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Using The Hybrid GA-Ant Algorithm To Find The Optimal Path In Computer Networks

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Abstract

Cost management is one of the performance standards in computer networks and routing strategies through which we can get effective paths in the computer network, reach the target and perform highly in the network by improving the routing table (jumps). This paper is an attempt to propose a new H design mixed algorithm (ACO-GA) that includes the best features of both ACO and GA with a new application that combines both previous algorithms called(H-Hybrid (ACO-GA) hybrid algorithm technology, which differs in its parameters. In order to research and find the optimal path, the improved ant algorithm was used to explore the network, using smart beams, getting the paths generated by ants and then using them as inputs into the genetic algorithm in the form of arranged pairs of chromosomes.

Experimental results through extensive simulations showed that H (ACO-GA) improves the routing schedule, represented by the pheromone values that ants leave when following their path in the network. The values given in the table(3.2) vary according to the quality of the pheromone concentration. In this case, it is possible to give the greatest opportunity to choose the best quality according to the concentration of the pheromone. For this purpose, a network consisting of four nodes (1), (2), (3), (4) was used starting with node (1) which is the source node and the destination node (2), by calling the selection technique to update the pheromone table by choosing the path to node (1). For this case and for selecting the destination node (2), the pheromone table for the nodes visited by the ant is updated. We calculated the final destination)2) by dividing the ratio. Thus, we get to reduce the search area, speed up search time, and improve the quality of the solution by obtaining the optimum set of paths.

Keywords:
Ants Colony Optimization (ACO); Genetic Algorithm (GA); Routing Table; Swarm Intelligence (SI).

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1. INTRODUCTION

Many organizations such as (institutions and The shortest path from one point (node) to another is known for efficient traffic network management; this is referred to as the shortest path. The term "optimal" refers to the quickest time, the shortest distance, or the lowest total cost. In any network or transportation analysis, determining the shortest path is critical. This issue appears as a primary choice question or as a stage in a circumstance. There are numerous versions, based on the type of network and expenditures involved, as well as source/destination node pairs for which we require a solution.Along the best-known path, each node is labeled with its distance from the source node. Because there are no pathways known at the start, all nodes are labeled with infinite. The labels may change as the algorithm progresses and better pathways are discovered. It is possible for a label to be temporary or permanent. All labels are tentative at first. When a label is found to reflect the shortest possible path from source to node, it is made permanent and never modified again.

Artificial intelligence-based optimization techniques perform exceptionally well on tackling problems involving combination optimization, such as the Genetic Algorithm (GA) [4] and Ant Colony Optimization (ACO) [5], They each have their own set of benefits, but they also have their own set of drawbacks. Finding the best solution with a single algorithm is tricky. The best route. We mix GA with ACO in this article. ACO then creates a superior optimization algorithm, by combining two procedures. With less time and greater precision, a network path optimization tool is available.

The ant colony optimization (ACO) is a meta conclusion inspired by the foraging behavior of ant colonies ،introduced by Dorigo and developed in a certain form which has been noticeable in the past few years [1, 2]. Similar to ACO, the genetic algorithm (GA) is also a metaheuristic optimization algorithm [3, 4], GA was inspired by the process of natural selection that relies on it and on natural genetics. Swarm intelligence is the apparent collective behavior of social insects. Although everyone in the insect swarm is relatively primitive and has little intelligence, these insects are able to solve difficult problems collectively. So, the swarm depends on easy internal cooperation and numerical strength, having no central control (over the individuals) and even the internal cooperation is not subject to monitoring.

The swarm shows the so-called self-organization that allows it to adapt to changing environments very quickly , giving it great flexibility as well. Even if one individual fails in its task, others may succeed, ensuring a high level of strength. An example of the difficult problems a swarm can deal with is "finding the shortest path to food or building housing". We can describe swarm intelligence as follows: We have female workers, and each of whom has a specific set of jobs. They seek to find a policy to solve the problem without considering the work of other workers, i.e. (IL, independent learning), a method whereby each individual learns an independent behavior without the participation of other individuals. A group of individuals learn the same task independently and is a form of simultaneous learning. Each worker takes a sample (a small part) of the problem area. In the effort to find an individual policy, the worker is able to store the individual experience in that environment. Other factors can influence this internal business outcome, leading to the emergence of coherent global functional patterns [5, 6]. Among these factors are the SI algorithms that are inspired by simple behaviors and self-regulating interactions between factors, such as Ant colonies, Ant colony optimization [5, 6,3, 7]. The focus of this research is on the optimization of the ant colony (ACO)." By using the genetic algorithm (GA) to obtain the optimal path, an efficient hybrid algorithm is designed that takes from each ACO algorithm an advantage in order to reduce the search area, improve the quality of the solution, and define distance and probability information that helps to identify more suitable paths in the initial stage of the algorithm. Ants algorithm (ACO) is a communication network consisting of signals and semantics (hints) to exchange information. An ant algorithm (ACO) is a communication network consisting of signals and hints for exchanging information. Two ants are designated representing the front and rear ants, and in further searching for food, the ants return to the nest (host) .The front ant is used while foraging and the back ant is used to return to the nest (host). The job of the front ant is to assign the next node based on the information about the lowest path mapping and the next node mapping. The data is updated and stored in the routing table and the data packet is sent to another node, so that a decision is made to return to the abode. The better the quality of the solution is, the more pheromone is deposited. The present node as an ant forward represents the transition and transformation act as the decision for the ant is backward. The signals enable direct communication between members of the ant colony by using a chemical called 'pheromone'. It deposits a fixed amount of pheromone that can be followed by other ants. So, when it meets ants in the path of the pheromone, each ant that moves randomly, must decide whether to follow it by reinforcing the pheromone, which in turn increases the likelihood of the next ants to determine the path, by increasing the pheromone. The ants that travel on the road will be more attractive to the next path of the ants. In addition, the ant uses the short path to the source of food and back to the nest by determining the path twice before the other ants return, and this will directly affect the likelihood of choosing the next ants to leave the nest, as shown in Figure (1).

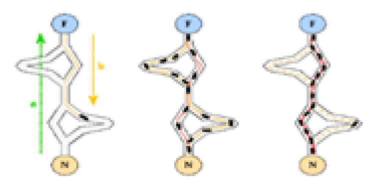


Figure 1:Ant use pheromone as indirect Communication build best tour

When ants choose their paths, they likely tend to choose pathways that feature strong pheromone concentrations. Once the ant finds a source of food, it assesses the quantity and quality of the food and carries some of which to the nest. During the return trip, the amount of pheromone an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone pathways will direct other ants to the food source. [8] This paper focuses on the application of a computer network, depending on the natural systems of an ant colony, and the genetic algorithm technology to improve the network's performance, in addition to describing a model for applying a hybrid algorithm to a network. This paper ends with conclusions and some potential future research directions. In summary, network route optimization is a multi-objective optimization issue that involves finding the shortest data transmission path between a source node and a destination nodes with the least amount of costs. Traditional optimization methods have extensive calculation periods, which does not meet the requirements of real-time communication. Traditional approaches for solving WSN route optimizations, such as Dijkstra and Floyd-Warshall, are based on Dynamic Programming (DP). Even if DP can find the best answer, the computation time is very long. Another reason is that the DP mathematical model is difficult to connect to the tough route optimization problem. Here is how the paper is organized: The second part summarizes the previous studies of the research topic, followed by a presentation of the proposed work in the third section, which is divided into two axes: a. Ant algorithm, b. Algorithm based on genetics Section 4 presents the experimental results of our improved model and gives the results. Conclusion is discussed in Section 5.

2. Related work

In recent years, there have been various studies related to the use of genetic algorithm while optimizing an ant colony, where two researcher have undertaken to solve the cycle scheduling problem. The experiment shows that choosing the appropriate ACO parameter is challenging, however we can see that the number of iterations is dependent on both the evaporation coefficient p and the number of ants M, and that the algorithm does not converge if p=0. When p is big enough (p=0.9), however, the method frequently converges to inferior solutions for complicated problems. This study is the initial step toward identifying the ideal amount of iterations for ACO in order to achieve the greatest result. The relationship between costs, alpha, and beta, as well as how these factors affect the ideal number of iterations and evaporation coefficient, must be evaluated. We must also choose the optimal value for chromosomal population and crossover for GA [9]. To tackle the problem of course scheduling, employ a genetic algorithm and an ant colony optimization algorithm, which is an algorithm metaheuristic. The two algorithms will be put to the test and compared to see which one performs the best. The program was put to the test utilizing Semarang University's data scheduling courses. Based on the results of the experiments, we can conclude that the genetic algorithm outperforms the ant colony optimization method in the situation of course scheduling.The results of the experiments revealed that the genetic algorithm outperforms the ant colony optimization technique. The genetic algorithm is well suited to the problem of msalah subject scheduling. Various genetic operators, such as selection and crossover, can improve results in a variety of ways. For example, through selection, we can choose the optimal chromosome fitness function based on chromosomes, and crossover can schedule as needed [10]. In recent years, a bio-inspired method has been used to automatically address routing optimization problems without the need for user involvement. By mapping ACO into ICN in this paper, we present a new Ant Colony Optimization (ACO)-inspired Information-Centric Networking (ICN) Routing mechanism (ACOIR). To begin, we create a content management approach based on the storing of name prefixes in order to manage and distribute material more efficiently and effectively. Second, to undertake interest forwarding, offer a continuous model for content concentration that takes into account the dynamic environment. Finally, we present a forwarding probability computation approach that takes physical distance and content concentration into account when determining the forwardable outgoing interface. Finally, we present a thorough routing technique for retrieving the best appropriate content copy based on probabilistic forwarding. We assess the recommended solution [11]. It's also focused on ants' random construction technique and how they employ the solutions they create to influence the search for ants by altering pheromone quantities. By shifting the perspective and elucidating the basic relationship between ACO algorithms and algorithms like stochastic gradient ascent (SGA) and cross-entropy (CE), This is accomplished by examining these algorithms in a framework known as model-based search (MBS) [2]. The least connected dominant set problem (MCDSP) is addressed in this study using an ant colony optimization (ACO) algorithm. Because of its application to mobile ad hoc networks (MANETs) and sensor grids, the MCDSP has grown in importance in recent years. We developed a one-step ACO algorithm based on a well-known simple greedy algorithm with the limitation of being susceptible to local optima. We've shown that by incorporating a pheromone adjustment technique and paying close attention to the ACO algorithm's initial state, this negative effect may be avoided. It is possible to produce decent results using this method rather than the previously proposed sophisticated two-step ACO algorithm. We've put our strategy to the test using standard benchmark data, and the results are in.demonstrating it is a viable alternative to existing algorithms [12]. Path planning is a fundamental combinatorial issue that is required for a mobile robot's navigation. Several research programs have evolved with the goal of delivering optimal answers to this challenge. The two most extensively utilized heuristics that have proved their efficiency in handling such a problem are Ant Colony Optimization (ACO) and Genetic Algorithms (GA). SmartPATH, a new hybrid ACO-GA algorithm for solving the global robot path planning problem, is presented in this work. An improved ACO algorithm (IACO) for efficient and rapid path selection, as well as a modified crossover operator to avoid slipping into a local minimum, make up the algorithm. Our system model includes a Wireless Sensor Network (WSN) architecture to facilitate robot navigation, with sensor nodes acting as signposts to help locate the robot.and direct the mobile robot to the desired area. We discovered that smartPATH beats both the Bellman-Ford shortest path method and the traditional ACO (CACO) and GA algorithms (as stated in the literature without modification) in solving the path planning problem. We further show that smartPATH reduces execution time by 64.9 percent when compared to the Bellman-Ford exact approach and increases solution quality by 48.3 percent when compared to CACO. [13]. The Internet of Things (IoT) is a modern-day wireless communication system in which energy efficiency is the primary concern. The Cognitive network is primarily concerned with this issue. The majority of CR networks are concentrating on battery powdered in order to make the most of the data dissipated in terms of spectrum sharing, dynamic spectrum access, routing, and spectrum allocation. Clustering and data aggregation are best-effort methods for improving energy modeling. With Deep Reinforcement Learning and the Double Q-learning method, multi objective Ant colony optimization (MOACO) and greedy based optimization are proposed. The majority of IoT bed models include data aggregation and energy-constrained devices, as well as optimization approaches to improve utilization. The Q-learning technique is used to suggest cluster-based data utilization, which improves inter-cluster data aggregation. The system To increase green communication, AI-based modeling with intra-network is used to improve lifetime. When compared to the artificial bee colony and genetic algorithm, the simulation trials reveal that the MOACO improves throughput, longevity, and jamming prediction and saves energy. The AI and MOACO algorithms are used to analyze the jamming activity at low, high, and moderate levels [14]. The NP-complete problem, or multiple sequence alignment, is one of the most significant and difficult jobs in computational biology. It is impossible to handle multiple sequence alignment problems directly, because they always end in exponential complexity. We introduce a unique genetic technique with ant colony optimization for multiple sequence alignment in this work. The suggested GA-ACO technique improves the performance of the genetic algorithm (GA) for multiple sequence alignment by adding local search and ant colony optimization (ACO). A genetic algorithm is used in the proposed GA-ACO technique to provide diversity of alignments. Then, to get rid of local optima, ant colony optimization is used. When compared to other algorithms, simulation results reveal that the suggested GA-ACO algorithm outperforms them [15]. The DTSP (dynamic traveling salesman problem) is a type of combinatorial dynamic optimization problem. A primary TSP sub-problem and a sequence of TSP iterations make up the DTSP; each iteration is formed by altering the preceding one. In this paper, a new hybrid metaheuristic method for the DTSP is proposed. Ant colony optimization (ACO) and simulated annealing are two metaheuristic ideas that are combined in this algorithm (SA). Furthermore, the method makes use of past iterations' information in the form of a pheromone matrix to exploit knowledge about dynamic changes. On benchmark examples, including small, medium, and big DTSP problems, the significance of hybridization, as well as the application of knowledge about the dynamic environment, is examined and validated. The outcomes are contrasted.to four existing state-of-the-art metaheuristic techniques, concluding that the suggested algorithm outperforms them significantly. Furthermore, the algorithm's behavior is examined from a variety of perspectives (including, for example, convergence speed to local optimum, progress of population diversity during optimization, and time dependence and computational complexity) [16] .

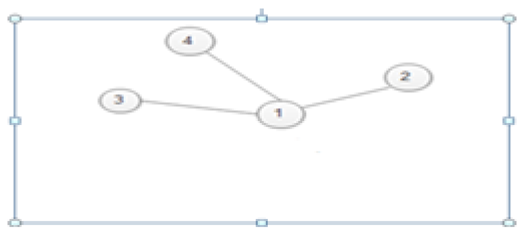
3. proposed work

There is a number of techniques to improve traffic flow in the network that represents flow and congestion control. Whereby nodes send packet acknowledgments from destination nodes either to increase or decrease the packet transmission speed [16, 17]. And with that, we are working on network routing and routing tables. These tables contain the information that the routing algorithm uses to decide on a local forwarding of the packet to the next node that will visit to reach its final destination. Here the basic idea is to abstract the behavior of ants into a logical model and use it to solve the problem of the shortest path (at the lowest cost). The entire network can be represented as a diagram containing costly edges, and each node (router) represents a geographic location. The edges (links in the network) are paths from one place to another. ANTNet uses hypothetical pheromone scales much like when an ant follows a path, the ant's nest serves as the source (node) and their food (destination). The current node acts as an ant in the routing process to find the next shortest nodes in the network. Generally, the ACO designates two ants as the front and back ants. The front ant is used while foraging ,while the back one is used when the ant returns to the host. But in transmitting information, only the front ant can be used. There is no use of reverse ants in the transmission process, but it can be used for decision-making purpose. Here the current node is set as a front ant during transformation. It can also act as a backward ant during cleaving. The ANTNet pheromone tables allow one to drop the pheromone to be reimposed. The faster the ants move down the path, the higher the rate of ant transport will be, and thus leading to a greater concentration of pheromones. Likewise, highways record a higher chance of selection, while less ideal paths have a lower chance of selection.

A. Ant Colony Optimization: An ant is placed on a network consisting of 4 nodes, the ACO that consists of (4) nodes, represents the initial value 0 and source 1 and target node. The opportunity and path selection mechanism are shown in figure. (2) ,

Table (1) pheromones for node.

the chance %	*Next node*
33.3333%	2
33.3333%	3
33.3333%	4



Figure(2) network diagram

Opportunities for selection are distributed over network nodes. Node (2) has a chance of choosing 33.3333, node (3) has a chance of choosing 33.3333, and node (4) has a chance of choosing 33.3333. The network representation of the level of enzymes is called the pheromone table, which is a list of the inputs associated with the nodes in the current network, and the path probabilities are chosen (2) as shown in Figure (2) and the second pheromone table.

the chance %	*Next node*
66.6669%	2
16.6669%	3
16.6669%	4

Table (2) pheromones for node(1)

The rates of next node selection opportunity are 66.6669%, 16.6669%, and 16.6669% for nodes 2, 3, and 4 respectively, as shown in Table (2) and Figure (2). The graph of the network through the routing table represents (pheromone table), showing that node No. (1) is related to the variable cost paths and is detected by pheromone. So if node (1) is the source (1) for Node No. (2), the opportunity is exploited as a mechanism to choose the best. In this case the highest percentage is taken, representing the concentration of the pheromone value mathematically. The mathematical calculation is done as follows: Node No. (2) is the final destination, i.e. the target. • The goal is reached by one jump. • Split the jump 100: 100%. • 100 is added to the probability value for node (2), which is currently represented (133.333). As such, the probability calculation is as follows: • Node (2): cost value (133.333) * Ratio value (0.5) = 66.6666%, and so for the rest of the contract • Node (3): Cost value (33.333) * Ratio value (0.5) = 16.6666% • Node (4): cost value (33.333) * Ratio value (0.5) = 16.6666% as it is illustrated in the following image: Figur (3)(Image No. (1)), the initial implementation of the algorithm,

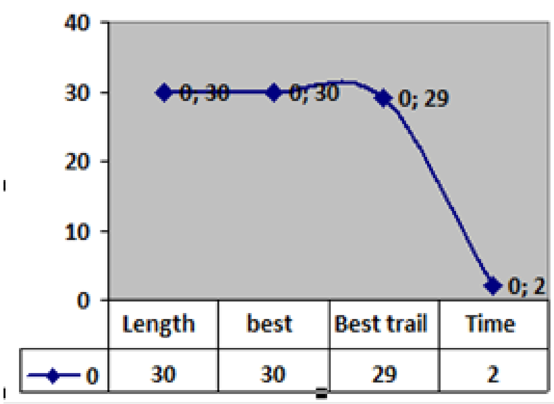


Figure (3)(Image No. (1) the initial implementation of the algorithm)

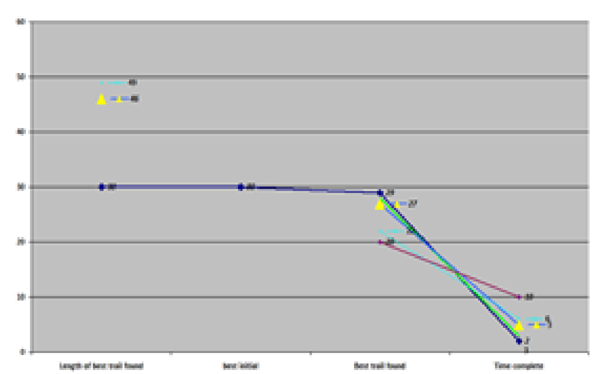
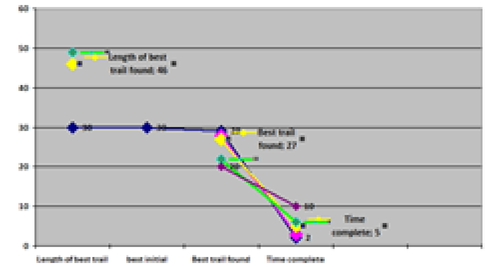


Figure (4)(Image No. (2) Algorithm Implementation)



Figuer (5) Final Implementation of the Algorithm is in Image No. (2,3)

If the nodes have the same distance, the optimal solution cannot be found. To overcome this problem we used the embryonic algorithm (GA) to find the fitness value GA to and get the optimal solution.

B. Genetic AL gorithm

An overview of the genetic algorithm: Genetic algorithm is a search algorithm that simulates genetics and evolutionary natural selection algorithms for NP problems [19 ,20,21] .The algorithm also has other uses, for example, solving the problem of suffocation and traffic congestion for transportation [22]. It has also been used with neural networks (CNNs) to prune mobile device networks. It achieves a better balance between trim ratio and precision [23 ,26,27,28 ,29,30].Genetic algorithms and method performance analysis have been relied on to identify dense sub-graphs in a time grid. Both synthetic and real networks should be taken into account when changing population size and number of generations ,its high performance in wireless sensor networks in reducing power consumption and increasing network life[24 ,25]. In this study we got the shortest path from the ACO to be entered into GA which represents the first census of population as it contains the entered path that will assess its suitability. We used a single junction point where the point was randomly selected from starting node and target node. Making the crossover, there may be a starting.The first population process starts by evaluating the cost node based on the fitness path and is selected randomly using the Monte Carlo method. The fitness of each path node is also calculated by removing the worst fitness condition, so that we have pairs of paths with the best fitness. And after a crossover application where pairs of paths are considered parents to produce children, new paths are pointed out, and then they go to mutation to modify and change the new path.

1) .Stages of the genetic algorithm

1. Parents' selection (path): There are many different methods, such as choosing an elite, choosing a rank, and choosing a roulette wheel selection. The roulette wheel selection method is used to choose an individual according to his relative fitness with competitors, i.e. similar division of the wheel into a number of slides for a larger slide to choose the new track.

2. Cross-over factor, the recombination factor combines the two sub-segments of the original chromosomes of produces offspring contain portion parent genetic material. Cross-over factor, or the recombination factor, combines the two sub-segments of the original chromosomes of produces offspring

contain portion parent genetic material. The intersection mainly consists of single point and multi point crossover. In a single point crossover, one offspring consists of a fragment before the transition on site lap(1) and a fragment after the site lap intersection(2). The other descendant consists of a fragment before the transition of gate (2) after part of the intersection tour location at section 1, as shown in the following table (3):

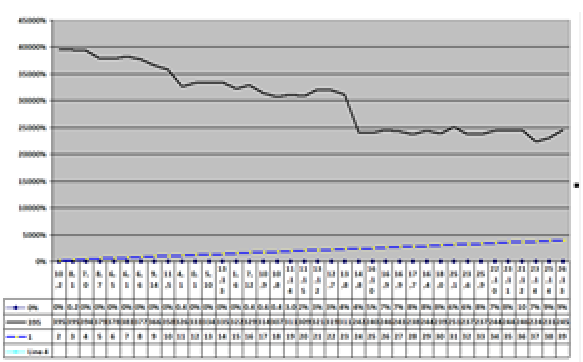
Table(3) intersection tour

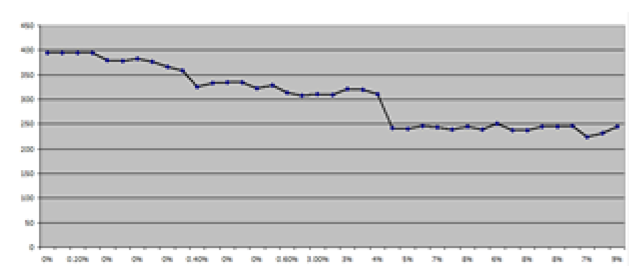
Fr(1)	12345
Fr(2)	35214
Son1	12314
Son2	35245

In the first iteration, it has been noticed that the son is (1): 13214, and in the second iteration, the son is (2): 35245, and eventually we get the offspring that represents a new path.

The offspring is obtained with a repeating node, and to modify that node the following mutation was used: -
The process of mutation can be reversal, introductory, reciprocal exchange, etc. When determining the reversal pattern, separate and reverse the series between them. If a node is entered, it is inserted at a random position in the chain. Nodes are reciprocal sites. Offspring in the first path are: 12314, node (1) was duplicated using the mutation-change method. We can insert node (5), which represents the missing node, in new route. Doing this process in GA will be the best solution as shown in Table (5). After implementing this operation in GA, the best solution is shown in Table No. (5), which highlights the results of the algorithm's work in the present study, and Figures (5.6) show the results of the implementation. The best solution will be as shown in Table No. (4)

Gioneneration No	*Cost*	*Mutated Rate%*	*Nod -NO*
1	395	0%	14,7
2	395	0%	10,2
3	395	0.20%	8,1
4	394	0%	7,0
5	379	0%	8,7
6	378	0%	6,5
7	383	0%	6,1
8	377	0%	6,6
9	366	0%	9,14
10	358	0%	11,5
11	326	0.40%	4,1
12	333	0%	0,1
13	334	0%	5,10
14	335	0%	13,13
15	322	0%	1,6
16	329	0.40%	7,12
17	314	0.60%	10,9
18	307	0.40%	10,8
19	311	3.00%	11,14
20	309	2%	11,15
21	321	3%	13,12
22	319	3%	12,7
23	311	4%	13,8
24	242	4%	14,8
25	240	5%	16,10
26	246	7%	16,9
27	243	7%	16,9
28	238	8%	17,7
29	244	8%	16,4
30	239	8%	18,0
31	251	6%	25,1
32	237	6%	23,6
33	237	8%	25,9
34	244	7%	22,10
35	244	8%	23,11
36	246	10%	21,12
37	224	7%	23,14
38	231	9%	25,14
39	245	9%	26,13





4. Results and discussion

The hybridization process takes place at the beginning of implementing the ACO algorithm to find the shortest path. It provides us with the value of the distance that is used as an input to implement the GA genetic algorithm. The paths obtained from the implementation of the first algorithm (ACO) act as inputs to implement the second algorithm

(GA) to be subject to the three stages of the genetic algorithm. As selection and intersection (crossing) occurs in the end, only one path is obtained, which is the optimum among the shortest paths, and this process continues in our research as shown as follows:

1. If the current node is the destination node, the routing table data is updated and the route is saved, if not, the next node is searched with the value of distance and the other adjacent node is checked with the value of the distance.

2. If all nodes have the same distance values, the routing table is updated and sent to the next node.

3. If (nodes available) update the routing table. Send it to the next node. Repeat these steps until you reach the destination node.

4. Naming a list of saved paths with the symbol n, then the comparison is done according to the following relationship: while n is less than the largest path, then it is placed in the list of random paths

5. For any node, calculate the fitness value (cost) and put it in a variable called fitness values. The fitness value is compared with the largest fitness value according to the following relationship:
If the fit of a node is greater than the largest fit value, then the values are exchanged

6. The comparisons continue while the existing generation is smaller than the largest generation and the existing path is smaller than the largest path. So, naming path 1 represents the roulette wheel test and path 2 represents the roulette wheel test
The x-over point is randomly selected.
Naming parent1 (head) and parent2 (tail) with the new path1
Naming Parent1 (Head) and Parent2 (Tail) with the new path2

7. The mutation parameter is named on a random selection of mutation points (new path), and the label of the new node parameter represents random selection of nodes. Then the following relationship applies the correct path equals node replacement (point - mutation, node - new).
8. The following relationship applies:
Equal Fitness Assessment (The Right Way)
If the fitness value is less than the largest fitness value, the values are exchanged, so the relationship becomes the largest fitness value equals fitness
Naming the fitness solution variable in fact equals the correct path
9. Then the right path is taken
10. End

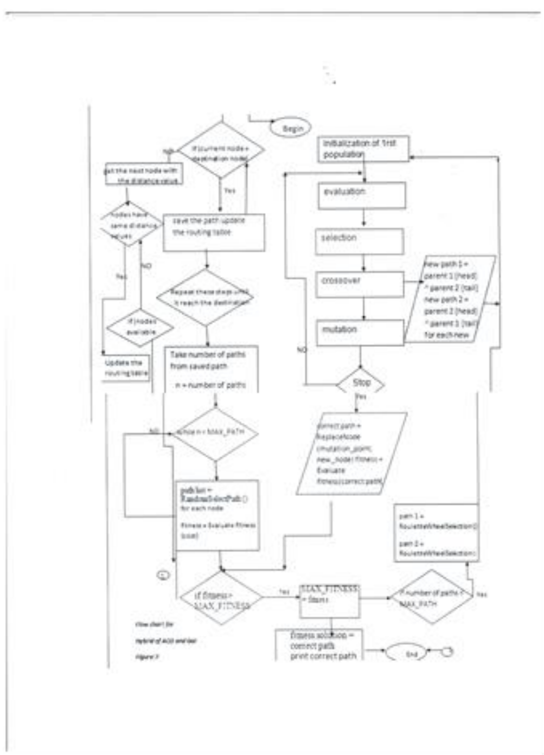


Figure (7) the diagram of the hybrid algorithm

5.Conclusions:

The goal of this research is to improve the network path problem. To begin, we use ACO as our primary tool for finding the shortest and most cost-effective approach. GA was included in the ACO solution to improve the results, and we proposed two processes to form a new optimization algorithm. The proposed algorithm achieves the best fitness value, according on experimental data.

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استخدام خوارزمية النمل المهجنة لايجاد المسار الامثل في الشبكات الحاسوبية

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الخلاصة:

تعد إدارة التكلفة أحد معايير الأداء في شبكات الكمبيوتر واستراتيجيات التوجيه التي يمكننا من خلالها الحصول على مسارات فعالة في شبكة الكمبيوتر ، والوصول إلى الهدف وتحقيق أداء عالٍ في الشبكة من خلال تحسين جدول التوجيه (القفزات). هذه الورقة هي محاولة لاقتراح خوارزمية مختلطة بتصميم H جديد (ACO-GA) تتضمن أفضل ميزات كل من ACO و GA مع تطبيق جديد يجمع بين الخوارزميات السابقة المسماة -H) Hybrid (ACO-GAتقنية الخوارزمية الهجينة التي تختلف في معلماتها. من أجل البحث والعثور على المسار الأمثل ، تم استخدام خوارزمية النمل المحسنة لاستكشاف الشبكة ، باستخدام الحزم الذكية ، والحصول على المسارات التي يولدها النمل ، ثم استخدامها كمدخلات في الخوارزمية الجينية في شكل أزواج مرتبة من الكروموسومات. أظهرت النتائج التجريبية من خلال عمليات المحاكاة المكثفة أن H (ACO-GA) يحسن جدول التوجيه ، ممثلة بقيم الفرمون التي يتركها النمل عند اتباع مسارهم في الشبكة. القيم الواردة في الجدول (3.2) تختلف حسب جودة تركيز الفيرمون. وفي هذه الحالة ، من الممكن إعطاء أكبر فرصة لاختيار أفضل جودة وفقًا لتركيز الفرمون. لهذا الغرض ، تم استخدام شبكة تتكون من أربع عقد (1) ، (2) ، (3) ، (4) بدءًا من العقدة (1) وهي العقدة المصدر والعقدة الوجهة (2) ، عن طريق استدعاء تقنية التحديد لتحديث الفرمون الجدول عن طريق اختيار المسار إلى العقدة (1). لهذه الحالة ولاختيار العقدة الوجهة (2) ، يتم تحديث جدول الفرمون للعقد التي زارتها النملة. حسبنا الوجهة النهائية) 2) بقسمة النسبة. وبالتالي ، نحصل على تقليل منطقة البحث ، وتسريع وقت البحث ، وتحسين جودة الحل من خلال الحصول على مجموعة المسارات المثلى.

الكلمات المفتاحية: ***Ants Colony Optimization (ACO); Genetic Algorithm (GA); Routing Table; Swarm Intelligence (SI).***