A Survey of Location Aware Ant Colony Optimization Routing Protocols in MANETs

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ABSTRACT

Mobile Ad hoc NETtworks (MANETs) are infrastructure-less and self-configuring networks which consist of wireless mobile devices. Due to these properties, routing in such networks is a challenging task. Developing highly efficient routing protocols for MANETs is an important issue, with solutions having to fulfill many requirements, such as being able to provide low packet delay, high packet delivery rate and effective adaption to network topology changes with low control overhead. Swarm intelligence inspired algorithms offer possible solutions that fulfill the requirements and so have attracted a lot of attention from academics. A successful example in the swarm intelligence category is the Ant Colony Optimization (ACO) algorithm which has been applied to balance the various routing related requirements in MANETs. This paper presents a survey which focuses on location aware ACO routing protocols in MANETs. The main contributions of this survey include 1) introducing the ACO routing principles, 2) surveying and comparing a selection of routing protocols from the perspective of design and simulation parameters, and 3) discussing open issues and future possible design directions of ACO based routing protocols.

CCS Concepts

•**Networks** → **Routing protocols;**

Keywords

ACO; ACO based routing; Swarm Intelligence; MANETs

1. INTRODUCTION

Mobile Ad hoc NETworks (MANETs) consist of mobile devices which are connected wirelessly with each other. Com-munication in MANETs is cooperative with multi-hop fash-ion. Nodes join and leave thenetwork at any time. Charac-are not made or distributed for profit or commercial advantage and that

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teristics such as the absence of infrastructure and dynamic topologies, require the self-configuration, self-optimization, and self-healing. To realize these self-organizing networks, algorithms inspired by nature have been considered in recent years. From naturalistic observation, it is found that the dynamics of many biological systems are based on simple generic rules which provide effective collaborative patterns for performing tasks without any external centralized entity [10]. Routing is one of the critical functionalities in communication systems. In this work, we focus on it in the special case of self-organizing MANETs. Due to the properties of MANETs, routing in such networks is a challenging task. Two of these challenges are due to constantly changing topology and transmission of large routing tables [40]. Ant Colony Optimization (ACO) algorithms have attracted a lot of attention as a design paradigm for new approaches that maintain and optimize routing in self-organizing and dynamic ad hoc networks. ACO is inspired by the foraging behavior of ants in nature. It is part of the swarm intelligence (collective behavior) approaches applied to solve hard static and dynamic optimization problems. In order to achieve the efficient routing in MANETs, several ACO based routing algorithms are proposed. In comparison with traditional routing mechanisms, bio-inspired ACO based routing algorithms are more effective. Additionally, these approaches are also applied in many other areas, such as protein folding, feature selection, graph coloring, scheduling and so on [37].

Different from other ACO related survey papers, we mainly look at the location information aware ACO routing protocols for MANETs in this comparative analytical paper. From the reviewed papers, We have observed that the successful implementations of location aware ACO routing protocols in MANETs have encouraged researchers to design new protocols for VANETs. We have also introduced the technical transition of location aware ACO routing protocols from MANETs to VANETs. The comparisons of the existing protocols are presented in terms of protocol design and simulation parameters. For a better understanding of how ACO algorithms are practically applied in these routing protocols, we have selected some particular ACO related parameters which are introduced in section 4.1.

The rest of this paper is organized as follows. In section 2 the background of ACO meta-heuristic is presented. Various of ACO based routing algorithms are presented in section 3. Then, in section 4 a comparative analysis of the studied protocols and a discussion of open issues and future possible design directions of ACO based routing protocols are presented. Finally, section 5 concludes the work.

2. THE BACKGROUND OF ACO

2.1 Ants in nature

Ants evolved from wasp-like ancestors more than 100 million years ago [34]. Today there are over 8800 known species of ants [17] and they can be found almost everywhere across the globe. In nature, ants are well known as eusocial insects. Although ant colony size can vary from a few dozen to millions, nearly in all ant colonies there are some "drones" and "queens", which are the fertile males and females. In a large ant colony there could be some other castes, such as "workers" and "soldiers", which are formed by the sterile, wingless females. Each caste in the colony has its own special task and all these castes of ants appear to work together collectively to support the colony [31] [12]. Ant colonies are superorganisms and have a division of labor. Due to their collective intelligence, ants also show a strong ability to solve complex problems, such as dealing with floods. Researchers have found that ants can link their body to built self-assemblages [1]. For example, fire ants can make rafts to beat floods. Once a colony of fire ants is flooded, the ants make living rafts using their own bodies. "Workers" from the colony spread themselves flat across the water's surface and connect with each other using their legs and mandibles to make the bottom layer of the living rafts. The rest of the colony gets on the living rafts and the whole colony floats along until they land on a dry area. In another study [27], N. J. Mlot et al. have also measured the strength and speed by which ant rafts are built. The results show that thousands of ants can rearrange themselves to make a two-layer stable raft in only 200 seconds. Moreover, ants can use a force of 400 times their own weight to hold on to each other in the raft. In [13] P.C. Foster et al. have launched an experimental study to discover the arrangement of the ants in forming the self-assemblages within three dimensional networks. Many observations made by different researchers show that such self-assemblages of ants can help them react to their environment quickly and survive under adverse environmental conditions. Assemblages of ants take on similar functions like those existing in the human societies, but ants provide and maintain these functions without any central control. Therefore, understanding how the systems of ant colonies work has long been an attractive subject of study.

2.2 From nature to artificial ants

A significant amount of research about ants has been performed. One of the early study was published by P. Grassé in 1959. He observed the behavior of nest building in termites and brought forward a theory to explain it [15]; In the 1980s, F. Moyson and B. Manderick studied self-organization among ants [29]. S. Goss et al. proposed the initial idea of ant colony optimization algorithms based on their study of the collective behavior of ants in [14]. In the early 1990s, M. Dorigo proposed the first ant-inspired system in his dissertation and published it in 1992 [7]. In cooperation with L. M. Gambardella, M. Dorigo proposed the Ant Colony System (ACS) in 1997 [8]. In the meanwhile, there were many other researchers who studied this area and proposed some popular variations of ACO algorithms. For example, B. Bullnheimer, et al. proposed the Rank-based Ant System in 1997 [4]. V. Maniezzo introduced ANTS: exact and approximate nondeterministic tree-search procedures for the quadratic assignment problem in 1999 [23]. T. Stützle and H.H. Hoos invented the MAX-MIN Ant System (MMAS) [36] in 2000. C. Blum et al. proposed a hyper-cube framework for ant colony optimization (HC-ACO) one year later [3].

2.3 The Ant Colony Optimization algorithm

The Ant Colony Optimization (ACO) meta-heuristic is part of the swarm intelligence field and it is inspired by the foraging behavior of ants in nature. Biological ants lay down pheromone on the traveled path to transport information. When subsequent ants come to the same place, they decide whether they should follow the same path, depending on the deposited pheromone. Once an ant deposits pheromone along the path, the trail value is reinforced and this might attract more ants to follow. Thus, the pheromone deposited by biological ants realizes the indirect information exchange between the individual ants.

Biological ants find a path between their nest (node N) and the feeding source (node F) as shown in Figure 1 a. If an obstacle is laid in the path as in Figure 1 b it shows the ants will choose to turn left or right with equal probability. Due to the obstacle, the two paths have different lengths. Ants turning right side need less time to go past the obstacle and therefore they could rapidly reconstruct the interrupted pheromone trail in comparison with those ants choosing the other side. As consequence, a short path would have a high pheromone concentration and the following ants are more likely to follow it as shown in Figure 1 c.

In ACO, the artificial ants communicate with each other in a way similar to the biological ants. While exploring the network, the artificial ants mark the nodes they have passed with an artificial pheromone. For choosing the next hop, they are usually attracted by the node with the highest pheromone value.

In a simple ant colony optimization meta-heuristic algorithm, when an ant which is named Forward ANT (FANT) departs from the source node S to explore the network, it

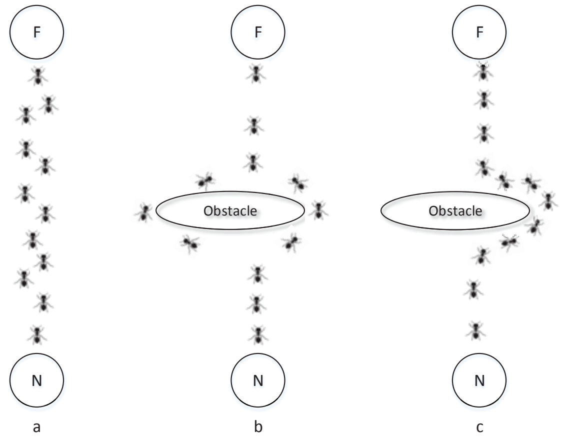

Figure 1: Ant follow the pheromone to find the shorter path.

chooses one neighbor of node S as the next hop node i. The probability of node i being chosen is defined by the following formulas [25]:

$$p(S,i) = \frac{[\tau_{S_i}]^\alpha \cdot [\eta_{S_i}]^\beta}{\sum_{j \in N(S)} [\tau_{S_j}]^\alpha \cdot [\eta_{S_j}]^\beta} \tag{1}$$

$$\sum_{j \in N(S)} p(S,i) = 1 \tag{2}$$

where τ_{S_i} is the deposited pheromone on the edge between node S and i; η_{S_i} is the goodness value of the link between node S and i; $N(S)$ is the list of all neighboring nodes of node S; α and β are respective weights for balancing the deposited pheromone and the goodness value of the link. According to formula 1, one artificial ant moves hop by hop until it has achieved its termination criteria, such as having reached the destination node or its lifetime having expired. Once the FANT has achieved the target location, a corresponding Backward ANT (BANT) backtracks to the source node. During the return trip, the BANT updates the pheromone table at each intermediate node, like shown in Figure 2, according to the reinforcement rule as below [25]:

$$\tau_{ij} = (1 - e) \cdot \tau_{ij} + \Delta\tau_{ij} \tag{3}$$

where τ_{ij} is the pheromone value laid by ants on the edge of node i and node j ; e is the pheromone evaporation rate which allows the ants to explore new paths; $\Delta\tau_{ij}$ is a constant amount of pheromone deposited by the ant. The common form to calculate $\Delta\tau_{ij}$ is as below [25]:

$$\Delta\tau_{ij} = K/f(c) \tag{4}$$

where K is a positive constant and $f(c)$ is the cost function which can be calculated based on the hop count from the current node to the destination, the delay of finding a destination, the available bandwidth of the link or the energy consumption of each node along the way. To consider which parameters in the cost function is according to the concrete application. If there are more than one type of cost, the cost function can be calculated as below:

$$f(c) = \sum_{k=0}^{n} w_k \cdot C_k \tag{5}$$

where C_k is the value caused by the k-th type of cost; w_k is the weight of the k-th type of cost; n is the total types of cost. Generally speaking, both FANTs and BANTs can collect the cost related parameters along their trips. When the delay of finding destination is consider in the application, BANTs are the better choice.

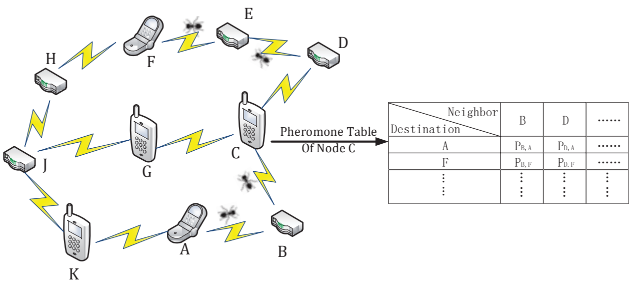

Figure 2: Example of Pheromone table.

The main merit of the generality of the ACO meta-heuristic is that it has presented a common framework for approximating solutions to NP-hard optimization problems and inherently dynamic problems like routing in telecommunication networks, in already existing applications. ACO adapts well to the dynamic changes in the networks and gives positive feedback accounts for the rapid discovery of good solutions. Moreover, the artificial ants can find multiple paths simultaneously and do parallel computing of their pheromone values [9]. Since the middle 1990s, the number of applications based on the Ant algorithms is booming. Until now, ACO algorithms have already been applied to solve routing problems in MANETs or WSNs with better scalability than other approaches. They also lead to improvements in other performance metrics.

3. REVIEW OF LOCATION AWARE ACO ROUTING PROTOCOLS IN MANETS

The location of nodes is important information when applying the ACO routing protocol in practical applications. Especially now that the Global Position System (GPS) [26] is popularized and mobile devices come equipped with it, the use of position information becomes possible.

3.1 POSANT

POSANT [20] is an early location aware multipath reactive ACO protocol for MANETs which aims to minimize the message delivery delay. It divides a node's neighborhood into three zones based on the physical location of all neighbor nodes and that of the destination. For route discovery, the source node sends one FANT to each area on demand. Additionally, POSANT assumes that each node can access a location service to acquire the current position of the destination.

3.2 Robustness-ACO

Unlike POSANT, D. Kadono et.al [19] have proposed an ACO routing approach based on robustness which requires no location service. We abbreviate the proposed protocol as Robustness-ACO from here on. The authors present two robustness functions to evaluate the robustness of a link. Each node predicts link disconnections by using the GPS [26] information of its neighbors and redistributes the pheromone to accelerate alternative path construction. This mechanism is better adapted to dynamic network change and frequent link disconnection.

The successful implementations of ACO routing protocol in MANETs also inspire the application in Vehicle Ad hoc NETworks (VANETs) which have high speed network nodes and reasonably predictable mobility patterns. There are three different types of communications in VANETs: the Vehicle-to-Vehicle (V2V) communication which is the communication between vehicles; the Vehicle-to-Infrastructure (V2I) communication which is the communication between vehicle and devices located in the margins of roads; and the communication between the roadside devices. The devices installed in the vehicles are called OBUs (On-Board Units), and the ones located in the roads are called RSUs (RoadSide Units). Figure 3 illustrates the three communication types in VANETs.

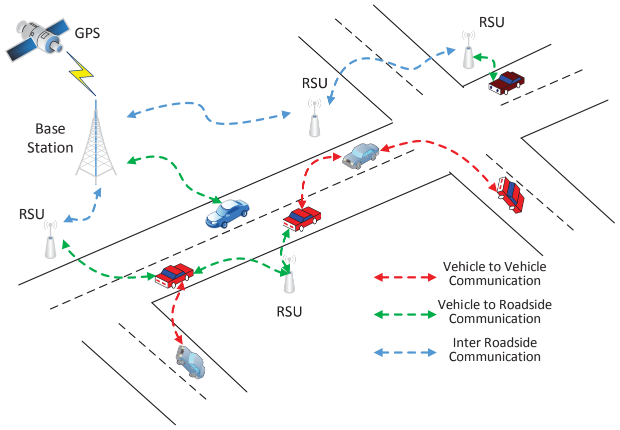

Figure 3: Communication in VANETs.

3.3 MAR-DYMO

S. L. O. B. Correia et.al [5] have likely proposed the first ant-based algorithm that adapted to Dynamic MANETs On-demand (DYMO) routing protocol in VANETs. The idea of this paper is to use vehicles' information to make routing decision that applies well in VANETs. As this algorithm is based on an ACO algorithm, it uses speed and position to update the pheromone. In their mathematical model, the amount of pheromone to be deposited for every link is given by the following equation:

$$\Delta\phi_{ij} = P_R + \frac{t_{\text{link}}}{t_{\max}} \tag{6}$$

In formula 6, $\Delta\phi_{ij}$ is defined as the amount of pheromone that is deposited in the link from node i to node j. P_R is the expected probability of successfully receiving a message sent over a given distance, such as the probability of node i receiving a message from j. It is estimated by using the Nakagami Fading Model [21]. It is a good indicator for path quality when the destination is within the sender's wireless transmission range. t_{link} is the route lifetime (given by the Kinetic Graph framework [16]) while the $t_{\max}$ is the maximum route lifetime. This ratio also shows the link's stability. For the pheromone evaporation process, this paper proposes a different evaporation rate for every link by using the following equation:

$$\rho = 1 - \left(\frac{\varepsilon}{\phi}\right)^{\frac{1}{k}} \tag{7}$$

Let ε be a smallest amount of pheromone and ϕ is the pheromone level; the pheromone evaporation rate ρ is associated with this link after it suffers the evaporation process k times.

The authors modify the reactive DYMO protocol by adding the pheromone level, evaporation rate and the predicted lifetime for each route to the routing table. It also works in the multi-path model in VANETs, which means there is more than one route to the same destination with different intermediate nodes. The actual route is chosen based on their pheromone levels, i.e., routes with higher pheromone level will have a higher probability of being chosen.

The proposed algorithm is tested using NS2 [18] and Vehicle Network Moment Generator (VNMG) [30]. The performance is compared with AODV [32], DYMO (DYMOUM [35] implementation) and Ant-DYMO [24] using performance metrics such as average delivery ratio, average end-to-end delay and routing overhead. The results show that it performs much better than pure DYMO in the aspect of end-to-end delay and good enough compared to the hybrid protocol Ant-DYMO. Moreover, it guarantees both the link quality and the link stability in the pheromone deposit process. However, this mechanism consumes a large amount of bandwidth and is not scalable [33].

3.4 MAZACORNET

In [33] H. Rana et al. introduce the first ant based routing algorithm for VANETs that uses the concept of zones. It uses ACO to find multiple routes between nodes and to mitigate link failure. In addition, it subdivides networks into zones to achieve scalability. To reduce broadcasting and congestion, they use a proactive approach to find routes within the zones and a reactive approach between zones. In MAZACORNET, the location information is provided by Global Positioning System (GPS) [26] providing the speed and position of each vehicle. The pheromone deposition and evaporation models are same with MAR-DYMO [5]. The hybrid MAZACORNET algorithm categorizes vehicles as three different types: interior vehicle (inside the zone), boundary vehicle (overlapping vehicle within the zone with the hop distance equal to the radius) and exterior vehicle (outside the zone). Two routing tables are used: an intra zone routing table to proactively update the information within the zone, and an inter zone routing table to reactively track the information between the zones. They also use five types of ants: internal forward ants, external forward ants, backward ants, notification ants and error ants.

For route discovery within the zone, the internal ants periodically update the vehicle's information in the intra zone routing table. When the sender needs to send a message to the destination, it first checks its intra routing table. If found, the route discovery process is done. Otherwise, the sender uses the inter zone routing table to identify the new route by sending external forward ants to boundary vehicles. If the destination is found, then the backward ant traverses the network back to the sender based on the inherited route. During route maintenance, if a broken link is detected within the zone, it will be repaired periodically because of the proactive part of the approach. Otherwise, the upstream vehicle of the broken link stores the packets and finds another path. After finding an alternative path, it sends a notification ant to the sender to update the new route. If there is no alternative path, an error ant is sent back to show the route failure.

The simulation is carried out using the NS2 simulator [18] and the VANETs MobiSim traffic simulation tool [28]. The result shows that MAZACORNET is more suitable for dense networks where there are more vehicles within the zone. At the same time, it generates more congestion due to vehicle density and proactive ants which keep updating the routing table frequently. The network achieves better connectivity because of its multipath properties due to being an ACO routing protocol. The sizes of the zones are defined by hop count, which is set to 2, 5 and 10 hops in the simulation experiments. However, this paper does not explain how zones could be formed in a fast dynamic VANET.

3.5 Cluster-based ACO

Unlike the flat architecture of the zone-based hybrid ACO routing protocol, S. Balaji et al. [2] introduce a hierarchical approach which combines a clustering architecture with ACO routing procedures in VANETs. We abbreviate this protocol as Cluster-based ACO from here on. In this protocol the network is divided into multiple virtual clusters for efficient management. All nodes that are not in any cluster will default to Orphan Node (ON) state, and broadcast a Member Packet (MEP) which contains its ID to show its existence to the neighboring nodes. After receiving the MEP, each node adds the source node to its neighbor list. A node becomes a Cluster Head (CH) only if all its neighbors are in ON state, and this group forms a cluster as a result. For cluster management, the CH broadcasts MEP periodically within the cluster. When cluster members receive an MEP, they send back a Member Acknowledge Packet (MAP) that contains its information. The CH generates a cluster-based tree and creates a list of cluster members. If the size of a cluster is greater than the upper bound U, then the cluster is divided into two clusters. However, if there are fewer cluster members than the lower bound L, the cluster will merge. After autonomous clustering, ACO-DYMO routing procedures are employed in the same way as in MAR-DYMO [5]. The simulation is carried out using the NS2 [18] and the Vehicle Network Moment Generator (VNMG) [30]. The proposed algorithm is compared with the AODV [32] protocol. It shows better results concerning end-to-end delay, delivery ratio and routing overhead. One notable idea in this protocol is that it uses reactive approach instead of using hybrid approach which is commonly applied in cluster-based networks.

3.6 S-AMCQ

M. H. Eiza et al.[11] have proposed a novel Secure Ant based Multi-Constrained QoS routing algorithm (S-AMCQ) for VANETs, which considers not only QoS constraints but also the security issues. S-AMCQ applies ACO algorithm to calculate the feasible routes which satisfy multiple QoS constraints determined by data traffic types in VANETs' communications and it uses an extended VANET-oriented evolving graph (VoEG) model for performing plausibility checks on routing control messages. In this scheme, an authentication mechanism is used in the route discovery process to defend against external attackers. In order to protect the network from internal attackers, eg. compromised vehicles, S-AMCQ employs plausibility checks. S-AMCQ not only ensures authentication, integrity and non-repudiation, but also protects vehicles privacy by using pseudonymous certificates. However, the simulation results show that the security overhead, i.e. route discovery delay, slightly affects its performance. Moreover, S-AMCQ is designed for V2I communications. Therefore, the authentication process applied in the protocol is centralized and relies on a Certification Authority(CA) which the local transportation authority or vehicle manufacturer can act as.

3.7 Summary

In this section, we have reviewed the above protocols designed for MANETs and VANETs. The papers represent a steady development of location aware ACO routing algorithms that leverage GPS [26]. POSTAN [20] is an early reactive protocol for MANETs which minimizes message delivery delay, while D. Kadono et al.[19] combine robustness-based path construction with predictions of link disconnection. The successful implementation in MANETs motivates many researchers to design new ACO based routing protocols for VANETs. MAR-DYMO [5] is proposed as the first ACO-based algorithm that adapted to VANETs. It guarantees both link quality and link stability. After the first ACO based protocol in VANETs, researchers focus on two main methods for managing the network, namely zone-based and cluster-based architectures. MAZACORNET [33] is the first ACO based routing algorithm that subdivides the networks into zones to achieve scalability. It uses proactive approach to find routes within the zones and a reactive approach between zones. It clearly states its communication procedures while the formation and management of zones are ambiguous. Different from MAZACORNET, S. Balaji et al.[2] introduce a hierarchical cluster-based approach that aims to reduce the number of routing control packets. However, it does not explain how message delivery within and between the clusters after the autonomous clustering works. ACO based routing protocols in VANETs are still a hot issue in recent years. They are not only adapted in V2V communications, but also associated with devices like Road Side Units (RST). J. Amudhavel et al.[39] have introduced the idea of using recursive ant colony optimization. They divide routes into sub-routes, which contain one or more RSUs in each sub-set. Then it finds the shortest path of each subroute by comparing the iteration count of RSUs and finally merging them. However, this paper does not provide any the simulation experiments. There also still exist several open issues, such as the avoidance of local optima for each subroute. S-AMCQ[11] addresses multiple issues in the routing process. It considers both the QoS constraints and the security issues. Thus it ensures reliable and robust routing in VANETs. In general, location aware ACO routing protocol have been well developed and show good prospects in both MANETs and VANETs.

4. ANALYTICAL COMPARISON

In this section, we summarize and compare the previously surveyed ACO based routing protocols. We focus on comparing the design patterns and simulation parameters of these ACO-based routing protocols.

4.1 Analytical parameters

We have chosen the following seven parameters to compare the different ACO based routing protocols:

Design goals: This parameter explains the aims of the proposed protocols. The goals usually indicate the categories which the routing protocol belongs to.

Ant types: In conventional ACO based routing protocols, there are usually two types of ants: FANTs and BANTs. However, depending on the design of the protocols, there could be other types of ants in the network. This parameter lists all types of ants in the protocol.

Pheromone reinforcement factors (Ph. reinforcement): Pheromone is one of the most important parts in ACO based routing protocols. This parameter specifies what is considered while reinforcing the pheromone values in the algorithm.

Pheromone evaporation factors (Ph. evaporation): In ant colonies pheromone evaporates over time. This allows ants to forget old paths. This parameter specifies what is

Protocol	Routing Approach	Tran. Type FANT	Ph. Activator
POSANT [20]	reactive	unicast	BANTs
Robustness-ACO [19]	hybrid	broadcast	FANTs,BANTs
MAR-DYMO [5]	reactive	broadcast	RREPs
MAZACORNET [33]	hybrid	unicast	unknown
Cluster-based ACO [2]	reactive	broadcast	RREPs
S-AMCQ [11]	reactive	unicast or broadcast	RQANTs

Table 1: Design parameter overview of location aware ACO routing protocols.

Protocol	Design Goals	Ant Types	Ph. Reinforcement	Ph. Evaporation
POSANT [20]	Minimize delivery delay	FANT,BANT	distance,location	constant rate
Robustness-ACO [19]	construct robust paths	Hybrid FANT/ BANT	robustness,cost	constant rate
MAR-DYMO [5]	adapt ACO to dynamic VANETs	Hello message, RREQ/RREP	reception probability, lifetime ratio	path lifetime
MAZA-CORNET [33]	scalability,robust to link failures	IFANT,EFANT, BANT,NANT,EANT	same with MAR-DYMO	same with MAR-DYMO
Cluster-based ACO [2]	improve MAC layer efficiency	Hello message, RREQ/RREP	same with MAR-DYMO	same with MAR-DYMO
S-AMCQ [11]	ensure reliable, robust routing	RQANT,RPANT REANT	QoS metrics, reliability value	individual variable

Table 2: Pheromone parameter overview of location aware ACO routing protocols.

considered while evaporating the pheromone values in the algorithm.

Routing approach: This parameter signifies if the routing protocol is proactive, reactive or hybrid.

Transmission type of FANTs (Tran. Type FANTs): This parameter explains the type of transmission for FANTs. The types used in all reviewed protocols in this work are unicast and broadcast.

Pheromone update activators (Ph. Activators): Pheromone in ACO based routing protocols changes dynamically. This parameter explains where the pheromone is updated in the routing protocol.

4.2 Comparison of design patterns

In this subsection, we divide the parameters mentioned in section 4.1 into two groups as shown in Table 1 and Table 2: the common basic design properties and the pheromone related core design properties. The first group introduces the basic routing structure, while the other group reflects the core ACO mechanism within the routing protocol.

Table 1 shows that all the reviewed protocols avoid to apply the proactive approach, due to the overhead caused by proactively maintaining of routing tables. As for the transmission type of FANTs, ca. 50 % of all approaches broadcast FANTs while the remaining protocols except S-AMCQ, unicast FANTs. S-AMCQ broadcasts the routing control ants only when there is insufficient information available at the pheromone table. Generally speaking, broadcasting a message produces more control messages, because the message needs to be transferred to all recipients simultaneously. On the contrary, using unicast method the message is sent to exactly one destination device. However, it has a relatively lower probability of finding global optima. In the pheromone update phase, only in the Robustness-ACO protocol both FANTs and BANTs can update the pheromone. Utilizing the location information from Global Position System (GPS) [26] helps ACO based routing protocols adapt better to MANETs, especially to VANETs. The main goals of many reviewed protocols in this subsection are to minimize delivery delay and establish robust routes. Various ant types are used in these approaches. Other than the basic FANTs and BANTs, there are internal FANTs (IFANTs), external FANTs (EFANTs), Notification ANT (NANTs) and Error ANTs (EANTs) in protocols which are designed for hierarchical networks, such as MAZACORNET. In some of the reviewed protocols, RREQs and RREPs are also used in the route discovery phase. Hop count and the cost of a route are two main pheromone reinforce factors in MANETs. In VANETs, however, this can be quite different due to frequent interruptions of paths. [5],[33],[2] in the VANETs scope use the probability of reception of a message, the ratio between the estimated lifetime of a path and the maximum allowed lifetime of a path, to update the pheromone. The protocols in MANETs use a constant rate for pheromone evaporation, while the VANETs protocols use the lifetime of a path or an individual variable value [11] to reduce the pheromone values.

4.3 Comparison of implementation metrics

Table 3 shows the representative performance metrics of the surveyed protocols. As can be seen in table 3, all of the surveyed protocols have implemented their ideas and evaluated their performance, ca. 67% are implemented in common simulators, such as NS2 [18] and OMNet++ [38]. The rest protocols are implemented in self-developed simulators. All of the studied protocols in the table have compared their performance to that of other standard routing protocols for MANETs. AODV [32] is one of the most popular protocols chosen for comparison. In order to evaluate the performance, researchers mainly focus on the Data Delivery Ratio (DDR), the end to end delay and the routing overhead. 83% of the studied protocols have shown results for all of these three metrics. Moreover, nearly 67% of the protocols in the table have also considered other special per-

Protocol	Compare with	Simulator	DDR	Delay	Overhead	Special
POSANT [20]	AntNet, GPSR, AntHocNet[6]	own simulator [20]	YES	YES	YES	NO
Robustness-ACO [19]	AntHocNet, LAR	own simulator [19]	YES	YES	YES	YES
MAR-DYMO [5]	AODV,DYMO, Ant-DYMO	NS2, VNMG [30]	YES	YES	YES	NO
MAZA-CORNET [33]	AODV,AMODV, GPSR	NS2, VanetMobiSim [28]	YES	YES	YES	YES
Cluster-based ACO [2]	AODV	NS2,VNMG	YES	YES	YES	YES
S-AMCQ [11]	IAQR [22],AMCQ [11]	OMNet++	YES	YES	NO	YES

Table 3: Simulation parameter overview of ACO based routing protocols.

formance metrics.

The comparison results shown in 4.2 and 4.3 show that significant efforts have been made to address the requirements of efficient and effective routing protocols for MANETs. However, most of the reviewed approaches have not been evaluated with large networks. Although all the surveyed protocols have shown good performance in small networks, the scalability of the proposed protocols has not been demonstrated. Moreover, security issues are not considered in the most of them and all the proposed protocols in VANETs lack completely the practical testing via real-time traffic models.

4.4 Discussion

Since 2007 location aware ACO routing protocols have attracted more and more researchers. Designing routing protocols which satisfy only the basic requirements of MANETs' communications was no longer the focus of this research area. During the last ten years, location information aware vehicle routing are becoming hot topics, due to the increasing ubiquity of GPS [26]. Location information aware routing protocols have been widely used, especially in VANETs. From the reviewed ACO based routing protocols in VANETs, we have recognized that most of the protocols are designed for V2V networks. As the V2I communication networks develop progressively, we assume that in the future new protocols will be proposed in this area. Moreover, since most of the reviewed protocols do not consider any security issues, we infer that designing security and location aware ACO routing protocols in MANETs, would be an interesting future research direction. S-AMCQ [11] is an good example. Considering multiple issues, such as QoS, security, energy, etc., in the design of a routing protocol can make the protocol more suitable for real world applications. Therefore, we infer that designing ACO routing protocols based on the multiple existing issues in MANETs and especially in VANETs, would be an interesting future research direction.

5. CONCLUSIONS

Routing in MANETs is a challenging problem, due to the self-organizing properties of these networks. ACO algorithms provide a promising approach for the design of cooperative routing protocols with favorable properties. In this work, we have studied various location aware ACO routing protocols in MANETs which have been proposed from 2007 up to now. We have briefly reviewed each selected protocol and also presented a detailed comparative analysis in terms of protocol design and simulation related parameters. Besides our reviews and comparison tables, we have also discussed the open issues of the surveyed protocols. Additionally, based on our observations we have pointed out promising future directions of research in ACO based routing protocols. The main goal of this work is to give a general overview of the existing location aware ACO based routing protocols for MANETs and we hope this work can encourage protocol designers to take into account the various protocol properties studied so far when designing new ACO based routing protocols.

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7. REFERENCES

[1] C. Anderson, G. Theraulaz, and J.-L. Deneubourg. Self-assemblages in insect societies. *Insectes sociaux*, 49(2):99–110, 2002.

[2] S. Balaji, S. Sureshkumar, and G. Saravanan. Cluster based ant colony optimization routing for vehicular ad hoc networks. *International Journal of Scientific & Engineering Research*, 4(6):26–30, 2013.

[3] C. Blum and M. Dorigo. The hyper-cube framework for ant colony optimization. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 34(2):1161–1172, 2004.

[4] B. Bullnheimer, R. F. Hartl, and C. Strauss. A new rank based version of the Ant System. A computational study. 1997.

[5] S. L. O. B. Correia, J. Celestino, and O. Cherkaoui. Mobility-aware ant colony optimization routing for vehicular ad hoc networks. In *2011 IEEE Wireless Communications and Networking Conference*, pages 1125–1130. IEEE, 2011.

[6] G. Di Caro, F. Ducatelle, and L. M. Gambardella. AntHocNet: an adaptive nature-inspired algorithm for routing in mobile ad hoc networks. *European Transactions on Telecommunications*, 16(5):443–455, 2005.

[7] M. Dorigo. Optimization, learning and natural algorithms. *Ph. D. Thesis, Politecnico di Milano, Italy*, 1992.

[8] M. Dorigo and L. M. Gambardella. Ant colony system: a cooperative learning approach to the traveling

salesman problem. *IEEE Transactions on evolutionary computation*, 1(1):53–66, 1997.

[9] M. Dorigo and T. Stützle. The ant colony optimization metaheuristic: Algorithms, applications, and advances. In *Handbook of metaheuristics*, pages 250–285. Springer, 2003.

[10] F. Dressler and O. B. Akan. A survey on bio-inspired networking. *Computer Networks*, 54(6):881–900, 2010.

[11] M. H. Eiza, T. Owens, and Q. Ni. Secure and robust multi-constrained QoS aware routing algorithm for VANETs. *IEEE Transactions on Dependable and Secure Computing*, 13(1):32–45, 2016.

[12] T. Flannery. *Here on earth: a natural history of the planet*. Grove/Atlantic, Inc., 2011.

[13] P. C. Foster, N. J. Mlot, A. Lin, and D. L. Hu. Fire ants actively control spacing and orientation within self-assemblages. *Journal of Experimental Biology*, 217(12):2089–2100, 2014.

[14] S. Goss, S. Aron, J.-L. Deneubourg, and J. M. Pasteels. Self-organized shortcuts in the Argentine ant. *Naturwissenschaften*, 76(12):579–581, 1989.

[15] P.-P. Grassé. La reconstruction du nid et les coordinations interindividuelles chezBellicositermes natalensis etCubitermes sp. la théorie de la stigmergie: Essai d'interprétation du comportement des termites constructeurs. *Insectes sociaux*, 6(1):41–80, 1959.

[16] J. Härri, C. Bonnet, and F. Filali. Kinetic mobility management applied to vehicular ad hoc network protocols. *Computer Communications*, 31(12):2907–2924, 2008.

[17] B. Hölldobler and E. O. Wilson. *The ants*. Harvard University Press, 1990.

[18] T. Issariyakul and E. Hossain. *Introduction to network simulator NS2*. Springer Science & Business Media, 2011.

[19] D. Kadono, T. Izumi, F. Ooshita, H. Kakugawa, and T. Masuzawa. An ant colony optimization routing based on robustness for ad hoc networks with GPSs. *Ad Hoc Networks*, 8(1):63–76, 2010.

[20] S. Kamali and J. Opatrny. Posant: A position based ant colony routing algorithm for mobile ad-hoc networks. In *Wireless and Mobile Communications, 2007. ICWMC'07. Third International Conference on*, pages 21–21. IEEE, 2007.

[21] M. Killat and H. Hartenstein. An empirical model for probability of packet reception in vehicular ad hoc networks. *EURASIP Journal on Wireless Communications and Networking*, 2009(1):1, 2009.

[22] M. Liu, Y. Sun, R. Liu, and X. Huang. An improved ant colony QoS routing algorithm applied to mobile ad hoc networks. In *2007 International Conference on Wireless Communications, Networking and Mobile Computing*, pages 1641–1644. IEEE, 2007.

[23] V. Maniezzo. Exact and approximate nondeterministic tree-search procedures for the quadratic assignment problem. *INFORMS journal on computing*, 11(4):358–369, 1999.

[24] J. A. P. Martins, S. L. O. Correia, and J. Celestino. Ant-DYMO: a bio-inspired algorithm for MANETS. In *Telecommunications (ICT), 2010 IEEE 17th International Conference on*, pages 748–754. IEEE, 2010.

[25] P. Memarmoshrefi, R. Seibel, and D. Hogrefe. Autonomous Ant-based Public Key Authentication Mechanism for Mobile Ad-hoc Networks. *Mobile Networks and Applications*, 21(1):149–160, 2016.

[26] P. Misra and P. Enge. *Global Positioning System: Signals, Measurements and Performance Second Edition*. Lincoln, MA: Ganga-Jamuna Press, 2006.

[27] N. J. Mlot, C. A. Tovey, and D. L. Hu. Fire ants self-assemble into waterproof rafts to survive floods. *Proceedings of the National Academy of Sciences*, 108(19):7669–7673, 2011.

[28] S. M. Mousavi, H. R. Rabiee, M. Moshref, and A. Dabirmoghaddam. Mobisim: A framework for simulation of mobility models in mobile ad-hoc networks. In *Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007)*, pages 82–82. IEEE, 2007.

[29] F. Moyson and B. Manderick. *The collective behavior of ants: an example of self-organization in massive parallelism*. Artificial Intelligence Laboratory, Vrije Universiteit Brussel, 1988.

[30] J. Nzouonta. Vehicular network movement generator.

[31] G. F. Oster and E. O. Wilson. *Caste and ecology in the social insects*. Princeton University Press, 1978.

[32] C. Perkins, E. Belding-Royer, and S. Das. Ad hoc on-demand distance vector (AODV) routing. Technical report, 2003.

[33] H. Rana, P. Thulasiraman, and R. K. Thulasiram. MAZACORNET: Mobility aware zone based ant colony optimization routing for VANET. In *2013 IEEE Congress on Evolutionary Computation*, pages 2948–2955. IEEE, 2013.

[34] V. Rico-Gray and P. S. Oliveira. *The ecology and evolution of ant-plant interactions*. University of Chicago Press, 2007.

[35] P. Ruiz and F. Ros. DYMOUM–A DYMO implementation for real world and simulation. *URL http://masimum. dif. um. es*, 2005.

[36] T. Stützle and H. H. Hoos. MAX–MIN ant system. *Future generation computer systems*, 16(8):889–914, 2000.

[37] T. Stützle, M. López-Ibáñez, and M. Dorigo. A concise overview of applications of ant colony optimization. *Wiley Encyclopedia of Operations Research and Management Science*, 2011.

[38] A. Varga et al. The OMNeT++ discrete event simulation system. In *Proceedings of the European simulation multiconference (ESM'2001)*, volume 9, page 65. sn, 2001.

[39] P. Vijayalakshmi, S. A. J. Francis, and J. A. Dinakaran. A robust energy efficient ant colony optimization routing algorithm for multi-hop ad hoc networks in MANETs. *Wireless Networks*, pages 1–20, 2015.

[40] Z. Zhang, K. Long, J. Wang, and F. Dressler. On swarm intelligence inspired self-organized networking: its bionic mechanisms, designing principles and optimization approaches. *IEEE Communications Surveys & Tutorials*, 16(1):513–537, 2014.