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A Novel Method to Find the shortest Path in Wireless Networks

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Abstract

In this paper, we propose a new method based on the combination of the ant algorithm and local search algorithm 2-OPT to find shortage path in wireless networks. According to the results of combined algorithms, it significantly optimizes the algorithm for finding the shortest route. While there are a few researches about wireless network routing by the ant algorithm in literature, this research mainly deals with finding optimized routing in big wireless networks by using ant algorithm and local search algorithm 2-OPT.

Based on the obtained results of the proposed algorithm, the route is shorter and more precise than the route resulted from ant colony, particle swarm optimization and genetic algorithm in a big wireless network.

Keywords: Ant algorithm, network routing, local search algorithm 2-OPT,cost routing

1- Introduction

Optimization is an important action in the designing step. The best plan is obtained when optimization is done for decreasing time, and cost [1]. Routing protocol has an important role in calculation and selection of a desired path for data transferring. Nowadays there are many efforts for finding suitable algorithm of the shortest path in wireless network, and according to the results different algorithms were suggested [1]. Based on different characteristics of proposed method it is possible to classify them as follows:

a)Natural algorithms are including genetic algorithm [2-3], particle swarm optimization [4] and the ants colony algorithm [5-8]

b) Artificial algorithms are including local search algorithm 2-OPT and Tabu artificial repetitious algorithm [9-10, 2].

Other methods include particle swarm optimization [11-13], traveling salesman problem algorithm [14-21] and Tabu search [22].

In this paper, significant results are obtained by combining ant colony algorithm and local search algorithm 2-OPT. The main result of combining is obtaining the optimized algorithm to find the shortest path between two nodes in wireless networks. The proposed algorithm is suitable for big networks with high loads.

This paper has different sections as follows: In section 2 fundamentals in the ant system along with graph theory modeling and solution of routing methods for finding the shortest path by ants is introduced. Then section 3 presents the proposed algorithm and obtained results in a dynamic protocol for wireless networks. Finally, conclusions are described in the last section.

2-Principles and Background

2-1 Ant Colony System (AS)

There are types of ants that spray pheromone during working. They put this chemical material in their work path. Then ants smell this special chemical from previous ants and thus go toward the food. They recognize the shortest route according to intensity of pheromone [23]. When an ant starts a complete travel, it leaves some pheromone on each i, j (selected) path. Consider τ_{ij} as the intensity in (i, j) paths at time of t. Each ant at time t will choose the next city and at time t+1, it will be there. So if one iteration of the Ant algorithm, m movements are done by m ants at the interval time (t, t+1), after d replication algorithms each ant has a full pheromone. At this point, the intensity is calculated based on $\tau_{ij}(t+1)=\rho.\tau_{ij}(t)+\Delta\tau_{ij}$ and ρ is a coefficient so that $(1-\rho)$ indicates amount of evaporation at the interval time (t, t+1), and $\pi_{ij}=\sum\pi_{ij}k$ where $\pi_{ij}k$ is the amount of the material per unit length that is left by the K^{th} ant at the interval time (t, t+1) [24].It is noteworthy that there are three types of ant algorithms: 1- Ant density 2-Ant quantity 3-Ant cycle. The first two algorithms are adjusted for the amount of pheromone in each replicate (the date is given), but after the third algorithm is a modification of the cycle.

According to equation 1 for the first algorithm:

$$\Delta\tau_{ij}^{k}=\begin{cases}Q_1 \; if\; at\; the\; time\; interval\; (t,t+1), k^{th} ant\; goes\; from\; i\; to\; j\\ \qquad 0\;\; otherwise\end{cases} \quad (1)$$

where Q_1 is constantthat is left per unit length in (i,j) path.

According to equation 2 [5] for the second algorithm:

$$\Delta\tau_{ij}^{k}=\begin{cases}\frac{Q_2}{d_{ij}} \; if\; at\; the\; time\; interval\; (t,t+1), k^{th} ant\; goes\; from\; i\; to\; j\\ \qquad 0\;\; otherwise\end{cases} \quad (2)$$

where Q_2 isconstant and $d_{ij}$is distance betweeni,jcity.

According to equation3 [6] for the third algorithm:

$$\Delta\tau_{ij}^{k}=\begin{cases}\frac{Q_3}{l^k} \; if\; at\; the\; time\; interval\; (t,t+1), k^{th} ant\; goes\; from\; i\; to\; j\\ \qquad 0\;\; otherwise\end{cases} \quad (3)$$

where Q_3 isconstantand L^K is traveling distance of K^{th}ant.

2-1-1How to model and solve the traveling salesman problem

ρ coefficient should be smaller than one to prevent unlimited accumulation of pheromone. This pheromone intensity at zero times ($\tau_{ij}(0)$) is considered equal to a constant value of C. In order to satisfy the constraint that an ant must pass all of the d cities, each ant is assigned a data structure called ban list that stores the cities that ant has ever crossed, and to prevent the ant from passing again before the end of d iteration (one cycle) [7, 19]. When the trip completes Tabu list is used to compute the solution of this ant. Then Tabu list is emptied, and again ants are free to opt out. $Tabu_k$is a growing dynamic vector that is including Tabu list of K^{th}ant. The value of $1/d_{ij}$ is definedforvisibility(η_{ij}) [19].So the probability of moving from city i to city j for K^{th} ant is as Equation 4 [20].

$$P_{ij}^{k}(t) = \begin{cases} \frac{(\tau_{ij}(t))^{\alpha} \times (\eta_{ij})^{\beta}}{\sum (\tau_{ik}(t))^{\alpha} \times (\eta_{ik})^{\beta}} & if\ j,k\ \varepsilon\ allowed_k \\ 0 & \end{cases} \quad (4)$$

$allowed_k = \{N - Tabu_k\}$, α and β are parameters on the relative importance of the pheromoneeversus control visibility[21]. Hence the probability of transmission between an exchange's visibility to nearby cities with a high probability of being selected and pheromone intensity at time tsays if there is too much traffic on the i and j path, and it would be a desirable way to work and apply a self-reinforcing process.

2-2 Introduction to Algorithms

At zero or starting stage, ants are located in indifferent cities. The initial value of smell is determined on the passes ($\tau_{ij}(0)$). The opening city enters at the list as the first element. Then each ant will move from the city i to city j according to probability function p_{ij}, which is a function of the desired criteria [25]. One $\tau_{ij}(0)$has information about number of ants that have gone through the pass (i, j) in the past, and another that says visibility for ants from nearby towns are far more desirable. After t iterations, all ants have completed travel ban list, and they are filled. At this point, for each ant the value of L^K is calculated and Δ_{ij}^{k} is adjusted (Updates the pheromone) [1]. Furthermore, ants finding the shortest path are stored, and Tabu lists are empty [1, 8]. This process continues until the number of cycles reaches its maximum or all ants do a similar trip. This is called a record behavior because algorithm stop search for other solutions. In both ant density(Fig. 1) and ant quantity (Fig. 2)algorithms, the pheromone values are updated at each iteration [1, 8]. But for ant cycle algorithm (Fig. 3), the pheromone values are updated at the end of one cycle [26]. After a few cycles, just for ants that travel the best way, pheromone release is allowed. This is done in order to signify the search so that ants search in this neighborhood the best path found so far. The first two algorithms are exactly the same and only differ in terms of updating the pheromone.

1: Initialize

```
Set t=0
For every edge(i,j) set an initial value τij(t) for trail intensity and
Δτij(t,t+1)=0
Place bi(t) ants on every nodei
Set s=1
For i=1 to d do For k=1 to bi(t) do
Tabuk(s) ϵ i
```

Fig.1.Pseudo code ant densityalgorithm

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2. Repeat until Tabulist is full (step repeated (d-1) times)

```
2.0 Set s=s+1
2.1For i=1to d do
For k=1to bi(t) do
Choose the town j to move to with probability Pij(t)
Move kth ant to j {this instruction creates new values bj(t+1)}

Insert node j in Tabu_k (s)
Set τij(t,t+1)= Δτij(t,t+1)+Q1 (Ant density model)
τij(t,t+1)= Δτij(t,t+1)+Q2⁄dij (ant quantitymodel)

2.2For every edge(i,j) compute τij(t,t+1) according to equation
```

Fig.2. Pseudo code ant quality algorithm

3. Memorize shortest tour found up until now

```
If (t<T) or(not all ants chose the same tour)
then
Empty all Tabu lists
Set s=1
For i=1 to d do
 For k=1 to bi(t) do
Tabu_k(s) є i
Set t = t+1
For every edge(i,j)set Δτij(t,t+1)=0
Go to step 2
else
Print shortest tour and stop
```

Fig.3.Pseudo code ant cycle algorithm

2-3Modeling in graph theory

Problem of finding optimal paths in computer networks is known for optimizing compounds that have simple modeling but difficult solution. One non-informed approach to this problem is counting all modes. For a problem with then-node since there is $(n-1)!$states for creating tour and each tour needs O(n) time, algorithm becomes the order of $(n-1)!\times O(n)$ =O(n!), that is completely preventive and quite disappointing [16]. Due to the extent of the problem solution space, we need methods for an informed count to avoid counting all the answers is essential. These informed methods are two groups [17]: exact methods and approximate methods.

A-Exact methods

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Deterministic algorithms to solve this problem are based on mixed linear programming modeling, branch and bound methods, and branches and cutting. This method with using the computing power of computers and spending a lot of time and money finds certain optimal solution. All problems expressed in Table 2 were solved in this method. Several branches and bound algorithms have been proposed for solving this problem, and research is continuing [5, 24].

B- Approximate methods

One of the drawbacks of certain algorithms for solving routing problem is their time-consuming and costly nature, while innovative or approximate algorithms bring answers that are close to optimal in large-scale problems in reasonable time. Innovative algorithms for solving this problem can be divided into three general categories [5, 24]:

- Innovative algorithms for creating tour: creating gradually a tour by adding one node at each step.
- Innovative algorithms for improving a tour: a created tour is improved by changing the position of the nodes, and reducing costs.
- Hybrid innovative Algorithm: it first created a tour and then improved.

Another class of approximate methods for solving this problem is super innovative algorithms [1, 15]. The most important super innovative algorithms for solving this problem are:

- Toothily, algorithm [5, 9]
- Genetic algorithms [2, 7, 10]
- Tabu search[5,22]
- Community of ants[23, 27]
- Simulation of annealing[28]
- Artificial neural networks[3]

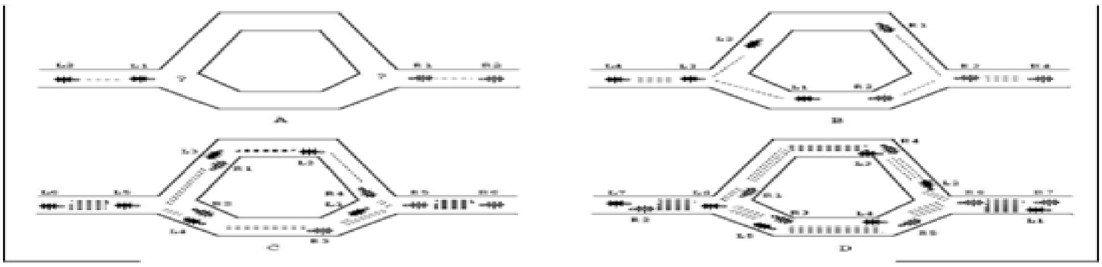

Fig.4. Community behavior of ants in routing [23]

3- The proposedalgorithm

Combination of ant colony and local search algorithm is successful in solving difficult problems such as the traveling salesman problem. This approach using capabilities of both methods, has reached the status of the criterion in solving the traveling salesman. Local search algorithm used in combination is 2-OPT algorithm. In this algorithm, first the tour is broken at both edges. The edges of the two mane are connected to the cross mode. In computer networks when the number of nodes in the network route passes to find the shortest and most efficient route, the issue should be examined from the perspective of the track. Away view, varying according to time and distance between two groups in the network are based on existing routes and route selection. Away view will be considered from this point, if

the selected current path can go from node A to node B in the shortest time relative to the rest of the existing routes from node A to node B, a part of the optimization process.
But this problem can be investigated from different aspects. If you want to send data from node A to node B in computer networks, and there is the number of node's router in this way, to optimize routing problem (detecting shortest path) we should recognize whether or not the used route is an away route.

3-1 -The definition of round

Around path can be defined as follows: there is a path from node A to node B, which a number of nodes such as D and C are between them. These two nodes are routing nodes from node A to node B that perform routing data task. When the round is appeared, routing process is in progress. However, it is necessary to mention that those nodes responsible for routing will make a round. Round mode is shown in Fig. 5.

Fig.5.Appearing the round.

In Fig. 5, at first glance it seems to be optimal routing, but this figure can be shot from a round since to move from node A to node B, it is necessary to pass from node router C and D. But there may be a shorter and more efficient route for moving from A to B, and this is one of the most important goals of an optimal routing solution, which means finding the shortest path. In Fig. 6 possible shorter paths between node A and node B are presented.

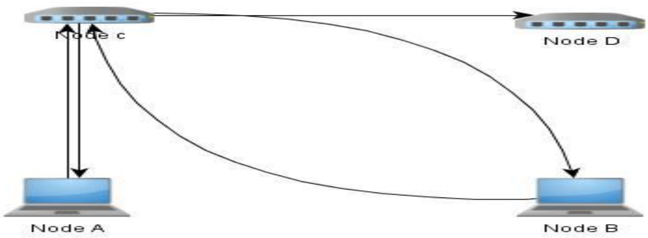

Fig. 6. Possible shorter and more efficient routes between two nodes.

3-2 - Round diagnosis and resolution on track

If this change leads to improvement (reduction) in the objective function, there would be a round. Otherwise, the change is not considered and there will be an effort to break round from the other two edges. This process is repeated until the objective function is not decreased by breaking any other two edges. In this case, we have reached a local minimum. Fig. 7 shows how the 2-OPT innovative algorithm works. Pseudo-code algorithm which

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results from a combination of local search and ant colony system algorithms is shown in Fig. 8.

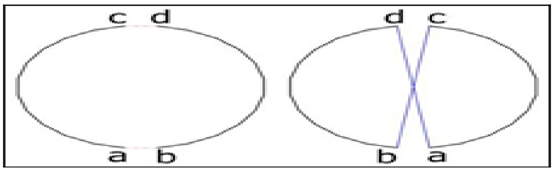

Fig.7. 2-OPT local search algorithm

In the proposed algorithm (a combination of ant colony and local search algorithms), after all ants have made their paths connecting nodes (when a repeat ends), 2-OPT local search algorithm is used to convert them to a local optimum. Furthermore, the locally optimal solution is used for general update of the pheromone. The use of locally optimal solutions for general updating pheromone causes more pheromone on the edges of locally optimal solution to remain, and it directs the search towards these answers. Although this can result in premature convergence of the ant colony to a local optimal solution, due to the nature of the next node selection which is done according to equations 5 and 6, practically the risk of premature convergence to a locally optimal solution will disappear. The pseudo code of the proposed algorithm is presented in Fig.8.

```
Procedure Ant colony system (one iteration)

Set pheromone trails to small constant

While termination condition does not meet do

Place each ant on initial node

  For i=1 to n do ( #nodes)

    For  k=1 to m do (#ants)

Apply state transition rule

 End (ants)

 Apply local update

End for ( one Iteration)

Local search OPT Algorithm ( for all CYCLE  made by ants)

Global update

End while
```

Fig. 8.Hybrid algorithm ASC and local search OPT algorithm.

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$$s = \begin{cases} Max(\tau_{ij})^{\alpha} \times (\eta_{ij})^{\beta} & q \leq q_0 \\ S & q > q_0 \end{cases} \quad (5)$$

$$P_{ij}^{k}(t) = \frac{(\tau_{ij}(t))^{\alpha} \times (\eta_{ij})^{\beta}}{\sum_{l \in N} (\tau_{ij}(t))^{\alpha} \times (\eta_{ij})^{\beta}} \quad (6)$$

3-3 - The proposed algorithm results in a network of 360 nodes

According to the discussion in section 2, finding the shortest path between 360 nodes in the network is a symbol of solution ability, which is used to test the proposed algorithm versus known ant colony, genetic and PSO algorithms. The comparison is shown in Table 1. Obviously, the choice of 360 points to calculate the shortest path is based on time constraints and especially the limitations in the available computational resources and in the availability of more computing resources (in particular, the use of parallel processing). Connecting paths can be solved with more nodes. In this case, 360 nodes in a network based on the desired parameters are selected. Then the latitude and longitude of these points are extracted, and finally the geographical distance is the interval on a sphere with 6378388 km radius. These points together (in kilometers) are calculated in the form of a matrix of 360 in 360. Table 2 shows the latitude and longitude related to a sample of n=5 containing 360 nodes.

Table1. Fivenodes selected in a network

	ACS	ACS+2-OPT	GA	PSO
Average Length Circle(kilometer)	26538,73203	19087,43445	27576,20431	32812,24906
ShortestLength Circle(kilometer)	24868,7985	18932,6113	26076,1361	31154,19233
Time(seconds)	4562	5523	4683	4875

Table2.Matrix of five nodes in the network

Number	1	2	3	4	5
1	-	7.1361	490.83	843.92	611.09
2	7.1361	-	483.81	850.89	618.03
3	490.83	483.81	-	1310.3	1078.7
4	843.92	850.89	1310.3	-	232.13
5	611.09	618.03	1078.7	232.13	-

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3-4 - Results of the Problem Solving

To solve the problem, ant colony System algorithm (ACS) and PSO and GA and the proposed algorithms in MATLAB programming language in a matrix of 360 ×360 nodes in the network are implemented. The innovative algorithm of ants colony system parameters based on the results of [3] is configured as Table 3.The work spaces Represented graphically by a neural network (Fig.9).In equation7, Lnn is the length of created round with a new innovative round producer called the nearest neighbor [10]. Fig. 10 depicts the pseudo code of PSO (particle optimization) multiple network paths for a specified number of iterations relation to the specific parameters such as the best position of the particle.

Table3.Parametersof heuristic algorithm ants

parameter	Value
	1
	2
	0.1
	0.1

$$P_0 = \frac{1}{(n \times l_{nn})} \quad (7)$$

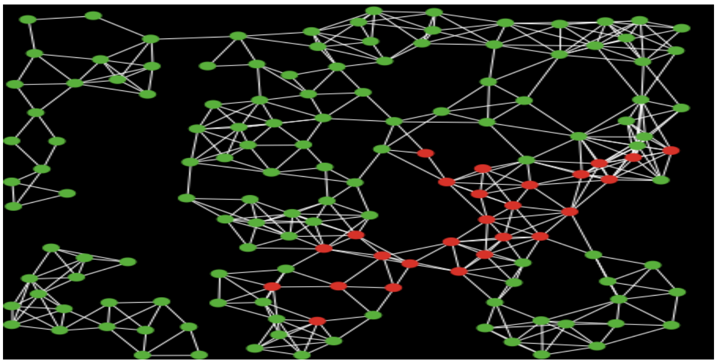

Fig. 9.Simulation of 360 nodes network with neural network.

Equation 8 is the fitness equation, and it is known for speed and position. The best position of particle and the best position in comparison with all other particles are determined by p best and g best respectively [12]. The pseudo code of Genetic algorithm is depicted in Fig. 11 to find a path in the networks. Population with chromosomes that show possible solutions in the network is defined. Population changes are evaluated based on fitness function. Chromosomes reproduce by being closest to the solution of the problem. Replication includes the crossover and mutation techniques. This process frequently is repeated to obtain the

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optimal solution. Genetic algorithm for searching large spaces and required time to solve the problem is appropriate [12].

$$Fitness = \frac{B_{Initial\ \ Link}}{\sum_{i=0}^{l_{particle}} B_i} \quad (8)$$

```
 k= 0;
 Compute initial population P0;
 WHILE k <=kmaxDO
 BEGIN
 Select chromosomes for reproduction;
 Create offspring's by crossover technique;
 Mutate few chromosomes for a chosen probability;
 Compute new generation;
END
```

Fig. 10.Pseudo code GA algorithm[12].

Results of routing optimization problem solving are in terms of the mean round (in kilometers), shortest round length (in miles) and the average solving time (in seconds) for 360 nodes, with each of the four methods. After running 20 times they are shown in Table 1. The paths of these two methods in Fig. 11 and 12, 13 and 14 are shown. As it is clear from these figures, in the round related to the ant colony system algorithm there are a large number of cross edges (paths). However, each of these intersections demonstrates that it is possible to improve this round. As the size of a round is closer to optimal round there would be a decrease in the number of such intersections so that there is no cross in the optimal tour. In fact, for the visual detection of a high-quality tour from a poor-quality round, this method can be used. Round from the proposed algorithm has much smaller intersections and consequently (as specified in Table 4) has better quality.

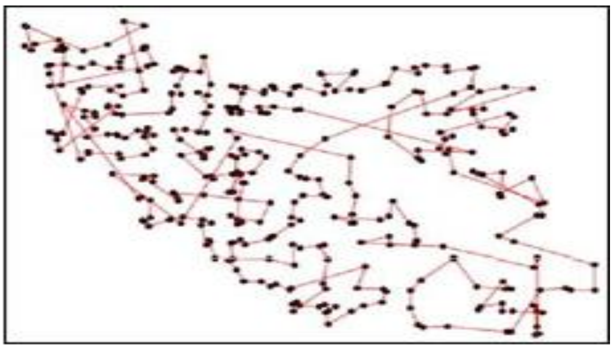

Fig. 11.the best route using the ACS

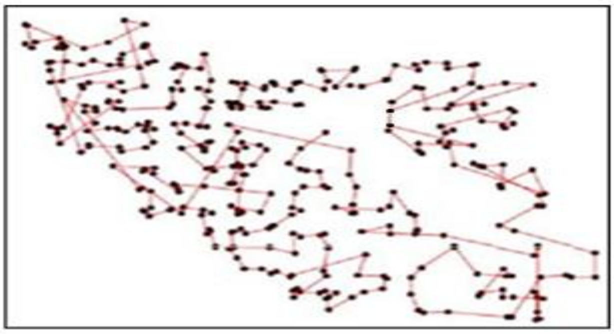

Fig. 12.the best route using the GA

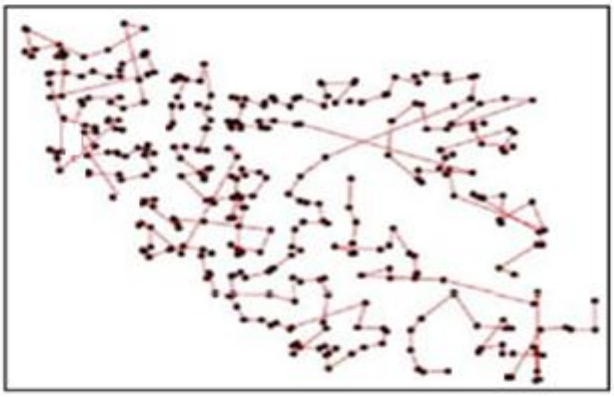

Fig. 13.the best route using the PSO

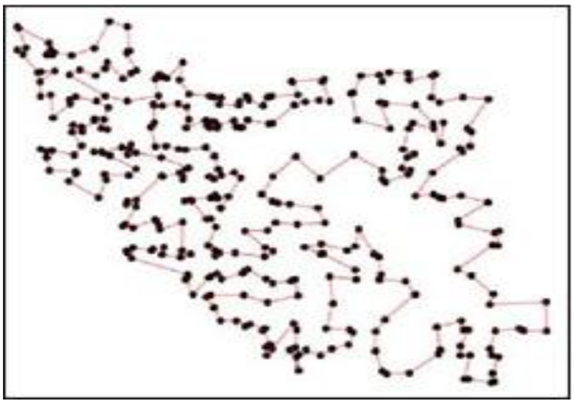

Fig. 14.the best route using the ACS+2-OPT

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Table 4. Results of 360 nodes in a network of problem-solving.

Number	Name	Longitude	Latitude
1	Node A	52.5`	36.4`
2	Node B	52.45`	36.45`
3	NodeC	48.20`	39.22`
4	Node D	56.35`	29.53
5	Node E	55.25`	31.4`

4- CONCLUSIONS

Routing is one of the most important and widely faced problems in optimization of the combinations, so that several methods have been proposed to solve them. Success in resolving this issue is a sign of using its capabilities in various fields of science and engineering such as the routing optimization. In this paper for the first time, we used solution of the routing problem for 360 different nodes combining ant colony algorithm and local search and compared the results with the results of ant colony algorithm, PSO and GA. This comparison demonstrated significant superior quality of the results of combined local search and ant colony algorithms in relation to the mentioned algorithms. Since our proposed algorithm involves fewer cross routes, it has considerable advantages over the GA, PSO and especially ant colony algorithms. So this combined attitude in such a difficult problem is a routing optimization algorithm. The difficulty of this kind of problems makes it necessary to use the strength of other methods. In our future study, we will consider fixed networks with wireless connections and will use more complete algorithms for finding the shortest and the most efficient routes in these networks.

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