

A Survey of Modern Ant Colony Optimization Algorithms for MANET:

Routing Challenges, Perspectives and Paradigms

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Abstract:-This paper seek to explore Ant Colony Optimization algorithms and how it framework could be applied to Mobile Ad-hoc Network routing. Then, it explored the work in the area; characteristics, capabilities and applications, architecture, topology and the routing anatomy of MANET. Finally, it highlighted further on the Ant Colony Optimization algorithms, its design, algorithm architecture and routing mechanisms. MANETs refer to networks that are created without any pre-configured or pre-existing network set-up. The nodes in MANET act as both a node and a router performing similar functions in a client server topology. Mobile Ad hoc Networks (MANETs) refers to a set of mobile nodes that form a wireless network without any pre-existing network infrastructure. Each node participates in the network by acting as host and router. Therefore, they are able to transmit packets to other nodes. Such a network possess certain characteristics which includes its dynamic topology, node mobility etc, makes it unique from other network architectures. Mobile Ad-hoc Networks routing are confronted with numerous challenges compared to other traditional routing mechanisms that occur in wired networks with fixed infrastructure. These wired networks normally have fixed bandwidth and power consumption requirements. Several protocols have been discovered in the process of reviewing MANET literature. These protocols were designed specifically to deal with the severe challenges encountered such a network system. There are numerous challenges that exist in this type of network. These include unstable topologies, high power consumption, low bandwidth etc, therefore, this paper would contribute to the existing literature in this area and provides a solid ground for more research to be conducted especially in the area of energy-efficient routing based on ant colony optimization algorithms.

Keywords: Wireless, Ad-hoc, Mobile, Nodes, Protocol, Survey

1. INTRODUCTION

Wireless routing algorithms most of the time are quite difficult to explain with mathematical models, therefore mostly explained wireless routing are done through simulation modelling. In the past, the development of Mobile Ad Hoc Networks (MANETs) focused mainly on unpredictable network conditions such as such as the one identified in wireless networks. MANET algorithms such as

distance vector or link state algorithms were developed to determine the shortest path from source node to destination node [1]. MANETs are basically wireless networks whose architecture is not built on any fix infrastructure instead mobile nodes form a multi-hop wireless network consisting of mobile devices with no fixed routers and without any centralized administration [2]. In this type of network, the nodes perform routing to discover and maintain routes within the network. MANET originally, was designed for military and battlefield simulations [3, 4]. Again, MANETs have been developed for applications that range from emergency, disaster relief to risk prone areas. Despite the existence of several optimization mathematical models applied in MANET routing algorithms, each of them (routing algorithms) is focused on determining the minimum or shortest route from source of data packets to destination [5,6]. Find below in Fig. 1, a summary of the various Ant Colony Optimization Algorithms for MNAET.

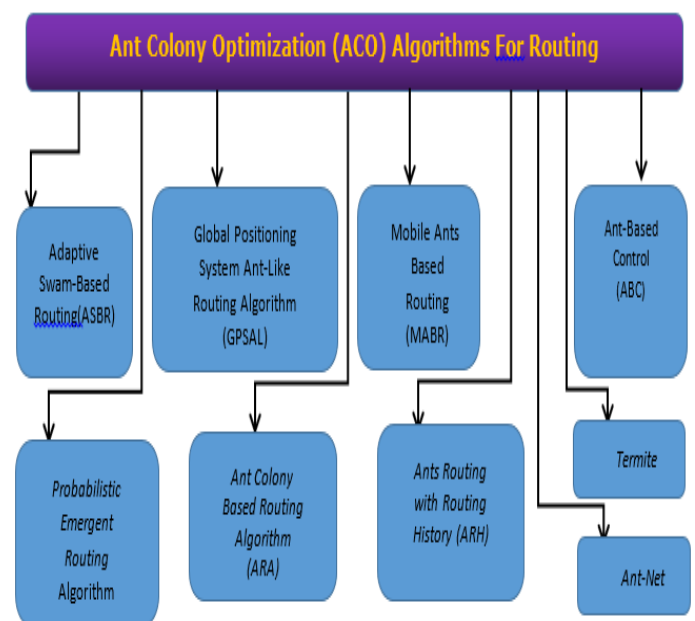


Fig. 1: Summary of ACO for MANET

II. ANT-BASED CONTROL ALGORITHMS

2.1 Ant-based Control

Historic research work focused on swarm intelligent routing algorithms and was carried out by [8]. The initial task of this of this special network was to implement an allocation scheme for calls so that multiple call could be allocated of multiple network switches thereby enabling the telephone to handle maximum number of calls during peak hours of telephone communication [8,9]. Another essential aspect of this design (ABC) is the congestion free mechanism introduced so that no calls may fail suddenly. ABC implementation is equally paramount since it has stimulated the curiosity of ACO researchers for dynamic optimal problems. ABC algorithms are designed especially for networks with specific assumptions under consideration and in many design as well as implementation details are glued to these assumptions. In [11, 12] for instance where Ant-Based Control algorithms were designed for specific kinds of networks with certain assumptions serving as the framework. In [11, 12] as well as [13], the network topology and routing updates in which routing path are conceptually modeled by means of a graph. Furthermore, each available node has is indicated by a total capacity C_i , a spare capacity S_i and an equally important routing table R_i . Links that are mostly of the form (i, j) demonstrates a vector of unique pheromone values $T_{ij,d}$, which suffices to say that, each destination d represents the desirability of going from i to j . Some of the typical assumptions of ABC refers to connection links that can potentially portray the property of carrying an infinite number of calls. A secondary-level assumption is made when the networking model was defined to signify that the transmission nodes and switches have limited connectivity. Therefore, the artificial ants originated as source nodes to several random destinations and they are disregarded once they arrive at their destinations. For this reasoning, the probabilistic values of the nodes' routing tables are quickly updated because the ants visit the nodes based on pheromone trails and its intensities.

2.1.1 ABC Protocol

		Next Hop	
		B	C
Destination	E	0.45	0.55
	F	0.75	0.25

Table 1. Table of ABC Routing Protocol

A hop count value is calculated for the node as indicated below:

$$\delta r = \frac{a}{T} + b$$

a and b represent variable (parameters). The parameters a , b , c and d , remain constant of the ant's age. D denotes the Delay at each processing node. The hop count rule is heuristically chosen with some parameters in mind as

explained earlier. This mechanism allocates a bigger value to those ants that reach their destination node successfully. The update of the routing table takes effect after this process using the formula below [14, 15]:

$$r^{i-1, s(t+1)} = \frac{r^{i-1, s(t)} + \delta r}{1 + \delta r}, n \neq i - 1$$

Per the routing table update formula s refers to the starting node, whilst i is called the active node. Finally $(i - l)$ refers to the last visited node. The age of the ant, T , is adjusted by computing the delay D_i of each node, given by $D_i = c.e.d.s$. In the formula above, c and d are the design parameters whilst s refers to the capacity of the nodes within the network. In [14, 15], it is that, the ants frequently updates the routing table. An example is the routing table in Table 1 above. As node F and node E (source and destination nodes) are traversed, the ant will attempt to rapidly fill in the values of the row for node F. It would then use the vales for node E to determine the next hop. Therefore, the rules of updating the table are applied in respect to the conditional formular:

$\sum r^n$ in, $s = 1$. In the formula above, n refers to the number of neighbors 1 to i , where researchers added an exploration factor g , within a defined probability of $(1 - g)$. The forwarded ants operate in a uniformly distributed fashion with the probabilistic value of g . The occurrence of this process is done in accordance with the entries in the route table. This algorithm, however is faced with the challenge of table probabilities are updated so far us the ants move in a forward-bias fashion. A schematic representation of the Ant Based Control (ABC) routing with update probabilities [15, 16] in Figure 2.

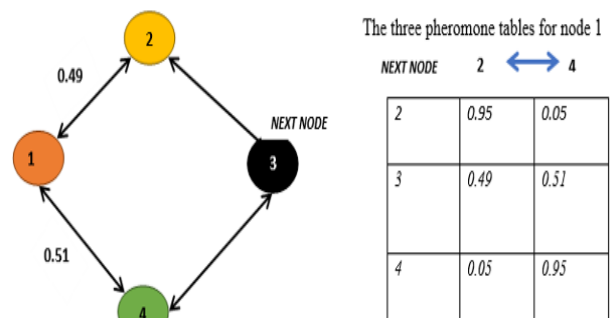


Fig. 2. Pheromone Table Update

Routing tables are normally replaced by pheromone tables. Every node within the Ant-Based Control network possess a specialized table known the pheromone route table for every other node once that one forms an integral part of the network [16]. Furthermore, all pheromone table entries for each neighbor indicates the probability of using that node as the destination node. Pheromone laying is the tendency of pheromone table to be update based on probabilistic values. Node choice is probabilistic while route creation is deterministic. Fig. 3 gives further explanation on ABC routing protocol [16, 17, 18].

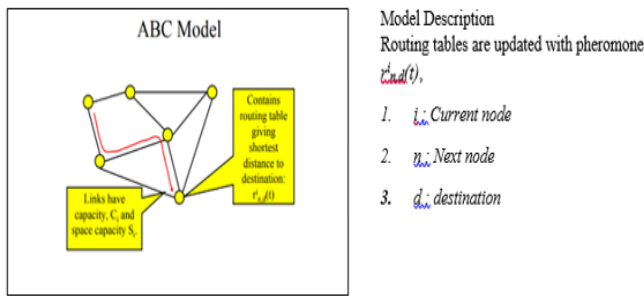


Fig. 3. ABC model for pheromone update

2.2 AntNet Algorithm

According to [18] and [19] developed an improve algorithm for pheromone update where, a colony of ants move systematically and asynchronously directs their movement by adjacent states through the problem by navigation through neighbour node G and this is also explained in [19]. This movement occurs by the use of stochastic decision making with local policy .Once an ant develops a possible solution to the problem or in the process of developing a solution , the ants evaluates possibilities of the solution and leaves pheromone trails (memory buffer) concerning the optimal solution about the connection the ants established and finally this special information would now determine the forward-bias movements of future ants [18,19,20] the traditional ACO algorithm employed the use of a fixed amount of pheromone as means of updating the pheromone table. Whereas strategy does not consider, the distribution (probabilities) characteristics of solution, it is also prone to slow convergence duration phenomenon relating to the pheromone table update, and this is prone to premature phenomena. [19,20] however develops an Adaptive Adjustment Strategy of pheromone introduced to make it a relatively uniform pheromone distribution based on the probabilistic values, which can effectively deal with the confusion of expanding search and finding optimal solution algorithms [20]. The objective of the algorithm is to explore the AntNet system with the intention of building as well as rebuilding the routing tables containing pheromone and maintaining their adaption to traffic conditions within the network. This algorithm is further improved as indicated below [19, 20].

The update of the routes is done by computing the quantity, r^i derived from:

$$r^i = \begin{cases} \frac{T}{C\mu}, & C \geq 1, \text{ if } \frac{T}{C\mu} < 1 \\ 1, & \text{Otherwise} \end{cases}$$

In the equation above, T refers to the trip time covered by an ant. μ represents the average of T , and C refers to the constant, normally it is set to 2. Each node maintains entries containing values of the mean and variance about the time it takes an ant to its destination. The variance to the mean equation, is (σ/μ) is represented as a quantitative measurement indicating the uniformity of the ants' travel time. With the stable value of r^i , it could be used in

determining the relative or the quality of the ant' travelling time and its mechanisms.

The maximum and minimum for the (σ/μ) was also selected [20]. Find further explanation in Table 2, AntNet Processing Cases.

The main objective of this update principle means that, values of r^i are mapped to values of T . During testing phases of network simulations, where the simulation result is reliable, it is a good indication, that algorithm needs the values of r^i to be very minimal. Therefore, the rate of decay is controllable through the a' and a parameters [19, 20].

	$r^i < 0.5$	$r^i > 0.5$
$\sigma/\mu > \delta$	$-(1 - e^{-a' \frac{\sigma}{\mu}})$	$-a' \frac{\sigma}{\mu}$
$\sigma/\mu < \delta$	$-e^{-a \frac{\sigma}{\mu}}$	$+e^{-a \frac{\sigma}{\mu}}$

Table 2. AntNet Route Processing Cases

2.3 Mobile Ants Based Routing (MABR)

This algorithm is orchestrated by social insects (foraging behavior of social insects). It was developed and intended to be an algorithm for to be in Mobile Ad Hoc Networks routing [19, 20]. Find below the diagram.

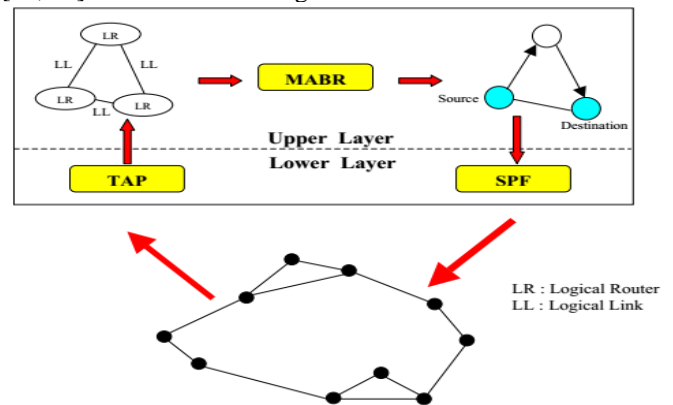


Figure 2.7 Interactions within TAP, MABR and SPF protocols. (TAS -Topology A. Protocol, MABR - Mobile Ants Based Routing, SPF - Straight Packet Forwarding)

The Logical routers within the network, represent a collection of mobile hosts (agents), where these mobile hosts have the tendency to build and share among peers vital routing information, which is meant for the update of routing tables. Furthermore, a set of logical links also denotes a logical path or links that connect the nodes distant across multiple hops or mobile nodes. In building these logical routers, the mobile nodes that are closed to each other geographically are also grouped together, thereby establishing virtual connections [19, 20, 21]. See on next page the flowchart of mobile ants-based routing algorithm. The further explanation in the diagram below.

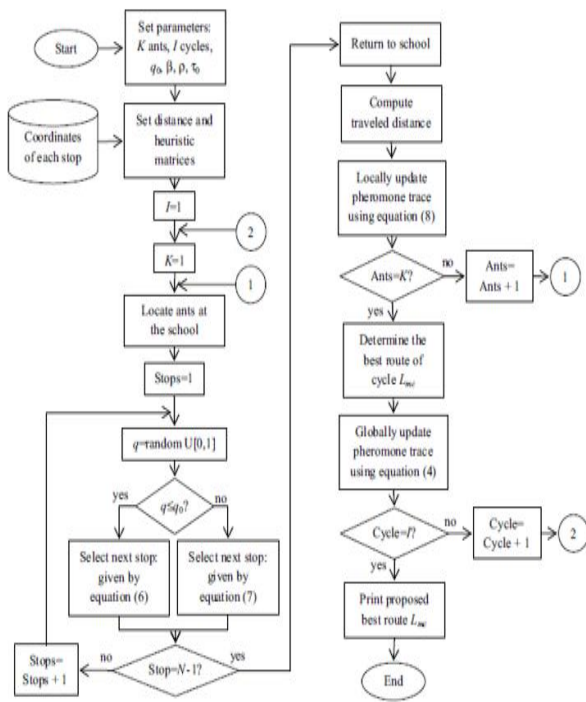


Figure 4. A Flowchart of (MABR) Algorithm

2.4 Termites Framework (Termite Colony Optimization)

The termite colony system is built upon swarm intelligence. The routing scheme within swarm intelligence is largely situated on distributed routing mechanisms for mobile wireless ad hoc networks [20, 21]. TCO (Termite Colony Optimization) routing is characterized by the foraging behaviour of termites and the eventual discovery mechanism for finding shortest routing paths especially during the termites “mound structure building process”. Furthermore, termites, arbitrarily search for food and deposit soil pallets soon after finding it, the termites’ deposit on the destined mound. This is a manifestation of the behavioral pattern of the foraging termites’ behaviour by dropping chemical trails referred to as pheromone on the routing path after depositing soil pallets on the termite mound. In addition pheromone deposit behaves as a stimulant to the remaining termite members of the colony to follow routing paths with higher intensity values. The design of this termite routing mechanism is based on the fundamental concept of swarm intelligence framework. This is intended to achieve improved adaptability and path selection with reduced overhead and decreased per-node computational cost of routing. Furthermore, the routing scheme is also influenced by the hill-like building characteristics of biological termites [21, 22]. The behaviour of the termite routing algorithms, is explained as follows; during the first phase, each node within the network, keeps a unique pheromone value that is sent as packets are transmitted within the network. In the second phase, links are established among the various nodes, as these links are followed, the termites are biased by moving towards the destination identified with pheromone gradients (increasing values of the pheromone trails). The packets that are being transmitted use this values in the process of dropping the pheromone trails on the links.. By the adoption

of this method of updating the routing tables with pheromone trails, the pheromone trails are constructed throughout the entire network irrespective of topological changes. The changes that may occur within the network environment, due to the updates on topology changes or path quality, are usually accounted for due to consistent pheromone decay occurring over a period of time [21, 22]. A summary is found in the diagram below.

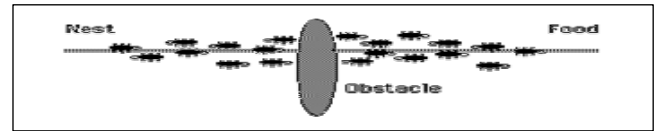


Fig. 8. Termites in Search of Food (Author’s Construct).

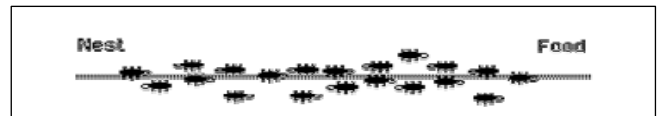


Fig. 9 Termites Routing Path

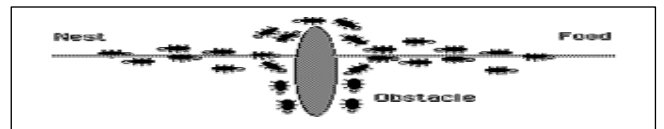


Fig. 10. Termites Routing Path

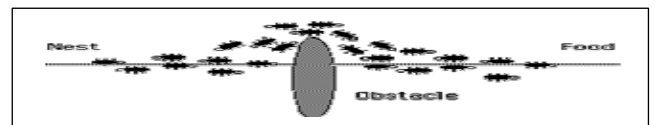


Fig. 11: Termites Routing Path

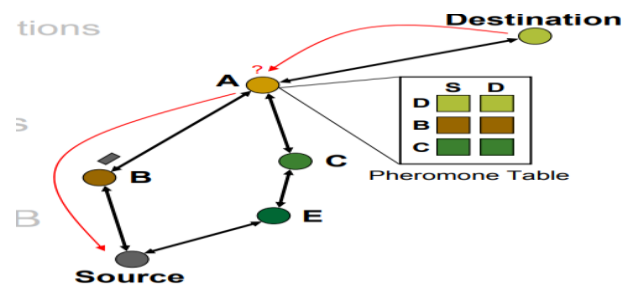


Fig. 12: The Swarm Intelligence (MANET) Routing and Path Selection Process.

2.5.1 Swarm Intelligent Routing

In Swarm Intelligence routing and path process, individual nodes possess a unique pheromone table for routing purposes, this table is a reflection of the list of neighbors and their destinations based on probabilistic values. When a packet arrives at the destination node B, from a source (previous) node A, the source pheromone of the routing link gets decayed while simultaneously, a new pheromone value called γ is updated on the new routing link to B. Therefore, the new routing path passes through B, from A as the destination node to the source node [21]. The process of pheromone update occurs due to the fact that, data packets keep traversing the network as compared to other ACO (Ant Colony Optimization Algorithms) based algorithms whereby all RREQ (forward ants), RREPLY (backward ants)

including the data packets update pheromone concentration to reflect topological changes on the network. Furthermore, the update equation for the pheromone trails is a representative function which is used to update the pheromone routing table.

This function is computed when packet originating from a source node is detected upon its arrival. The update function illustrated below is the traditional approach function and is popularly refers to as the Pheromone Filter. The pheromone on all links would decay concurrently as the packets arrive instantaneous arrival at a particular time sequence. This time sequence is also proportionally to packet inter-arrival time frame and this process is also known as the Continuous Pheromone Decay function as presented in [21, 22]. Whenever packets arrived at a node n originating from source s with a previous hop r , then the new pheromone

concentration table entry $P_{i,s}^n$ where the source of the packets are increased by constant pheromone value of γ as shown below in the mathematical equation. The equation below represents pheromone filter update equation for a routing algorithm.

$$\forall i P_{i,s}^n = P_{i,s}^n \cdot e^{-(t-t_{s,obs}^n)^\tau} \quad \text{and} \quad P_{r,s}^n = P_{r,s}^n + \gamma^n$$

With $P_{i,s}^n$ serving as pheromone amount at the source nodes, the link from the neighbor node i is i , located at node n , while the previous hop of the packet is represented by node r . Furthermore, the variable γ refers to the amount pheromone conveyed by the sending and receiving packets from various nodes, varying characteristics depending on its

routing path. Finally, the function of packet time, $t_{s,obs}^n$, refers to the last instant pheromone trails by the source node s , observed at node n , due to either behaviour of the packet sending or packet receiving, while τ refers to the rate of pheromone decay [22, 23, 24]. A forwarding equation is a mathematical formula is used to determine the probability of using or accessing the amount of pheromone deposited on it as described in the equation below:

$$P_{i,d}^n = \frac{(P_{i,d}^n + K)^F}{\sum_{j=1}^{N_n} (P_{j,d}^n + K)^F}$$

In the equation stated above, $P_{i,d}$ refers to the probability of computing for the neighbor node i in order to reach the destination node d , from n . N_n refers to the number of neighbors of node n . The function, $K \geq 0$, is known as the pheromone threshold while, $F \geq 0$, refers to the pheromone sensitivity level [24, 25].

A review of termites foraging behavior demonstrated that, termite algorithms perform well, most importantly in areas of high level of nodal mobility as explained in [25]. This is evident in the fact that, packets normally take paths that are longer than the shorter paths. Partly because, it is necessary so as to constantly maintain fresh pheromone updates within the entire network. But approach to routing could also

generate significant resource utilization deficiencies. Even though, the AntNet algorithm is somewhat similar to the termite algorithm, its forward and backward ant characteristics is not fully utilized. Termites as well as ARA significantly share similar data routing mechanisms, Eventhough, they differ with respect to the route discovery processes. They also in terms of failure recovery performance characteristics [25, 26].

2.5 Routin Algorithm for Ants Routing with Routing History

In case of ARH, each node has the capacity to refer to the routing table entry in calculating the next hop and this is achieved according to the stochastic values available in the table entry. This mechanism is different from the algorithm that could select next hop deterministically. Furthermore, this algorithm is a type of stochastic routing algorithm that is able to choose the most appropriate routes. Again, the algorithm is able to acquire information of a route efficiently and this occurs as the nodes communicate in a peer to peer ad hoc fashion [25, 26]. This type of optimization algorithm (ARH) regards each node as an agent of packet routing, and its able to adjust to the frequent changes within its environments. This is achieved by the gradual process of updating the routing tables during route mechanism. It can perform efficiently in packet routing by probabilistically selecting the most efficient routes or redundant paths and also efficiently managing the information acquired by the route by relying on the route history based on two MANET routing algorithms namely, the Ants-Routing and AntNet were developed to facilitate and improve learning efficiently and path discovery and selection by updating the routing history in a data packet [26]. The selection process involves, determining the best path required at each node by selecting the next hop based on the stochastic or random values deposited on the routing table. The normalization condition that is achieved based on the stochastic values is:

$$\sum_{z \in \text{Neighbour of } k} P_k(d, z) = 1$$

With the parameters in the equation above, each destination node is represented by d , the function, $P_k(d, z)$, refers to the probability of sending messages across hops. This function of sending messages, start from k to z as the next hop count based on the number of hop counts and s , represents the neighbor node of k . Each node in this process is able to store its own unique ID and the sum total of packet transmission time including the packet processing time of the message. Other relevant information such as the data packets are transferred. Finally, the oldest outdated routing history is discarded and gives rise to the new routing history is stored due a low reliability of the oldest routing history [27].

2.6.1 The Ants Routing with Routing History with No Return Rule (ARHnr)

This algorithm was developed as an improved routing algorithm of the ARH algorithm where a new mechanism. This new mechanism was added to the ants' foraging behaviour with a no rule of return to simply overcome the

routing-lock problem [27]. The routing-lock problem is a routing probability whereby a route becomes fixed due to a routing packet that congregates in the neighborhood of a single route in the cause of the learning process. The function of the no return rule is to overcome the problem of return rule when selecting the best path through the next node. When there occur topological changes and it is difficult to access the routes based on this condition. Under this situation, a lot more processing time is needed to rediscover the new routes or next node. Finally, by choosing the conventional route, it would be continued without the ability or tendency to discover a new route, even though a new route may be discoverable and the no return rule mechanism is intended in eliminating the "return rule" (back track path) and simultaneously select the next node [28].

2.6 The Global Positioning System, Ant-Like Routing Algorithm

According to [27, 28], the modus operandi of this algorithm occur by mapping the destination node's physical location to agents influenced ants. These software mobile agents (ants) are programmed to extract and broadcast vital information concerning the location of the mobile nodes in MANET. A mobile node joins MANET, by first of all listening wireless medium in order to detect a neighbor n . Once that node is detected, the host detects a neighbor node n , and quickly sends a request to the neighbor requesting for a copy of the routing table, related to the mobile host. By this process, communication is established, then the host can now initiate the routing process by sending packets within the MANET. This is because the mobile routing algorithm works by locating the geographical location of the destination host d located inside the routing table entries [28, 29].

2.7 The Ant Colony Optimization Algorithms(ACO) and Swarm Intelligent Routing(SIR)

This section elaborates on ACO and SIR. Swarm Intelligence (SI) describes to the main branch of the studying intelligent algorithms with other sub divisions of algorithm beneath it. Swarm Intelligence (SI) denotes the collective and intelligent of a group of simple agents modelled as biological agents. It's noted from the definition above that, swarm intelligence algorithm is a combination of intelligent and skills behavior of swam of social insects. Swarm Intelligence can be said to be a system that is modeled according to social insect behavior.

Their characteristics includes [28]:

- i. It is made up of many simple agents.
- ii. Likelihood of directly communication with each other agent.
- iii. Exhibits Stigmergy process (thus gents may communicate indirectly by affecting their environment).
- iv. It is made up of intelligence and communications among agents as a network.
- v. Agent's local behavior causes emergent global behavior.

Aside these characteristics swam of ants exhibits other behavior or techniques that help them to find food sources using the shortest paths to their nest [29].

These techniques are:

- i. Trail-laying
- ii. Trail-following.

They both explains that every one of the ant leaves a trail by the drop of a chemical substance referred to as pheromone in the course of searching for food, starting from the nest to the food source. The ants continuously follow these pheromone deposits directly to the food sources in that suit. Ant's use this pheromone trails as an indirect form to communication among them. In another vein, a French entomologist named Pierre-Paul Grassé in 1959, was the first to have introduced Stigmergy. Grassé grounded his research study on the fact that, the biological characteristics of insects have complete inter-individual stimulus. These stimuli generated are highly stereotyped in their behavior, consequently resulting in the creation of individual colonies with the competence which helped them to perform multifaceted responsibilities as compared to simple events. Ant Colony Optimization (ACO) algorithm had many kinds which were not known until in the year 1991, by the courtesy of Dorigo and others, the came up with the first anticipated algorithm known as the Ant System (AS) algorithm [28]. This has directed the focus of recent research to ACO algorithms which has yield productive results as compared to AS on TSP. There existed three versions of the Ant System according to.

What ASelite does is it enhances the convergence by stressing on the best solution established. The simplest version selects suitable number of elitist ants which helps AS to locate suitable paths earlier during the run. An early halt of the search is encountered when too many elitist ants are used. Selecting the best possible solution during the algorithm cycle of has led to the development of two cycles and these are (Aditi et al., 2016).

This phase is very important during the pheromone deposit as it would improve and advance the routing algorithm convergence [30].

2.8.1 MAX-MIN Ant Systems (MMAS)

Another essential methodology used to modifying the algorithm was named as the MAX-MIN Ant Systems (MMAS), as introduced in. In this algorithm, only the best ant updates the pheromone values in MMAS. To reinvent the development of rapid convergence, a small quantity of pheromone Δmin is used but as soon as the pheromone values drop below a certain thresh hold, it readjusts to the minimum value [30]. Similarly, a deduced routing algorithm, named the Ant-Q, had been in [29, 30]. Ant-Q has some features which are listed below; In the first place, these new ideas characterize a moderate, evaporation of the pheromone as a basic task. A broader search is made when the pheromone is evaporating and this creates a slight discouragement to the next ant to follow the same path [29, 30]. To ensure that large routes is explored, the routing algorithm adjusts the level of pheromone to a maximum value of Δmax which is to indicate an upper bound for the pheromone trail intensity. In a different scenario, another ant routing algorithm was developed out of a popular reinforcement learning algorithm popularly referred to as the Q-Learning introduced in [30] for details.

Finally, the main goal of ACO metaheuristic was to provide a standard categorization scheme of algorithms. A reference below concerning the structure of new cases of ACO algorithms is described in the diagram below [29,31].

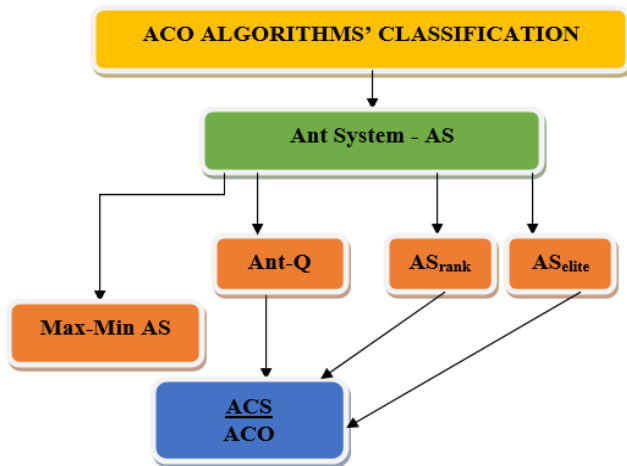


Fig.13. Real and Artificial Ants, Differences and Similarities.

2.8.2 Ant Algorithm Characteristics

The following are the characteristics of ant algorithm [31].

i. Natural algorithm

This is because, the algorithm behaves real ants in finding the best paths.

ii. Parallel and distributed

This is due to the fact that it demonstrates anxieties of a colony of agents foraging simultaneously, independently without a superior or commander.

iii. Cooperative.

In a cooperative fashion, each agent carefully selects a trail value from among the pheromone deposits laid by the other agents (ants) designated on that particular path.

2.8 Ant Algorithms and Optimization Approaches

Some basic similarities of ACO algorithms includes but not limited to optimization problems.

The similarities are discussed as follows:

i. Heuristic Graph Search

In this technique of routing, each ant carries out a prior knowledge search within the search spectrum. The ants make a biased probabilistic set of choices. This is an attempt to select the next value to move especially, where the bias is computed by an evaluation function in favor of components identified as more auspicious. Interestingly this is not the same as what happened in the Simulated Annealing routing scheme, described by [30].

2.9 Evolutionary Computation

The comparison of ACO meta-heuristic and evolutionary computation (EC) is necessary since they have some general similarities. These algorithms, poses bioinspired techniques that is, they are both caricaturist in a way. This tendency enables them to undergo a natural process of accomplishing a good solution of the problem being solved. Furthermore, these algorithms use the population of individuals to characterize problems and their solutions. Finally, both

methods adopt the knowledge acquisition technique, using the population during the algorithm run-time in order to stochastically generate a refined set of the population of individuals [32].

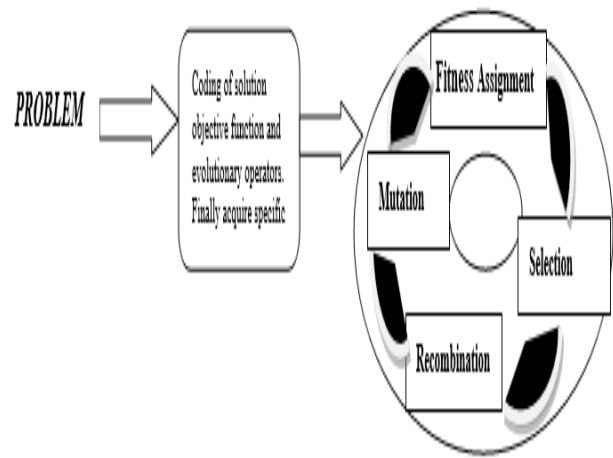


Figure 3.25 Problem Solving Approach Using Evolutionary Algorithms. (Author's Construct).

In EC (Evolutionary Computation) routing algorithms, possess the knowledge of the problem confined within the current populace, whereas in ant colony a record of the historical performance is preserved in the nature pheromone deposits.

Similarly, the issue is that while evolutionary computation can employ numerous transformations and limit operators, ant colony routing could make use of a single construction rule in order to produce a set of new possible solutions [32].

III. CONCLUSIONS AND FUTURE WORK

The generation of routing algorithms for Mobile AdHoc Networks (MANET) are important aspect of studying the future of MANET routing protocols. MANET generic protocols namely; Adhoc On demand Distance Vector Routing (AODV), Dynamic Source Routing (DSR), Destination Sequenced Distance Vector (DSDV), routing, etc have provided a foundation of empirical routing in the context of MANET routing.

However, these generic algorithms are unable to efficiently forward packets within MANET, especially during network congestion sessions. Above all wireless networks suffer from certain network limitation such as limited bandwidth, unstable routing domains, nodal mobility and path loss characteristics. Due to the enormous challenges being confronted by routing protocols in MANET, a newly proactive and bioinspired breed of algorithms popularly referred to as Ant Colony Optimization algorithms are classified as the future of MANET routing. ACOs, which are also known as bio-spired algorithms are able to learn and quickly adapt to the frequently changing topologies and routing mechanism with high probability of 99.99% packet delivery. Their quick adaption to the constantly changing network topology and the tendency to learn from such unstable wireless network interruptions is what had given their power and the advantage over other form of routing

protocols for Mobile Ad-Hoc Networks. After the discovery ACO algorithms by Dorigo et al., it is now evident that, the future of MANET routing is characterized by bioinspired algorithms, hence Ant Colony Optimizations algorithms.

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