Bio-Inspired Topology Convergence Algorithms in Resource-Constrained VANETs

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***Abstract*— Frequent changes caused by IP-connectivity and user-oriented services in Inter-Vehicular Communication Networks (VCNs) set great challenges to construct reliable, secure and fast converged topology formed by trusted mobile nodes and links. In this paper, based on a new metric for network performance called topology convergence and a new Object-Oriented Management Information Base - active MIB (O:MIB), we propose an ant-based topology convergence algorithm that applies the swarm intelligence metaphor to find the near-optimal converged topology in VCNs which maximizes system performance and guarantee a further sustainable and maintainable system topology to achieve Quality of Service (QoS) and system throughput. This algorithm is essentially a distributed approach in that each node collects information from local neighbor nodes by invoking the methods from each localized O:MIB, through the sending and receiving of ant packets from each active node, to find the appropriate nodes to construct a routing path. Simulation results show this approach can lead to a fast converged topology with regards to multiple optimization objectives, as well as scale to network sizes and service demands.**

***Index Terms*— Vehicular Communication Networks (VCNs), Ant Colony Optimization (ACO), Self-Organization, Swarm Intelligence (SI), Quality of Service (QoS)**

I. INTRODUCTION

Vehicular Ad-hoc Communication Networks (VANETs) are becoming an active area in telecommunication research community [1]. As a Wireless LAN incorporating Mobile Ad-hoc Networks (MANETs), VCNs target the design and deployment of the QoS-assured, secure and high-speed communication connectivities on mobile platforms such as buses, trains, cars, ships, marine squad of battlefields, where dispersed portable devices are enabled to establish on-demand pervasive communications in decentralized manners. Inter-vehicular, Intra-vehicular ad-hoc mobile networks and vehicular-to-Internet communication networks are indispensable parts for the envisaged ubiquitous communication scenario, this adds more alternative ways for internetworking of WLANs, Satellite and Cellular systems. Currently, vehicular communications are typically required to: (1) construct and maintain QoS-assured links, treat dynamic/static workload fairly and further assign reasonable resources to support user-oriented services; (2) provide acceptable reliability; (3) secure communication links and provide fault-tolerance and self-restoration mechanism; (4) scale to future expected network expansions and growths.

To incorporate all these issues, topology convergence aims to find the converged topology which maximizes system capacity and throughput by minimizing interference and management costs, optimizing node cooperation and efficiently utilizing battery power as much as possible to self-adapting the topology such that the required QoS and security concerns are satisfied.

A. Topology Control vs Topology Convergence

A huge body of literature has been dedicated to topology control. However, topology convergence is different from the topology control. Topology control targets the maintenance of the chosen topology in a wireless network by adjusting transmission power at each node [2] and such that an objective function of the transmission powers are optimized. While topology convergence targets the convergence of mobile hotspots or Access points internetworking paths to an optimal topology not only before but also while the maintenance phase is invoked. By establishing/updating a fast, reliable, secure and cost-effective topology under multiple QoS constraints and management costs, it must be able to autonomically survive any hazards, resist any malicious attack, show certain adaptability when roaming from one wireless LAN to another type of wireless LAN. And system throughput, data routing and security requirements are achieved afterwards. Several successive stages leading to topology convergence include (1) distributed topology discovery (e.g., gateways discovery for mobile hotspots); (2) multiple objectives optimization process; (3) behavior/pattern matching with a known optimal topology; (4) configuration/reconfiguation/activation. However the nature of the formation of a converged topology in complex, dynamic, heterogeneous environments is unknown yet. This paper seems to be a first attempt in exploring this domain and carry out a preliminary simulation test to better understand the contributions from node cooperations as well as to understand the effects of the convergence on network performance.

B. Research Question and Contributions

It is the authors' belief that the formation of the converged topology should relate to the (1) routing mechanism (2) Availability of IP-connectivity (3) Optimal on-demand service-instantiated topology (4) Security issues. Our main research question is: *how do we address these new Network Management challenges, factoring in the ingredients of a distributed environment, to construct efficient, robust, secure, scalable and* *mobile VANETs that are capable of providing the ubiquitous connectivity required by multimedia applications such as VoIP and TVoIP? We argue that autonomic management paradigm can be the solution to scalability and QoS requirements for distributed VANETs.*

Specifically, our goals are to address the unexplored nature of topology convergence for VANETs by creating a new routing protocol - an ant-based topology convergence algorithm based on resource orientated cost function, topped with an efficient self-managed network management paradigm. This new routing protocol is unlike conventional shortest path-based routing algorithms such as DSR [3]. The multimedia streaming experimental results test performance of the QoS of routing protocols for VANETs. We believe that our 4/3 management structure [4], combined with the notions of an proposed O:MIB and biomimetic learning and adaptation strategies will help to resolve the topology convergence issue.

The remainder of the paper is organized as follows. Section 2 presents the ant colony biological model. Section 3 describes our algorithm and its application to learning and adaptation. As a validation test, the performance comparison in Section 4 shows the effectiveness and robustness to guide QoS-assured topology convergence process in VCNs with respects to the known testing metrics. Conclusion and future development are stated in section 5.

II. ANT COLONY BIOLOGICAL MODEL

A. Ant Agent Behavior Model Mapping to Network OSI Model

The *ant agent behavioral model* is inspired from the foraging behavior of an ant colony. The ant model is working between the *networking* layer and the *application* layer in order to improve the routing performance of IP data packet in VCNs. In doing so, this biologically-inspired scheme can be seamlessly integrated into current Internet infrastructure economically and flexibly.

A fully devised mobile vehicle having wireless bi-directional connectivity to Base Station/Satellite ca classified as a node. Each node in VCNs contains one ant colony, which can be classified into 4 parts: (1) packets queue repository, (2) application/service repository, (3) communication channels and (4) Heterarchy ant agents in the container.

The structure of an ant nest is shown in Figure 1. The packet queues repository is the interface to the PHY and MAC layer while application/service queue repository is the interface to the application layer. All the packets are sent out or received in through the ant nest interfaces. The information flows go through the environment inside and outside ant colony all the time, which facilitates ant agents to communicate with each other through *communication channels*. The communication channels include two modes: (1) indirect stigmergic communication channel and (2) direct contact communications. The ant agent container contains *heterarchy* ant colony, where ant colony is constructed via a *heterarchical* way but not in a *hierarchical* way as described by Wilson & Holldobler in [5] and Dréo in [6]. Heterarchical structure makes the ants communication with each other close without the level restriction as of hierarchical network. Heterarchy functions as a bottom-up designed system, where the system is highly self-organized without the centralized control, emergent properties are emerged in that each entity operates by following simple rules, when the whole colony population is self-organized to work together and finally exhibits desirable patterns and behaviors to reach system goals. While *hierarchical* structure follows a top-down design, communications are restricted to go through various levels to reach the final destination, and most of the time, a centralized control may be needed.

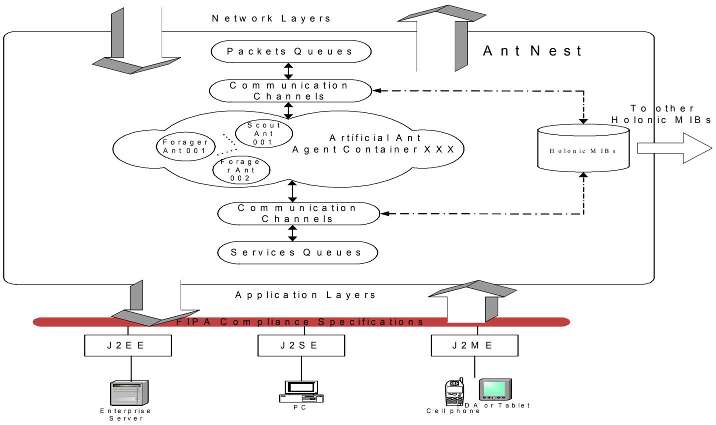

Fig. 1: Ant Nest Model

B. Conventional MIB vs Proposed Holonic MIB

1) Holonic O:MIB vs MIB: Inspired from Active Network approach [7], we propose an object-oriented Management Information Base termed as O:MIB in this paper. The active MIB is different from traditional MIB. We apply the Object-oriented concept into the construction of conventional MIBs. By referring to Active Network (AN) *[7]*. The active packet is similar in terms of containing data and code.MIBs usually have 3 branches: iso, user profiles, and vendor profiles. The unique Object Identifiers (OID) is applied to represent each managed object, or MIB object. The whole MIB is constructed by many managed objects which form a hierarchical tree structure for managed information represented. The top level of the tree structure is controlled by ISO and ITU organization for any additions to the MIB trees for new managed objects, interfaces, or devices. Figure 2 is an example of a MIB tree structure and naming scheme, and the dotted line in figure 2 representing those subentries from O:MIB that can be added on afterwards.

On the basis of widely-adopted RFC1213 specification for MIB-II [8], we believe it is possible and efficient to add up more sub entries in current MIB structure, for instance, these subentries consisting of more attributes and methods can be added on below (object identifier) OID = 1.3.6.1.2.1 (i.e., **iso.org.dod.internet.mgmt.mib**). On some circumstances, more subentries could be embedded into private enterprise network OID = 1.3.6.1.4.1 (i.e., **iso.org.dod.internet.private.enterprise**). We hope this O:MIB can partially replace the NGOSS Shared Information/Data (SID) model [9] to some extent in that the infor-

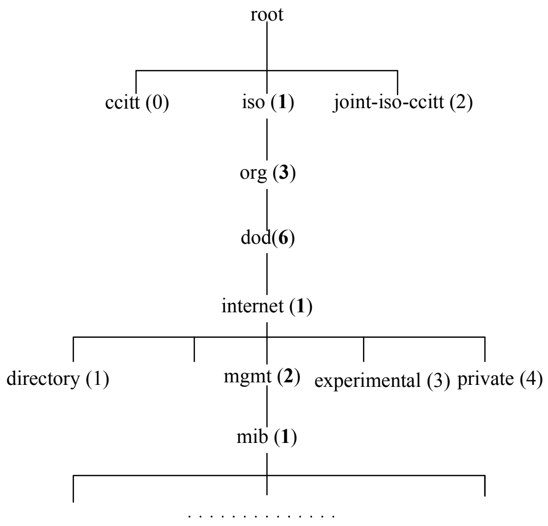

Fig. 2: The Functional Domain of O:MIB in MIB Tree Structure

mation synchronization process [10] is not necessarily periodically invoked as current database-derived scenarios, rather, only act on the on-demand requests (ODREQ) which trigger the *get/set/update/trace* information processes together with customized methods in O:MIB (e.g., getUpdateFrequency() or setAccessPermission()) to get the information, update information contents and other more actions defined in methods. The on-demand approach is more efficient in distributed networks with less messaging overhead where resources (e.g., bandwidth, battery power, capacity) are limited.

Conventional MIB	Object-oriented MIB
Hierarchical Structure	Hierarchical Structure
Information Elements Stored	Information Elements + functions, Algorithms + Embedded Agent Semantics
Data Oriented	Object-oriented/On-demands
SMI/ASN.1- Standardized	O:XML-Enabled
Static/Fixed	Dynamic/Extensible/Reconfigurable

Fig. 3: Comparison Between Conventional SNMP MIB and O:MIB

III. CONSTRAINED ANT-BASED TC PROTOCOLS

The *off-line* ACO optimization applied into service management domain has been tested in our paper [11] . This paper attempts to try *online* optimization instead in the Network layer. The information interchanging are done in real-time mode by the localized autonomic entity - O:MIBs which reside on each network devices and services. Each local O:MIB establishes an information environment where an artificial ant colony lives. The network system consisting of many local O:MIB comes into being an *information ecosystem*, which mimicks the behaviors and patterns of the nature ecosystem. Network activities such as IP packet transmission, forwarding, management information collection, decision making processes are all happening in this ecosystem. Recent work [12] shows that the congestion in manhattan networks are often undesirably worse in that the large number of vehicular access points aggregated into some areas such as the crossing area. The performance of getting fast converged topology for communications can be improved by the proposed ant-based algorithms, which works according to the network status, traffic balancing behaviors can be expected.

A. Ant-based TC Protocol

As we design in previous section, each vehicular node i could be either source node or destination node and functions asynchronously and independently from each other, the node can interact with other nodes via sending and receiving ant packets which is similar to the mechanism used in active networks. This protocol is driven by on-demand events which can be roughly classified into four stages: (1) Initialized by user-oriented on-demand service requests (2) Checking local active O:MIB. (2) Preconfigured periods of ant packets sending and receiving. (3) Update pheromone trails (4) Start another round of searching cycle in case of unexpected disruptive events. Each node i needs to maintain a pheromone table which contains time-varying pheromone value $\tau(C_{E_{ij}}, t)$ for different $C_{E_{ij}}(\cdot)$ level. We use three different levels $\omega_1(C_{E_{ij}}(\cdot))$, $\omega_2(C_{E_{ij}}(\cdot)), \omega_3(C_{E_{ij}}(\cdot))$ to simply distinguish them as the weights for pheromone calculations and set the rules accordingly for pheromone updating process. Table I shows the pheromone trails for $node$ 1 with its all neighbor nodes.

The edge parameter $C_{E(i,j)}$ between vehicles denote a function of multiple factors that the topology convergence process needs to cover. The optimal convergence process is then transformed into an ant traversing through the graphical network where a certain number of vehicle nodes are visited until the stopping criteria are reached. Moreover, each node is assumed to be traversed once at most.

Suppose the ant is randomly placed on node i, the probability of an ant k choosing the next adjacent node j as denoted in [13] is:

$$P_k(i,j) = \begin{cases} \dfrac{[\tau_{i,j}]^\alpha [\eta_{i,j}]^\beta}{\sum\limits_{l \in U} [\tau_{i,l}]^\alpha \left[\eta_{i,l}\right]^\beta} & \text{if } j \in U \text{ and } l \neq j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $\eta_{i,j}$ is called *visibility* and represents the *heuristic desirability;* U is the set of neighbor nodes of node i that has not transpassed, and U is the set of feasible components which can be potentially selected to fulfill a successful configuration process. In our present method, information from holonic MIBs contribute to the main part of $\eta_{i,j}$, denoted as $\eta_{i,j} \triangleq \frac{1}{C_{E(i,j)}}$, which is the reciprocal of the *weights value* from node i to node j. The parameter $\eta_{i,j}$ is used not only to calculate the probability but also as a measure to determine the goodness of the selection of configuration components. The pair parameters α and β indicate the trade-off of affective importance between heuristic information and pheromone trail

Node n_1	Neighbour n_2	Neighbour n_3	Neighbour n_4	Neighbour n_5	Neighbour n_6
$C^{\omega_1}_{E_{ij}}$	$\tau_{n_1,n_2}(C^{\omega_1}_{E_{1,2}}, t)$	$\tau_{n_1,n_3}(C^{\omega_1}_{E_{1,3}}, t)$	$\tau_{n_1,n_4}(C^{\omega_1}_{E_{1,4}}, t)$	$\tau_{n_1,n_5}(C^{\omega_1}_{E_{1,5}}, t)$	$\tau_{n_1,n_6}(C^{\omega_1}_{E_{1,6}}, t)$
$C^{\omega_2}_{E_{ij}}$	$\tau_{n_1,n_2}(C^{\omega_2}_{E_{1,2}}, t)$	$\tau_{n_1,n_3}(C^{\omega_2}_{E_{1,3}}, t)$	$\tau_{n_1,n_4}(C^{\omega_2}_{E_{1,4}}, t)$	$\tau_{n_1,n_5}(C^{\omega_2}_{E_{1,5}}, t)$	$\tau_{n_1,n_6}(C^{\omega_2}_{E_{1,6}}, t)$
$C^{\omega_3}_{E_{ij}}$	$\tau_{n_1,n_2}(C^{\omega_3}_{E_{1,2}}, t)$	$\tau_{n_1,n_3}(C^{\omega_3}_{E_{1,3}}, t)$	$\tau_{n_1,n_4}(C^{\omega_3}_{E_{1,4}}, t)$	$\tau_{n_1,n_5}(C^{\omega_3}_{E_{1,5}}, t)$	$\tau_{n_1,n_6}(C^{\omega_3}_{E_{1,6}}, t)$

TABLE I: Pheromone Table

density. The parameter $\tau_{i,j}$ is the pheromone density on the path $(i,\ j)$ from node i to node j.

The main steps of our proposed method for the topological convergence process are summarized as follows:

Step 1) Initialize cost values and ACO parameters, such as predefined iteration times t, initial pheromone values $\tau_{i,j}(t)$ and stagnation conditions, etc.

- Create M artificial ant agents for one ant colony, where M is usually set to be equal to the number of nodes; Each ant colony is used to instantiate one topology.
- Set initial iteration variable $t_0 = 0$; set predefined iteration times t=200; and set the initial pheromone value in all trails equal to a constant initial value $\tau_{i,j}(0) = C$. C should not be zero because a non-zero finite constant could delay the process of evaporation into zero pheromone density so as to further avoid the earlier local optima.
- Dispatch each ant in this ant colony from one node. The ant retrieves *heuristic* information from Holonic MIB, e.g., available bandwidth information, delay information, capacity and cost information, connectivity information.

Step 2) Build the Solution

M ants start to follow the transition rule to build solutions asynchronously. Meanwhile, heuristic information, as a transition constraint, ensures ants should only traverse the *feasible* nodes in our problem domain before making a decision of a move. Whenever the period of predefined time is due or the receiving of the ant packets which require certain actions to be taken.

The edge parameter $C_{E(i,j)}(t)$ is calculated [1] and usually less than 1. Until now, all the *heuristic* information and edge vector values are determinate. The probability of selecting next relaying vehicle at one iteration step is recorded into a table. When the destination nodes are reached by all M ants, we consider it as the completion of one round of iterations. There are 3 possibly successful ant traversing scenarios:

1) Ant traverses through possible nodes until it reaches destination node i and sleep there.

2) Ant reaches the destination nodes within the maximum limits of hops counts $\mathbf{H}$.

3) Suppose some node goes faulty, the ants will be awaked up on this node to find an *alternative* node from the same class of nodes as the faulty nodes, or the next available ant will find an alternative node.

- Let "X" illustrate that a particular node is NOT possibly to be visited by the related ant because it is not connected or logically dependant. This can happen anywhere according to the HMIB
- Let Pr($n-$th Ant) represent the probability of being selected by the n-th ant; the n-th ant in node i will select the next node j to visit with probability equation (1)

The algorithm for calculating probability is shown in the following pseudocode:

```
For ant → $N = 1$ to $n$
    For Object Nodes → $O = 1$ to $m$
        If (there is no neighbor vehicle node available)
            Break;        % one of the stopping criteria
        Elseif (the connectivity status between objects is ON);  % $i$ and $j$ are two adjacent nodes
            Check holonic MIB to get heuristic information
            Calculate the selection probability for this ant to next adjacent node by Equation (1) and Record it;
        Elseif (connectivity status between objects is OFF);
            Record "0" as selection probability for this node;
        Elseif (there are available neighbor nodes  and all connectivity status between objects is OFF);
            Record "X" as selection probability for this node;
        EndIf
    If (Error tag shows this is a faulty node) and (there are available neighbor nodes  and all connectivity status between objects is OFF);
        Calculate the selection probability for this ant to alternative adjacent nodes by Equation (1) and Update this;
    EndIf
    EndFor
        1) Find out the network nodes with highest selection probability in the probability table;
        2) Plot out the feasible topologies for vehicles;
        3) Subtotal the minimum sum value at this stage and record which topology get the minimum;
        When the period is due, send another ant packet and Start another ant traversing;
    EndFor
```

Not all ants are able to finish a complete traverse path from product to resources. For ants which are able to finish traverse paths during this iteration, we *match* the components with the nodes on paths and *record* the minimum sum value for $C_{E(i,j)}(t)$;

In addition, there are two modifications of the conventional ACO process for our method:

1) *Stopping criteria:* Whenever ants reach destination vehicle node, they will stop searching and sleep there (No need to go back to source node)
2) *Random factors:*
    a) In the early phase of our algorithm, each ant packet will be sent out via broadcast and this is an asynchronous process
    b) After receiving heuristic information from Holonic MIB, ants travel randomly among the *feasible*

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[1] Due to page limits, this equation is omitted. It is available under requests.

objects without the knowledge of the existence of the real-world connection.

Step 3) Update pheromone trails

Upon receiving the ant packet from node i, equation (2) is applied to increase pheromone value along the path. The insertions and reductions will influence the searching process for the next iteration. We adopt the conventional ACO pheromone update rule as:

- Intensify pheromone: an absolute amount of pheromone $\triangle\tau_{i,j}^{k} > 0$ is added to the existing pheromone values on the paths completed by k-th ant

  $$\triangle\tau_{i,j}^{k} = \begin{cases} \frac{Q}{Z_{\min(k)}} & if\ (i,j) \in T_k \\ 0 & if \notin T_k \end{cases} \qquad (2)$$

  where T_k are the paths having been traversed by k-th ant. Q is a constant, more research on Q value have been done in Dorigo [14].
- Evaporate pheromone: When the wireless *link life time* is due or no more packets go through, the pheromone on the edges are reduced in order to minimize the chances of being selected by other ants as equation 3.

  $$\tau_{i,j} = (1-\rho) \times \tau_{i,j} \qquad \forall i,j \in [1:m] \qquad (3)$$

  where $\rho \in [0,\ 1)$ is the pheromone evaporation rate. $\tau_{i,j}$is the current pheromone density on the trail $a(i,j)$.
- Mutate pheromone update process:
  In order to increase the algorithm's convergence speed, we try to combine the *mutation* parameter into our pheromone update rules, where the concept of *threshold* is also involved. This mutation parameter involved into our algorithm are partly based on *Best-worst Ant Colony Algorithm* (BWACA) as well as *Max-min* Ant system.

```
Let $\tau_{threshold} = \frac{SumOfPheromoneViaGoodSolutions}{|V_{global\_best}|}$
    $V_{current\_worst} = worst\_solution(V_k)$
  For each edge $a(i,j) \notin V_{global\_best}$
  Do
     $\tau_{ij} = (1-\rho) \cdot \tau_{ij}$
  End For
     $Mutation{=}Mutation(current\_iteration,\ \tau_{threshold})$
  For each node $O \in (1,\cdots,n)$
  Do
       $r = \mathrm{rand}(0,1)$
     If $(r \leq P_k)$
      $V = \mathrm{rand}(1,\cdots,n)$
      $a = \mathrm{rand}(0,1)$
     If $(a = 0)$
       $\tau_{ij} = \tau_{ij} + Mutation$
     else
       $\tau_{ij} = \tau_{ij} - Mutation$
```

Step 4) Start another round of iterations

Before the predefined searching iteration times are reached, another round of iterations always starts again, immediately after the previous round of iterations ends. Meanwhile, the predefined iteration times t is increased by 1: $t = t + 1$. Go to step 2). This process will continue till t reaches its limit. Moreover, the pheromone information from previous iteration is utilized in the new iteration, and being kept updated.

```
While (t <= predefined value) Do
     t=t+1;
Go to step 2, Repeat;
```

IV. SIMULATION

A. Simulation Platform and Configuration Parameters

Vehicle Density (VD) in a lane is defined as the number of vehicles in a single lane (n/km), hence, the maximum VD in a single lane can be calculated as: $Max\{VD\}_{lane} = \frac{L}{l}$

The recent extension work by Treiber and Helbing [15], who developed the highway car following model further into a community *intelligent driver model* (IDM) is given as:$\frac{dv_j}{dt} = a_{\max}\left[1 - \left(\frac{v_j}{v_{desired}}\right)^{\lambda} - \left(\frac{d_{desired}(v_j,\triangle v_j)}{d_j}\right)^{2}\right]$.

We implement the community mobility model into a simulation scenario that emulates the real traffic patterns in community road with various driving states. Based on this simulator, we apply our proposed scalable ant-based TC protocols into this dynamic road condition and compare the performance of topology convergence with other existing routing protocols such as DSR, AODV.

TABLE II: Speed-Density in Syndey CBD

VD(Vehicles/Km)	Speed(Km/h)
40	58
80	52
120	40
240	10

Metrics used in evaluating the performance of topology convergence for proposed ant-based TC protocols: 1.) Packet Delivery Ratio; 2.) Message Overheads; 3.) Delay; 4.) System throughput and capacity

B. Experiment Results

As for the conventional DSR and AODV, we consider the 3 performance measures: (1) Packet Delivery Ratio, (2) Message Overheads, (3) end-to-end Delays. They are shown in the following figures. We compare the proposed TC algorithm based on those metrics and prove it can efficiently improve the packet delivery ratio and system throughput/capacity, and robustness and scalability can be achieved too. Figure 5 and Figure 6 presents the simulation comparison results on Packet Delivery Ratio (PDR) and end-to-end average delay between our proposed scheme and AODV routing scheme.

V. CONCLUSION AND FUTURE WORK

This paper proposed Ant-Based Topology Convergence Algorithm (ABTCA) to guide QoS-assured vehicular communication in future complex wireless networks. The paths found by this ABTCA algorithm are actural converged communication paths with regards to multiple hops. In this paper, an innovative active O:MIB is designed and implemented.

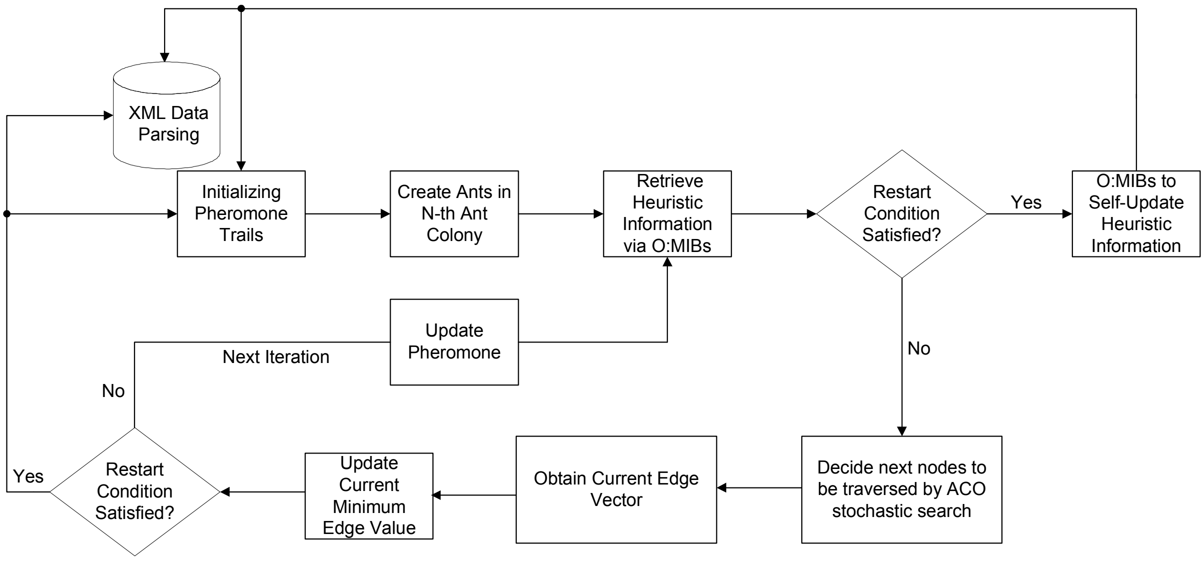

Fig. 4: Schematic of Ant-Based Topology Convergence Model

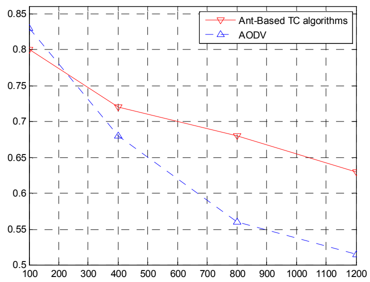

Fig. 5: Comparison of PDR

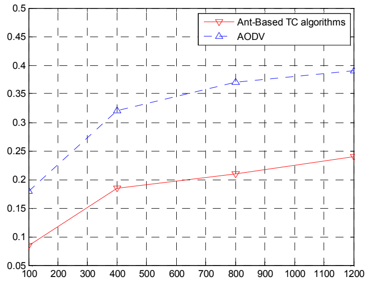

Fig. 6: Comparison of Average Packet Delay

The efficiency of the approach outperform the current DSR and AODV. Future work includes: (1)Bi-directional vehicular communications to be implemented into our simulator; (2) Scalability and security issues to be taken into consideration.

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