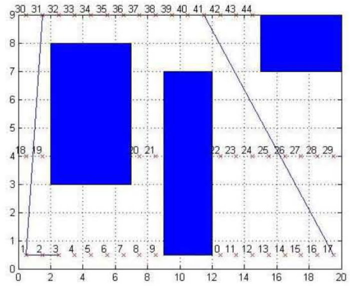

Fig 7 Model 1: Approach 1 - 3 obstacles best distance for 17-31-3 – Best path 17,41,31,1,3 Distance 30.51 feet, Number of bends 3

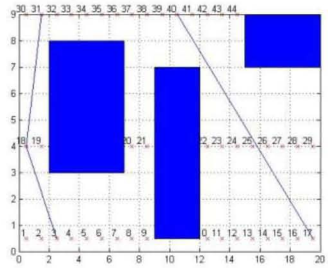

Fig 8 Model 1: Approach 2 - 3 obstacles best distance for 17-31-3 – Best path 17,40,32,31,18,3 Distance 30.51 feet, Number of bends 4

Table 3 presents the best routes given by all the instances of both approaches in model 2. Results of model 2 shows that the best distances given by the approach 2 is better than the approach 1. But there is no difference between number of bends for both approaches. There is a significant different between the times and the approach 2 is much faster than the approach 1.

TABLE 3: BEST DISTANCES OF MODEL 2

	Approach 1			Approach 2		
Start, Intermediate and Target	Best Distance (Feet)	Number of Bends in the Best Path	Time (Seconds)	Best Distance (Feet)	Number of Bends in the Best Path	Time (Seconds)
44-35-3	33.16	5	35.17	33.16	5	13.68
44-22-3	36.61	6	75.81	33.71	6	24.25

Table 4 presents the average performance of each instances in the two approaches. The average results show that the approach 2 is better than the approach 1 considering the average lengths of the routes, number of bends in the paths and when considering the speed. Approach 2 shows the shortest route with less number of bends. Following Figures from 9-12 show the best routes given in all instances of both approaches of the model 2.

TABLE 4: AVERAGE RESULTS OF MODEL 2

	Approach 1			Approach 2		
Start, Intermediate and Target	Average Distance (Feet)	Average Number of Bends	Average Time (Seconds)	Average Distance (Feet)	Average Number of Bends	Average Time (Seconds)
44-35-3	36.35	6	51.45	34.14	6	14.07
44-22-3	37.08	7	65.90	34.89	6	15.01

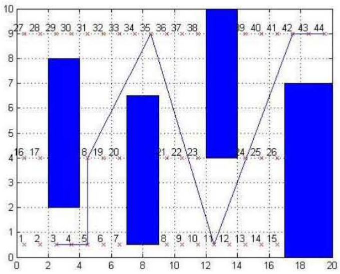

Fig 9 Model 2: Approach 1 - 4 obstacles best distance for 44-35-3 – Best path 44,42,11,35,18,5,3 Distance 33.16 feet, Number of bends 5

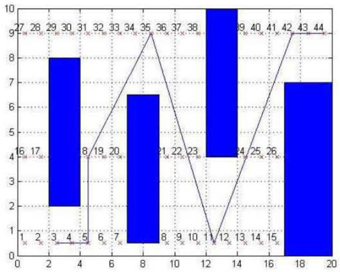

Fig 10 Model 2: Approach 2 - 4 obstacles best distance for 44-35-3 – Best path 44,42,11,35,18,5,3 Distance 33.16 feet, Number of bends 5

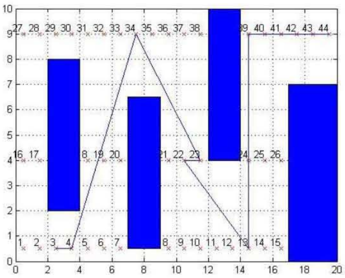

Fig 11 Model 2: Approach 1 - 4 obstacles best distance for 44-22-3 – Best path 44,39,13,22,23,34,4,3 Distance 36.61 feet, Number of bends 6

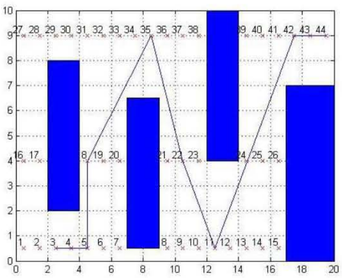

Fig 12 Model 2: Approach 2 - 4 obstacles best distance for 44-22-3 – Best path 44,41,11,22,35,18,5,4,3 Distance 33.71 feet, Number of bends 6

VI. CONCLUSION

In this study, new approach of ACO has been introduced to optimize the electrical wire route between three points (start, intermediate and target points). The algorithm is implemented in MATLAB environment. The study forces on enhancing the MOACS-EWR algorithm to cover several points when generating optimized path considering number of bends and obstacle avoidance. The algorithm was tested with two models of walls adhering to the BS7671 standards of permitted cable routing zones. Two approaches were designed with modifications and the performances were tested. Both approaches were performed with promising results, but the second approach with the modified local pheromone updating rule performed better and faster than the first approach.

The modified algorithm can find the optimized distance between the start and the target point through an intermediate point effectively. This can be applied to electrical wiring circuits which need to connect more than two points. Also, the algorithm can optimize multiple objectives: length and the number of bends in the path. Algorithm is designed considering the constrains like obstacle avoidance and adhering the standards. Optimizing electrical wire routes can lead to several advantages like minimizing the cost, complexity of installation and the voltage drops of the circuits. When the voltage drops are reduced, we can ensure the safety of the electrical equipment's. Results of this algorithm can be easily used to design the circuit layout of the electrical wiring.

This study can further develop to cover several points in the circuit as required. At the next stage, algorithm can improve to optimize electrical wire routes in an entire 2D room environment. The algorithm can optimize the several objectives simultaneously and can apply to environments with obstacle avoidance. This simulation can provide clear guidance to the installation engineers finding the best layouts. This can be further developed to apply in situations when designing electrical plans for different types of applications such as construction machinery, aircraft, automobiles, spacecraft, ships, and building industries.

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