Node Movement Control Based on Swarm Intelligence for a Mobile Medium Ad hoc Network

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***Abstract*—A Mobile Ad hoc Network (MANET) is a network of wireless mobile devices capable of communicating with one another without any reliance on a fixed infrastructure. A Mobile Medium Network is a set of mobile forwarding nodes functioning as relays for facilitating communication between the users of this Mobile Medium. The performance of the Mobile Medium depends on the Mobile Medium node density, distribution and movement. In the proposed new paradigm for node movement control based on swarm intelligence, the movement is determined based on whether the nodes are at the locations where data forwarding activity recently took place or not. Simulation results show that directing the nodes to the locations where the forwarding activity has recently happened significantly affects the delivery rates in the Mobile Medium networks. For some networks, with a few forwarding nodes initially dispersed in a large region, applying the swarm intelligence algorithm increases the delivery ratio by up to 50%.**

Keywords-mobility models; self-organizing mobile network; swarm intelligence; Mobile Medium; M2ANET

I. INTRODUCTION

A MANET is a set of mobile devices that cooperate with each other by exchanging messages and forwarding data [1][2]. A Mobile Medium Ad hoc Network (M2ANET) proposed in [3] is a particular configuration of a typical MANET where all mobile nodes are divided into two categories: (i) the forwarding only nodes forming the so called Mobile Medium, and (ii) the communicating nodes, mobile or otherwise, that send data and use this Mobile Medium for communication. The advantage of this M2ANET model is that the performance of such a network is based on how well the Mobile Medium can carry the messages between the communicating nodes and not based on whether all mobile nodes form a fully connected network. An example of a M2ANET is a cloud of autonomous drones released over an area of interest facilitating communication in this area. The movement of nodes in a M2ANET can be predefined by the user, selected at random or purposefully controlled for the best performance. When the mobile nodes select for themselves their movement, we call to such a network a Self-organizing Mobile Medium Ad hoc Network (SMMANET). A sample node movement control for a SMMANET based on attraction/repulsion paradigm was proposed by Almutairi et al. [4]. There, the mobile nodes can move in any direction, except when they get too far apart: then they turn back to stay together. This type of autonomous control was shown to improve the mobile network performance.

Recently, a number of projects that match the M2ANET model have been announced; they include Google Loon stratospheric balloons [5] and Facebook high altitude solar powered planes [6] for providing Internet services to remote areas, and the Swarming Micro Air Vehicle Network (SMAVNET) project where remote controlled planes are used for create an emergency network [7].

In Section II, we present background on self-organizing systems and swarm intelligence. The new movement pattern based on ant colony control is discussed in Section III. Simulation experiments of this movement under different scenarios are in Section IV. Finally, we present the experimental results in Section V, followed by the conclusion and future work.

II. STATE OF THE ART

A M2ANET is mobile network comprised of interconnected mobile nodes, which make wireless multi-hop communication possible for mobile users. M2ANETs exhibit a fault-resilient nature, given that they are not operating with a single point of failure and are very flexible. The deletion and addition of new nodes, forming new links are a normal part of operation of a M2ANET [1][8][9]. This paper focuses on applying the self-organization principles for controlling the movement of nodes in the Mobile Medium, aka M2ANET.

W. Ross Ashby formulated the original principle of the system of self-organization in 1947, although it was not published until 1962. In his paper, Ashby explained the fundamental concept of organization, and the integration of machines, and how they lead to what he referred to as a system of self-organization [10]. Later, in 1999, Bonabeau et al. defined the concept of self-organization relating to "Swarm Intelligence". Self-organization can be defined as a set of dynamic spontaneous global structures that appear out of the local interactions between lower-level components of an initially disordered system [11][12]. Spontaneous means that the process is not controlled by any agent inside or outside the system. Based on purely local information, an agent chooses which rules the process and its initial conditions should follow. This is distributed across all the agents in the system, which follow the same process in

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parallel. As a result of this, the organization is very robust, and self-repairs any damage or perturbations. Any elimination or replacement of individual agents will not affect the system. In such a complex system, the agents directly interact locally with other agents near them, by visual contact, chemical contact or by exchanging messages wirelessly, and affect the remote agents indirectly by changing the environment around them. The agents are goal-directed and select one outcome over another during the evolution of the system [12][13]. Self-organization can be found in many different areas of science, e.g., physics, chemistry, biology, and telecommunication. Swarming in groups of animals, flocks of birds, schools of fish, and colonies of insects are common examples of self-organization in nature. Individuals in swarms behave in a simple way that collectively create more complex behaviors. They interact locally with each other and with the environment around them to create a self-organization system able to solve complex problems [12][13].

Implementing a swarm system with self-organization features in wireless networks is a real challenge. Bonabeau et al. [11] present self-organization in swarms through positive feedback, negative feedback, fluctuations and multiple interactions. Positive feedback as a simple behavior may be presented as a recruitment and reinforcement. For example, the dancing of bees, or laying of pheromone and following these trails of ants, are kinds of recruitment for their fellow species to reach a food source. On the other hand, negative feedback represents a way of balancing positive feedback and stabilizing the collective pattern. Fluctuations, such as random searches and errors, are important for self-organization in swarms in order to create creativity, innovation and discover new solutions. Finally, multiple interactions appear from sharing and spreading information between agents in the swarm [11][13].

Swarm Intelligence (SI) is an artificial-intelligence approach to problem-solving using algorithms based on the self-organized collective behavior of social insects such as ants, bees, birds, fish, wasps, and termites that follow very basic rules [11]. Beni and Wang introduced the expression "Swarm Intelligence" in 1989 in the context of cellular robotic systems [14]. Natural swarm systems made up of millions of flexible individual agents following simple rules demonstrate complicated group behavior. Such systems can be found in ant and bee colonies, flocks of birds, and schools of fish [15][16]. SI based on the nature of insects provides a basis on which it is possible to explore collective (or distributed) problem-solving methods without centralized control or the provision of global models such as MANETs [16][17][18]. Swarm Intelligence algorithms can be used in MANETs and in M2ANETs to control the movement of the nodes in order to follow an optimal forwarding path during the network run time. Nodes using an SI algorithm have the same ability to connect as any other mobile nodes, except that they move dynamically and are called agents. The agents follow very simple rules, although there is no centralized control structure dictating how individual agents should behave. These interactions between agents may lead to "intelligent" global behavior, unrecognized by the individual agents [19][20][21].

The Particle Swarm Optimization (PSO) algorithm was introduced to solve nonlinear function optimization based on swarm intelligence by Kennedy, Eberhart and Shi in 1995 [22]. Particle Swarm Optimization is an Artificial Intelligence (AI) technique, related to both genetic algorithms and evolutionary programming, to model group movement behavior inspired by flocks of birds and schools of fish. An example is birds flying randomly searching for food in different places, until one of the birds is close to the food source. The other birds then need to learn which bird is nearest to the food and how far away the food is. At this point, the bird shares the information about the position of the food with the other birds in the flock. Transference of the correct information will enable the flock to follow the bird closest to the food to reach the food [23] [24]. In this example, the flock represents the swarm solution and the food source represents the optimal solution.

Ant Colony Optimization (ACO) is a type of optimization algorithm modeled on the actions of an ant colony using a swarm intelligence method. In 1996 Marco Dorigo, Vittorio Maniezzo and Alberto Colorni proposed the ACO approach based on their observation of ant behavior in nature [25]. ACO methods are useful in problems that need to find paths to goals. The first ACO algorithms aimed to solve the NP-complete Travelling Salesman Problem [TPS] with the goal of finding the shortest round trip between a series of cities [25][26][27]. In nature, ants without vision (almost blind) explore the environment around the colony searching randomly for a food source. When an ant finds food, it leaves a chemical pheromone trail on the path taken returning to the colony carrying that food. The other ants start following that pheromone trail to reach the food source [28] [29]. Pheromone is not permanent, it evaporates over time and distance. The pheromone evaporates from the longer paths faster than the shortest one and in this way ants always find the shortest path to the food source. Artificial 'ants' as simulation agents locate optimal solutions by moving through a parameter of space representing all possible solutions to solve a problem [30][31][32].

Colorni, Dorigo and Maniezzo developed the first and simplest Ant Colony Optimization algorithm, called Ant System (AS) [25]. The Ant System algorithm was inspired by the parallel search over different paths for real ants in nature. Real ants take several ways to solve their problems based on the data and information stored in their memory about previously obtained results [25][33]. The AS transition probability was modified to include heuristic information. Also, a tabu list was added to the AS implementation as a memory capacity. In AS, a set of agents (Ants) follows local decisions to move through nodes (places) to solve a problem [34][35]. The probability rule used by the ant to move from place i to place j during iteration is:

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$$p_{ij}^{k} = \begin{cases} \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{k \notin tabu_k} \tau_{ik}^{\alpha}\eta_{ik}^{\beta}} & if\ j \notin tabu_k \\ 0 & otherwise \end{cases} \quad (1)$$

τ_{ij}- amount of pheromone trail,
η_{ij}- visibility $(0 \leq \eta_{ij} \leq 1)$,
α- impact of trail defined by the user $(0 \leq \alpha \leq 1)$,
β- attractiveness defined by the user $(0 \leq \beta \leq 1)$,
$tabu_k$- tabu list contain the visited cities by ant_k during current iteration.

The visibility value represents the heuristic information, which can be calculated by using the following expression:

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (2)$$

d_{ij}- distance between place i to place j.

Each ant leaves a trail called pheromone τ after completing a solution to attract the other ants. This pheromone trail τ can be modified by other ants moving along the same path or it can just evaporate over time [35]. The pheromone τ_{ij} laid on the connected edge between place i and place j is updated by using the following equations:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(\mathrm{t}) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (3)$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (4)$$

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k & if\ ant_k\ used\ path(i,j) \\ 0 & otherwise \end{cases} \quad (5)$$

ρ- the evaporation coefficient defined by the user $(0 \leq \rho \leq 1)$,
m-the number of ants,
$\Delta\tau_{ij}^{k}$- the pheromone quantity laid by ant_k on the path (i,j),
Q- constant, often 1,
L_k-the tour length of the solution obtained by ant_k.

The ant agents use the pheromone trail information to control movement through the search operation to find the optimal solution for the problem [32][33][35].

III. ANT COLONY MOVEMENT CONTROL IN MOBILE MEDIUM

M2ANET is a high dynamic network, also called Mobile Medium, where all the mobile nodes are moving in many directions at different speeds. This rapid movement of the mobile nodes causes changes in the M2ANET topology, which increase the rerouting and possibly disconnections between the source node and the destination node. This continual rerouting affects network performance and decreases packet transmission rates. In order to improve M2ANET performance, a dynamic-movement node-control algorithm based on SI is proposed to control the mobile node movement according to the node's awareness of the traffic condition. The proposed Ant System Node Control (ASNC) algorithm is implemented to control the mobile node movements in M2ANET according to the traffic condition in the network. The proposed ASNC is adapted from the ACO algorithm, and more specifically from the AS algorithm [35]. In this paper the proposed ASNC algorithms is used for movement control of mobile nodes in a Mobile Medium, and not simply for routing. It should be noted here that a variety of related SI studies and algorithms are already used specifically for routing: Ant-colony-based Routing Algorithm (ARA) [36], Simple Ant Routing Algorithm (SARA) [37], Ad-hoc Networking with Swarm Intelligence (ANSI) [38], AntHocNet hybrid algorithm [39], AntNet routing algorithm [40], and HOPNET routing algorithm [41].

At the start, the mobile nodes are moving randomly in a M2ANET without any control. A stationary source node represents the ant colony while the destination node represents the position of the food source. The mobile nodes act like Ant-agents, they explore the simulation area randomly until the routing protocol detects the first forwarding path between the source and the destination. At this time, each active forwarding node, ant-agent, leaves a pheromone trail at its position, and the accumulation of the deposited pheromone shows the forwarding path that the packets transmit through from the source to the destination. Next, the other mobile nodes, ant-agents, start moving towards these pheromone trail positions deposited by the forwarding ant-agents. Each time a forwarding path is detected in the M2ANET, the active forwarding ant-agents deposit new pheromone trails at their forwarding positions. The pheromone trails are not permanent, they evaporate over time. Regarding a possible implementation of the ASNC approach in a M2ANET, while depositing the actual pheromone at a particular location may be possible in a biological system, the actual mobile network would have to use different means for marking and communicating the pheromone locations. While the means of implementing this pheromone marking is beyond the scope of this paper, one might consider having each node broadcast the intensity and the location of deposited pheromone trail to all other nodes in the network.

In the ASNC approach, the deposited pheromone locations are modified by ant-agents, mobile nodes, moving toward new forwarding positions, otherwise the pheromone evaporates from the forwarding position over time as specified in the AS update equation (Equation 3). The ant-agents follow the pheromone trail and move from one position to another using the AS probability rule (Equation 1). A sample evolution of the pheromone trail recorded in our sample experiments is illustrated in Figures 1 and 2. The pheromone trail marks the locations the forwarding activity took place recently and, we hypothesize, where the forwarding activity is likely to take place again. The size of each circle indicates the pheromone intensity, different colours are used to better visualize separate pheromone deposits. Circles at locations (50, 400) and (950, 600) mark the location of the data source and the destination, and not the pheromone deposits.

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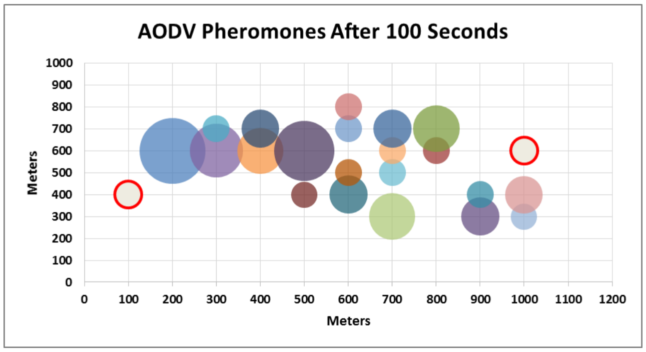

Figure 1. Initial pheromone trail.

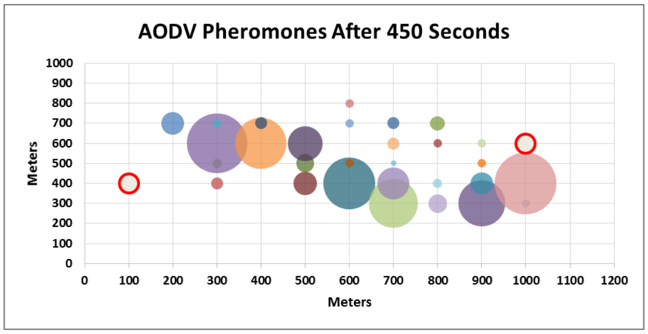

Figure 2. Evolved pheromone trail showing preferred node locations.

The pheromone trail is deposited based on the traffic condition of M2ANET and is used to control the movement of ant-agents during the simulation allowing them to find a position on a forwarding path between the communicating nodes, the source and the destination, and consequently to improve the network performance.

IV. SIMULATION EXPERIMENT

We used simulation in ns2 to test the new proposed ASNC algorithm that aims to control the mobile node movement in M2ANET based on awareness of the traffic condition in the network. ASNC used to control the random movement of mobile nodes is adapted from the AS algorithm, which is one of the existing ACO algorithms. For comparison, we used the random mobility model as a reference case scenario, mostly because it is a standard model used in network simulation. The base case model used is the Random Way Point (RWP) model available in ns2 [42]. In RWP, nodes are moved in a piecewise linear fashion, with each linear segment pointing to a randomly selected destination and the node moving at a constant, but randomly selected speed.

All ASNC experiments simulated in ns2 initially utilized the RWP model in a restricted area of 1000x1000 meters. The mobile nodes, representing the ant agents, move toward random destinations at random speeds with an average speed of 4 m/s. In the experiments based on ASNC, two stationary nodes, the source and destination nodes located at (50,400) and (950,600) coordinates respectively, are communicating with each other using the CBR traffic generator over UDP. The experiments run over two different ad-hoc network routing protocols, Ad hoc On-demand Distance Vector (AODV) and Destination Sequenced Distance Vector (DSDV), on simulated mobile networks with five different node densities: 5, 10, 20, 30, and 40 nodes. Node density indicates the total number of mobile nodes in the 1000 m by 1000 m square region modelled in the experiments. Each mobile network scenario has been simulated three times for 500 second simulation run time and the average results taken; simulation details are summarized in Table 1.

TABLE I. SIMULATION PARAMETERS

Parameters	
Simulator	NS-2.34
Channel Type	Channel / Wireless Channel
Network Interface Type	Phy/WirelessPhy
Mac Type	Mac/802.11
Radio-Propagation Type	Propagation/Two-ray ground
Interface Queue Type	Queue/Drop Tail
Link Layer Type	LL
Antenna	Antenna/Omni Antenna
Maximum Packet in ifq	50
Area (n * n)	1000 x 1000m
Source node location	(50, 400)
Destination node location	(950, 600)
Source Type	CBR over UDP packetSize_ 512 interval_ 0.05
Simulation Time	500 s
Routing Protocol	AODV and DSDV

At the beginning of each experiment, the mobile nodes move randomly to explore the simulation area without any control. The traffic of the network is observed during the entire simulation run time, waiting for the routing protocol to detect a forwarding path. The control mechanism starts when the first forwarding path is detected by the routing protocol. At this moment the information about the forwarding path becomes available including the ids of the active forwarding nodes and their positions. At the same time each forwarding node deposits a pheromone trail τ marking the location where the forwarding activity took place. (In the experiment, the simulator kept the locations of the pheromone deposits and made them available to all the network nodes.) The amount of the deposited pheromone trail τ on a new forwarding position is initially equal to one. These pheromone trails demonstrate the forwarding path that has been used to transmit data packets between the communicating nodes. For the ant agents, the source node represents the ant colony while the destination node represents the food source in the simulation. Rather than moving randomly, the nodes, ant-agents, move toward the positions where the pheromone deposits are the strongest marking the locations where the forwarding activity took place recently. The closest pheromone trail position to the current position of the mobile node with the highest pheromone amount will be selected.

The decision about where to move next during the

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simulation is taken by applying the probability rule, which is also adapted from the AS algorithm (Equation 1). In ASNC the values of the probability rule parameters for α, the impact of the trail, and β, the attractiveness, were set to 0.5 while the distance value in the visibility $\eta_{ij} = \frac{1}{d_{ij}}$ (Equation 2) was calculated based on the distance between the communication nodes and the forwarding position. Changing the values of α and β in the experiments did not affect the Packet Delivery Ratio (PDR) results. When the mobile nodes reach their destination positions, they pause for three seconds before determining again where to move next.

A pheromone trail deposited on a forwarding position is modified when another mobile node moves toward this forwarding position, otherwise the pheromone evaporates over time. To update the pheromone trail τ the update equation (Equation 3) has been adapted from the AS algorithm where the evaporation coefficient ρ value is equal to 0.01 and the constant Q is equal to 1. Also, changing the values of Q and ρ did not affect the PDR result of the experiments. The update equation increases the pheromone amount on the visited forwarding positions and reduces and/or evaporates the pheromone amount on the unvisited forwarding positions. A new pheromone trail τ is deposited by the forwarding nodes each time the routing protocol detects a new forwarding path in M2ANET. The mobile nodes visit several forwarding positions before they find the perfect positions to transmit packets between communicating nodes.

V. Results and Analysis of ASNC

The performance of a Mobile Medium network implementing the ASNC node movement control algorithm was investigated using the simulated networks with varying number of nodes and running two different routing protocols AODV and DSDV. The experiments were conducted using the ns2 simulator and the performance of a M2ANET was measured in terms of PDR, End-to-End Delay and Forward Path Time Detection (FPTD).

A. AODV performance: PDR

Attracting the mobile nodes to move toward the best forwarding positions based on the deposited pheromone trails resulted in a significant increase in the delivery ratio in M2ANET (Figure 3). At a very low density, with only five mobile nodes, no forwarding paths were detected by the routing protocol AODV during the entire simulation run time. As a result, zero packets have been delivered in these experiment. Increasing the mobile node density to 10 showed a PDR of 26% for ASNC, compared with 4% in the Random movement experiment. The experiment with 20 mobile nodes in ASNC showed the most interesting results and the best benefit of controlling the node movements based on the behavior of ants in nature. With 20 mobile nodes, 89% of the data packets have been successfully delivered to the destination resulting in an improvement of 57% over the Random movement. The network with 30 or 40 mobile node, i.e., at high node density, performed very well at any circumstances giving a delivery ratio of 90% and 97% in ASNC compared with 74% and 88% with the Random movement, respectively.

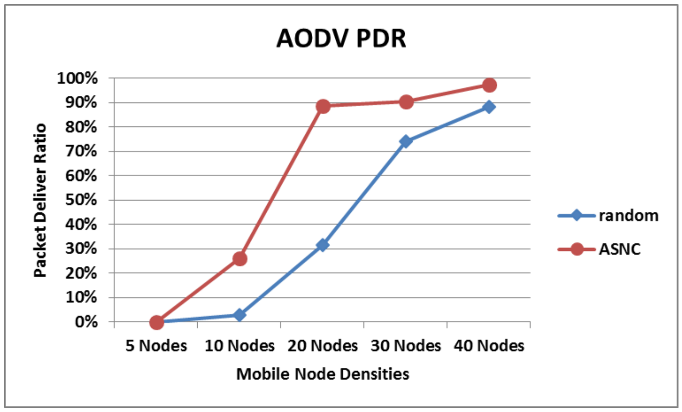

Figure 3. AODV performance: delivery ratio.

B. AODV performance: end to end delay

At five mobile nodes density, no packets have been delivered to the destination, (Figure 4). The longest packet delay, observed in the network with 10 mobile nodes, dropped from 786 ms in the Random scenario to 239 ms in ASNC. For a network with 20 mobile nodes, the packet delay decreased to 73 ms (together with the increase in the PDR) from 583 ms in Random movement. For the high mobile node densities of 30 and 40 nodes, the end to end delays were 70 ms and 69 ms in ASNC and 201 ms and 125 ms in the Random scenario.

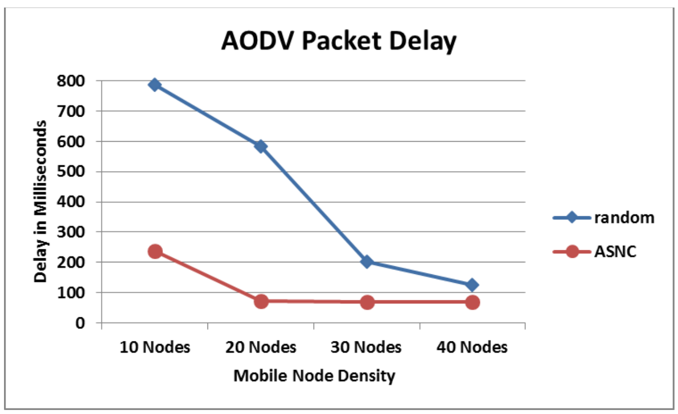

Figure 4. AODV performance: delay.

C. AODV performance: FPTD

For the experiments with 10 mobile nodes, the average FPTD for AODV was 279 seconds, reduced to 87 seconds by increasing the number of the mobile nodes to 20, (Figure 5). With high mobile node densities, the AODV routing protocol was able to detect the first forwarding path in a very short time, less than 10 seconds, which also improved the overall delivery ratio during the experiments.

D. DSDV performance: PDR

As expected, no packet were delivered in the very low mobile node density experiments (Figure 6). For 10 mobile nodes, 1.3% of the total packets have been delivered, compared with 0.6% delivery ratio in the Random movement over the DSDV routing protocol. These result changed when more mobile nodes are added in the experiments, i.e., when using 20 mobile nodes rather than just 10 nodes. The PDR reached 55% during the experiments with only 20 mobile nodes, almost 50% higher than the Random movement even with 40 nodes. In all previous experiments using either DSDV or AODV, scenarios with 20 mobile nodes showed the best absolute improvement in performance when using the ASNC algorithm for controlling the movements of mobile nodes in M2ANET. With a density of 30 mobile nodes, the PDR in the Random movement was 21% of packets delivered, which improved to 55% with ASNC. The density of 40 mobile nodes resulted in the PDR of 58%, which is higher than in the Random scenario.

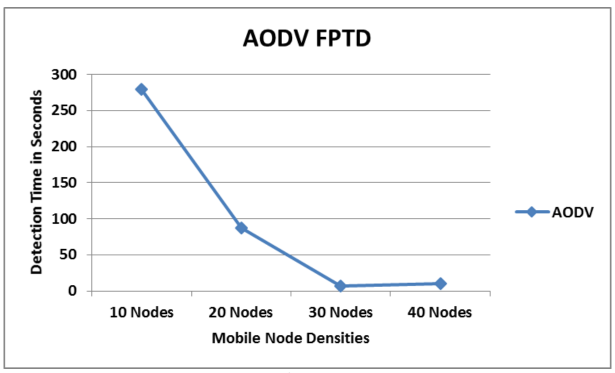

Figure 5. AODV performance: path detection.

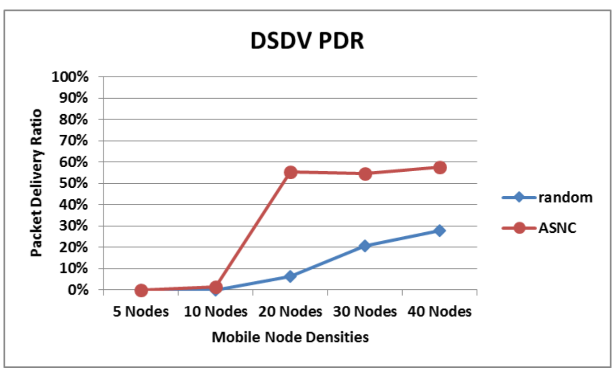

Figure 6. DSDV performance: delivery ratio.

E. DSDV performance: end to end delay

No packets were delivered in a network with only five nodes. The packet delay for a network with 10 mobile nodes and when ASNC was used improved to 208 ms, compared with 760 ms in the Random movement, (Figure 7). Increasing the mobile node density to 20 nodes decreased the delay to 49 ms, which was half the delay experienced in the Random movement. The packet delay at the high mobile node density of 30 and 40 nodes reached 39 ms and 50 ms respectively, while in the Random movement the results were above 80 ms.

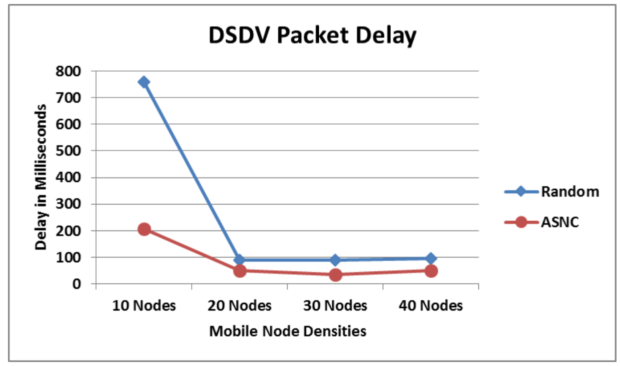

Figure 7. DSDV performance: delay.

F. DSDV performance: FPTD

Unlike in AODV, detecting a forwarding path in DSDV proactive routing protocol took a considerable time. In the ASNC experiments with 10 mobile nodes, it DSDV took 299 seconds to find a good route for transmitting data packets between the communication nodes, which was 20 seconds longer than in the experiments with AODV (Figure 8). The FPTD for the network with 20 mobile nodes utilizing DSDV was 90 seconds, followed by 71 seconds for 30 nodes and 50 seconds for 40 nodes. For ASNC over AODV experiments (Figure 5), the FPTD with 20 mobile nodes was 87 seconds, then dropped significantly for the high mobile node densities, showing a difference of at least 50 seconds compared to the DSDV results. The DSDV delay in detecting forwarding paths, which was larger than the delay in AODV, negatively affected the PDR network performance, Figures 3 and 6.

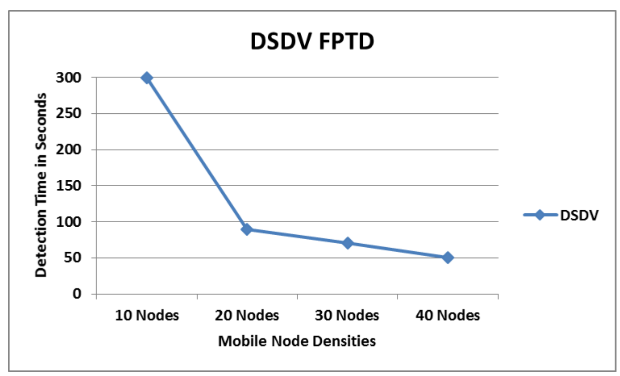

Figure 8. DSDV performance: path detection.

Please note again, that in the experiments with five mobile nodes, no forwarding paths were detected during the entire 500 second simulation experiments with either AODV or DSDV routing protocol.

VI. CONCLUSION AND FUTURE WORK

The new proposed ASNC algorithm is an adaptive ACO algorithm that aims to control the movement of mobile nodes in M2ANET. The adaptive ASNC algorithm is a complex

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self-organization paradigm used for controlling the movement of mobile nodes and make them behave in a way similar to a swarm of ants in nature. The ASNC algorithm observes the traffic condition in the network, waiting for the right moment to move the mobile nodes in the direction of where the forwarding activity is taking place. The mobile nodes in ASNC represent the ant-agents; they leave a trail in their path, called the pheromone trail, to attract other ant-agents to move toward the places they marked. These marked locations are the positions in the network where forwarding activity took place recently, and moving toward these positions was shown to improve the network performance. The ASNC experiments were simulated for different mobile node densities over AODV and DSDV routing protocols. The ASNC PDR results showed significant improvements over the scenarios with the Random movement, at all the mobile node densities. As expected, the experiments with the low mobile node densities showed a low delivery ratio compared with the PDR results for the high mobile node densities, for both AODV and DSDV. Moreover, the experiment with 20 mobile nodes demonstrated the highest benefit of using ASNC in M2ANET for controlling the movement of the mobile nodes. In ASNC, the networks running AODV routing protocol performed better than the ones with DSDV. AODV performed better in a highly dynamic network, such as M2ANET, due to its quick discovery and maintenance of the routes. In the experiment with high mobile node densities, AODV was able to detect the first forwarding path in less than 10 seconds, while it took DSDV between 50 and 70 seconds. The performance of ASNC in M2ANET over AODV showed better delivery ratio results, where 10% to 50% more packets were delivered than in the experiments with the Random movement. DSDV experiments showed performance improvements of 20-50 percent when compared to the reference Random movement.

In future, other scenarios may be considered in experiments, such as changing the source and destination positions during the simulation rather than keeping them stationary for the entire time. In addition, a scenario with multiple communication nodes, two senders and one receiver or one sender communicating with different receivers may provide interesting results. Also, as the ASNC approach requires that all mobile network nodes have access to the locations indicating where the pheromones have been deposited, the means of distributing this information to all nodes may need to be developed. The obvious means of accomplishing this would be to use broadcast messages sent by each node at the time when it deposits a pheromone trail, however, the effectiveness of broadcasting in a network like M2ANET, and any delays involved in this process would require further investigation. Other routing protocols may also be considered, e.g., Dynamic Source Routing (DSR), in order to compare the performance over different routing protocols. As the ASNC algorithm adapts the AS from the ACO algorithms in order to control the movement of mobile nodes, other SI algorithms could also be considered to control the movement of the mobile nodes, for example Rank-Based Ant System, Max-Min Ant System and Best-Worst Ant System. Algorithms from BCO rather than ACO could also be explored using, for example, the Artificial Bee Colony approach.

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