

RESEARCH ARTICLE

Tuning the Evaporation Parameter in ACO MANET Routing Using a Satisfaction-Form Game-Theoretic Approach

MARWAN A. HEFNAWY¹, SAAD M. DARWISH², AND AMR A. ELMASRY³

¹IT Director, Health Insurance Organization, Alexandria 21531, Egypt

²Department of Information Technology, Institute of Graduate Studies and Research, Alexandria University, Alexandria 21526, Egypt

³Faculty of Engineering, Egypt University of Informatics, New Administrative Capital, Cairo 11865, Egypt


Corresponding author: Saad M. Darwish (saad.darwish@alexu.edu.eg)

ABSTRACT A Mobile Ad Hoc Network (MANET) is a communication network that links communicating devices (nodes) and does not contain permanent infrastructure. There are no dedicated routing devices in MANETs, in which the routing task is assigned to a routing algorithm installed on all communicating nodes. In this work, communicating nodes utilize one of the most widely used algorithms: Ant Colony Optimization (ACO) routing algorithms. The ACO algorithms aim to balance between exploring new routes for the communication packets vs. utilizing the best-known routes discovered during the communication session. Achieving the optimality in this tradeoff is traditionally set manually by assigning many values to some parameters and measuring the network performance after the simulation session. This manual optimality tuning approach depends on human intuition and does not cope with MANET's dynamic topology. In this research, we introduce a novel method to find an optimal balance for the exploration-exploitation tradeoff during the communication session. We formulate weighing the benefits of exploring new routes vs. exploiting known ones upon the MANET performance as a game between the two semantic players. This equilibrium is reflected as an optimal value for the pheromone evaporation parameter of the ACO algorithm during the communication session. Experimental results show a higher performance of this online tuning algorithm than the traditional offline tuning algorithms.

INDEX TERMS MANET routing, ACO routing, game theory, parameter tuning.

I. INTRODUCTION

Mobile Ad Hoc Networks have emerging utilization in many real-life applications. They are used in the military sector such as communication on battlefields [1], and in disaster relief theaters such as volcanic eruptions and forest fire areas [2], [3]. MANETs are also used to connect protesters in street demonstrations, such as in Hong Kong [4], to avoid using monitored communication networks. Vehicular ad hoc networks (VANETs) are implementations of MANETs and the communicating nodes represent moving vehicles [5], [6], [7]. In such theaters, the communication session is temporary by nature, in which permanent infrastructure for the communication network cannot be established or is better to be avoided.

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Communicating nodes in MANETs take the responsibility of extending the communication range of other nodes by re-sending the data packets on behalf of the sender node. Routing in these conditions is a challenging task because of: (1) the dynamic topology of the network wherever nodes arbitrarily enter and leave the network; (2) the lack of dedicated routing devices; and (3) the limited power resources of the nodes [8]. Due to the challenges, many approaches have been suggested to tackle the routing problem in MANETs.

Routing algorithms in MANETs are classified based on the update mechanism of the routing table into three main categories: Proactive (table-driven), Reactive (on-demand), and Hybrid routing protocols [9], [10]. In proactive routing protocols, routes are preserved in the routing table even if they are not needed. This means that nodes continuously learn about the network topology changes by sending hello

messages and updating their local routing tables accordingly [11]. In highly dynamic networks, this technique may become impractical from two perspectives: (1) it requires high routing overhead traffic to propagate network status information to all nodes as soon as any change occurs to the network topology; and (2) the size of the routing table kept in the memory of each node becomes greater as more nodes join the network. OLSR and DSDV are examples of proactive routing protocols [11]. In reactive routing protocols, routes' data is gathered only when required. It is not needed to exchange regular update messages all over the network to keep nodes updated with network topology changes. Although this reduces the routing overhead, it may suffer from latency in discovering the required route when needed [12]. AODV and DSR are examples of reactive routing protocols [13]. Hybrid protocols gather both proactive and reactive techniques in the routing algorithm to benefit from the advantages of both of them. In some taxonomies of hybrid routing protocols, nodes are grouped either into meshes, trees, or zones. A proactive routing approach is used for the nodes lying within the same subgraph (mesh, tree, or zone). On the other hand, reactive routing techniques are used to locate routes for nodes outside the same subgraph, tree, or zone [14]. Fisheye State Routing (FSR) and Zone Routing Protocol (ZRP) are examples of well-known hybrid routing protocols [12], [14].

ACO as a swarm intelligence algorithm has been used for the MANET routing task by many researchers [15], [16]. The ACO algorithms' capabilities fit well with the MANET routing requirements, which are mainly: (1) the presence of autonomous agents trying to reach some physical target; and (2) the absence of any central administration entity in the network that controls the agents' search process. ACO-based MANET routing is based on releasing discovery-packets inside the network called "ant agents". They mimic the real ants' behavior of searching for food starting from their nest. Real ants communicate in an indirect method called stigmergy by depositing pheromone substance over the routes they traverse as an indicator for the incoming ants to follow. In MANET terminology, the sender node and all intermediate nodes (when performing their routing duty of delivering the sender's message to the destination) generate ant agents. The task of these agents is to classify the alternate paths from the source node to the destination node according to the paths' quality as they experiment. Similar to real ants' stigmergy, ant agents in MANET remark the path with accumulative values of the utilized QoS measures. Good paths, after a while, obtain high values of the QoS measures (pheromone) as a result of the passage of more ant agents. Abandoned paths have low pheromone values due to a pheromone evaporation rate that is adjusted in the algorithm [17]. Ant agents also have an important task of discovering new good routes as an alternative to the best discovered ones. This is implemented by routing a portion of the ant agents along less quality paths to discover some suboptimal paths. Fig.1 shows the analogy between the real ants' method of finding alternate routes

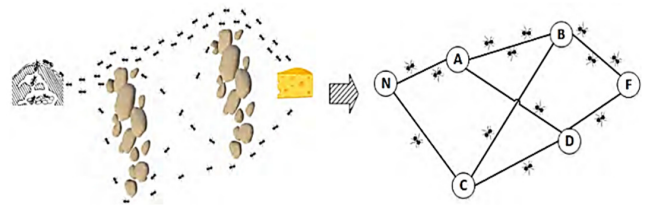


FIGURE 1. Analogy between real ants and artificial ants routing.

from their nest to the food vs. the notion of artificial ants in communication networks.

Parameter tuning in ACO routing algorithms is either performed online or offline. Offline parameter tuning is performed before the algorithm's execution. It is performed in a trial-and-error method and relies on human experience to adjust the optimum parameters' values. It may be useful in stationary environments, but it is not suitable for dynamic ones somewhere the parameters have to cope with different instances of the problem [18]. Online parameter tuning, on the other hand, is more adaptive somewhere the parameters' values are adjusted while solving the problem instance. This adaptability has a computational cost. The authors of [19] categorized online parameter tuning approaches for meta-heuristic algorithms generally into 3 categories: Simple, Iterative, and High-Level. All categories utilize the notion of generating some values for the parameters and then evaluating them according to the performance metrics. The simple approach is a single step of setting parameters' values and then evaluating them. The iterative approach is a repeated process of generating parameters' values and then evaluating the outcome performance metrics. The high-level approach is also iterative, but the generate-phase involves producing elite selected values of the parameters according to search methods instead of random values. Researchers work to get the benefit of dynamic parameter tuning and reduce computational cost at the same time.

AntHocNet as an ACO-based routing algorithm [20] utilizes the notion of pheromone to rate the suitability of possible routes for ant agents. Pheromone deposition is performed with the passage of ants over the route. The pheromone amount increases accumulatively on any route with the passage of more ants over it. An exploratory parameter exists to identify which route the ant agent will follow based on the pheromone level of the available routes. This exploratory parameter has been studied in our previous research [21] to perform online tuning for it. On the other hand, a pheromone evaporation process exists to decrease the amount of pheromone in each route. The aim of the evaporation process is to avoid keeping high pheromone values for abandoned, low quality paths. The evaporation rate is controlled by an evaporation parameter that is tuned offline in the AntHocNet algorithm.

This paper is an extension of our previous conference paper [21]. In the previous paper, we introduced an online parameter tuning method for the exploration parameter of the MANET

routing algorithm using game theory. In this paper, we tune another parameter, which is the pheromone evaporation rate parameter, using another game theory approach which is satisfaction game.

A. PROBLEM STATEMENT AND MOTIVATION

MANETs have increasing utilization in today's world. Autonomous agents are the core component in the MANET routing process. The goodness of possible routes for the agents is remarked by depositing pheromone amounts with every passage of an agent over any route. Accumulating the pheromone amounts infinitely over all used routes leads to misidentification of the best available routes. The notion of pheromone evaporation arises in ACO algorithms based on the requirement of decreasing the pheromone amount of less utilized routes. In the AntHocNet algorithm, the pheromone evaporation rate is controlled by a parameter that is tuned offline. Offline tuning has the disadvantage of rigidity of the chosen value for the parameter. On the other hand, online parameter tuning methodologies are remarked with a high computational cost. A successful algorithm should balance between the benefits of online tuning and utilizing low processing power.

B. AIM OF THE WORK

By covering the parameter tuning approaches in ACO based MANET routing algorithms, we find that the offline tuning algorithms suffer from not coping with the dynamic nature of the MANET environment. On the other hand, online tuning algorithms suffer from high computational cost. In this research, we introduce a game theoretic approach to tune (online) the pheromone evaporation rate parameter in the AntHocNet routing algorithm. This approach combines the adaptability of the online tuning methods with the low computational cost associated with game theory.

C. CONTRIBUTION, AND METHODOLOGY

This research introduces online tuning for the pheromone evaporation parameter in the AntHocNet algorithm using game theory. Our approach is based on two semantic players, which are the Exploration player and the Exploitation player. The Exploration player aims to force the autonomous agents to explore more new routes in the MANET. Its goal is to maintain more alternate routes to be utilized in case of failure of the best used ones. On the other hand, from the Exploitation player's point of view, this exploration process consumes time and resources. The Exploitation player aims to identify the best routes in the MANET for once and then utilize them extensively. The two players have contradicting intentions towards the evaporation parameter. The Exploration player aims to increase the parameter's value, so the routes marked with their high pheromone values lose their preferability to the incoming agents. The Exploitation player aims to reduce the evaporation rate for the opposite purpose. It aims to keep the gained pheromone amounts in the routes as long as possible to utilize them as an identifier of the best routes.

The game notion creates a balance between the two competing players based on the QoS parameters measured from the network environment.

The rest of this paper is structured as follows: Section II presents a literature review of the research that tackles ACO usage in MANET routing and methods used for parameter tuning. Section III introduces the details of the approach contributed in this paper. In section IV, we validate the introduced algorithm with a set of experiments and evaluate its results against those of other algorithms. Section V discusses the obtained results and highlights the possible extensions of this research.

II. RELATED WORK

A well-known reactive routing protocol is the Ad hoc On-demand Distance Vector (AODV) [22]. The source node searched for a route for the destination node in its routing table. If no direct route is found, a chain of broadcast processes is performed to expand the search till a route to the destination node is found. Although AODV ensures finding the destination node, it has a high routing overhead. Naserian [23] used a game theoretic approach to enhance the AODV protocol. The aim is to reduce the flooding behavior in the route discovery process. Each intermediate node is considered a player. When it receives a RREQ packet to propagate it to other nodes, it takes a decision (game strategy) whether to propagate the packet or drop it. The decision is taken based on a network gain factor vs. the cost of forwarding the packet.

The Destination Sequenced Distance Vector (DSDV) is a typical proactive routing protocol in MANETs that is based on the Bellman-Ford algorithm [12]. DSDV keeps at each node a routing table that contains the up-to-date routing information for all nodes in the network. This is achieved by forcing each node to send two types of packets frequently to its neighboring nodes, namely: full dump packets and incremental packets. Full dump packets carry all the information in the routing table. The incremental packets carry only the updated information since the last sent full dump packet. The aim of this process is to keep all nodes aware of the network changes. Although this technique is useful in keeping an up-to-date routing table in all nodes, it has a performance drawback in the case of large-scale networks.

The AntHocNet routing algorithm is one of the ACO implementations in MANET routing [24]. It is a hybrid routing algorithm. It contains two phases: (1) the reactive path-set up phase and (2) the proactive path maintenance phase. In the reactive path-set up phase, ant agents of the ACO are used to find a path to the required destination, and the pheromone information is kept in a pheromone table in each node. The aim of the proactive path maintenance phase is to sample paths while no destination is required in order to update the local pheromone table. Parameter tuning in AntHocNet is done offline and the best parameters' values are obtained by performing multiple communication sessions. In each communication session, the QoS measurements are

		List of destination nodes				
		d_1	d_2	d_3	d_k
List of neighboring nodes	n_1	$T_{n_1 d_1}^i$	$T_{n_1 d_2}^i$	$T_{n_1 d_3}^i$	$T_{n_1 d_k}^i$
	n_2	$T_{n_2 d_1}^i$	$T_{n_2 d_2}^i$	$T_{n_2 d_3}^i$	$T_{n_2 d_k}^i$
	n_3	$T_{n_3 d_1}^i$	$T_{n_3 d_2}^i$	$T_{n_3 d_3}^i$	$T_{n_3 d_k}^i$

	n_i	$T_{n_i d_1}^i$	$T_{n_i d_2}^i$	$T_{n_i d_3}^i$	$T_{n_i d_k}^i$

FIGURE 2. The structure of the pheromone table at any intermediate node i .

recorded against the selected value of the parameters till the value that yields the best QoS measures is identified [20].

Online parameter tuning in ACO MANET routing has been handled from many perspectives. A swarm intelligence approach has been used in the work of Deepalakshmi et al. [18] to tune 3 routing parameters. These parameters are namely: (1) the exploration parameter α , (2) the β parameter that controls the significance of routes having low end-to-end delay, and (3) the δ parameter that determines the priority of paths marked with high available bandwidth. Although this approach provides a near optimal solution, it is characterized by high computation time that may not be adequate for some MANET devices having low processing capabilities. In [25], Sandhya et al. utilized fuzzy logic to tune online the routing parameters of the ACO vehicle routing problem. Three strategies are used in their research, namely: FACO-1, FACO-2, and FACO-3, to tune three parameters in the ACO routing algorithm. The first two strategies tune a set of the parameters and consider the rest as constant. The last strategy, FACO-3, tunes all the parameters simultaneously. Although the fuzzy approach has low computation cost, it suffers from depending on an expert system to assign the membership function of the system.

III. PROPOSED GAME THEORETIC APPROACH FOR TUNING THE PHEROMONE EVAPORATION RATE PARAMETER

A. ACO COMPONENT PROBLEM FORMULATION

In the AntHocNet routing algorithm, if a sender node s needs to establish a communication session with a destination node d , the sender node scans its local routing table to see if a unicast route exists. If no such route exists, it sends multiple forward ants (FANTs) to crawl the network and waits until backward ants (BANTs) return with some route information to update its routing table. The routing table in any communicating node is a 2D table with rows representing the neighboring nodes and columns representing the prospected destination nodes. Fig. 2 demonstrates the structure of the pheromone table T^i at any intermediate node i .

Each value $T_{nd}^i \in R$ represents the pheromone amount that indicates the goodness of the path through neighbor n to reach

the destination d beginning from the current node i . To choose a certain neighbor n as a next hop for the succeeding ants to reach a certain destination d , the node i takes a probabilistic decision according to the following formula:

$$P_{nd} = \frac{(T_{nd}^i)^{\beta_1}}{\sum_{j \in N_d^i} (T_{jd}^i)^{\beta_1}}, \quad \beta_1 \geq 1 \quad (1)$$

P_{nd} is the probability of forcing a FANT to reach the destination node d through the neighbor node n . β_1 is the exploration parameter, and N_d^i is the set of all neighbors of the current node i that carry route information to destination d . The pheromone amounts T_{nd}^i are built accumulatively by receiving more and more BANTs carrying the QoS measurements they encountered. The QoS metric used in this work to calculate τ_d^i , as in [20], is the number of hops that the BANT passes-over through its journey back to node i . The BANT uses the inverse of this hop count (τ_d^i) to update the corresponding pheromone value T_{nd}^i in the pheromone table T^i as follows:

$$T_{nd}^i \leftarrow \gamma T_{nd}^i + (1 - \gamma) \tau_d^i, \quad \gamma \in [0, 1] \quad (2)$$

The parameter γ controls how the pheromone table value T_{nd}^i is affected by the arrival of the new information τ_d^i . For large values of γ , the old (accumulated) value of T_{nd}^i has the greatest effect upon determining the new T_{nd}^i value, while the new τ_d^i carried by the BANT has a little effect. In this case, we consider that the pheromone evaporation is small, and the accumulated pheromone values are relatively resistant to change. On the other hand, if γ is a small value, then the greatest effect upon calculating the new pheromone value T_{nd}^i is based on the information carried with the BANT (τ_d^i) while a little consideration is paid to the old accumulated value T_{nd}^i . In this latter case, the pheromone evaporation is considered high.

B. GAME THEORETIC COMPONENT PROBLEM FORMULATION

Assuming we have a normal form game that consists of: a set of players (I) containing m players, a strategy profile S and a set of utility functions U . Any player selects a single strategy s_k from a set of available strategies S_k such that $s_k \in S_k$. The strategy profile of the game is a vector $s = \{s_1, s_2, \dots, s_m\}$, which represents the set of strategies chosen by all the m players such that s_k is chosen by player k . We denote the set of strategies chosen by all players except a specific player k by the symbol s_{-k} . So, the strategy profile chosen by all players of the game can be expressed as $s = \{s_{-k}, s_k\}$. The utility function $u_k(s)$ is the gain of any player k when the set of users I choose the strategy profile s .

A Nash equilibrium is said to be achieved if a strategy profile s is agreed upon among the players of the game, such that no single player can gain a benefit by changing its strategy s_k unilaterally [26]. A specific strategy profile $s = \{s_1^*, s_2^*, s_3^*, \dots, s_m^*\}$ is said to be the Nash equilibrium

of the game if:

$$\forall k \in I, \text{ and } \forall s_k \in S_k, \text{ we have}$$

$$u_k(s_{-k}^*, s_k^*) \geq u_k(s_{-k}, s_k) \quad (3)$$

Let f_k denote the set of all satisfied strategies (actions) under a constraint of the player k given the strategies of all other players [27]. The satisfaction equilibrium is defined as a strategy profile $s^* = (s_{-k}^*, s_k^*)$ such that for any player i

$$s_k^* \in f_k(s_{-k}^*) \quad (4)$$

A satisfaction form game (SFG) is a game, and players are individually interested in satisfying performance constraints rather than performance optimization. Equilibrium in this context, means all players can simultaneously satisfy their individual constraints [28]. There is a distinction in the literature between the Pareto optimality and game theory equilibrium. In our implementation, we followed the approach of *satisfaction equilibrium* described in [27], [28], in which the concept and the proof can be obtained.

Von Neumann’s Minimax Theorem states that: “Every zero-sum matrix game A has a unique number v , called the value of A , which is the maximum guarantee of a mixed strategy for Rose and the minimum guarantee of a mixed strategy for Colin.” [29]. In our implementation, we associated the gain of each player with a different network QoS metric (SNR and EED as stated in Section III - C3), which are not comparable in their numeric scales. So, the Minimax concept is not applicable in our implementation.

C. GAME THEORETIC COMPONENT IMPLEMENTATION

1) NOVELTY IN OUR IMPLEMENTATION

Most game-theoretic implementations of MANET routing consider each communicating node as a game player [30], [31]. Since there is no central entity in MANETs that has information regarding all nodes, such as a network server, for example, this approach hence assumes that all players share their game information. Nodes should share two pieces of information: (1) the strategy chosen by each player and (2) the gain obtained by each player (utility function). This information regarding each node must be available to all other participating nodes in order to make the game information clear for all the participants. This leads to routing overhead, especially if the game players are a large number of communicating nodes.

The novelty in our approach is in choosing only two local semantic players, that are the Exploration and the Exploitation players, which have opposite intentions towards the parameter to be tuned. So, the game is played locally at each node without the need for the global perspective assumed in other game-theoretic implementations. Fig. 3 demonstrates the flowchart of the proposed algorithm.

2) STRATEGIES OF THE PLAYERS

The aim of the Exploration player to minimize the value of the γ parameter in (2), while the aim of the Exploitation player to

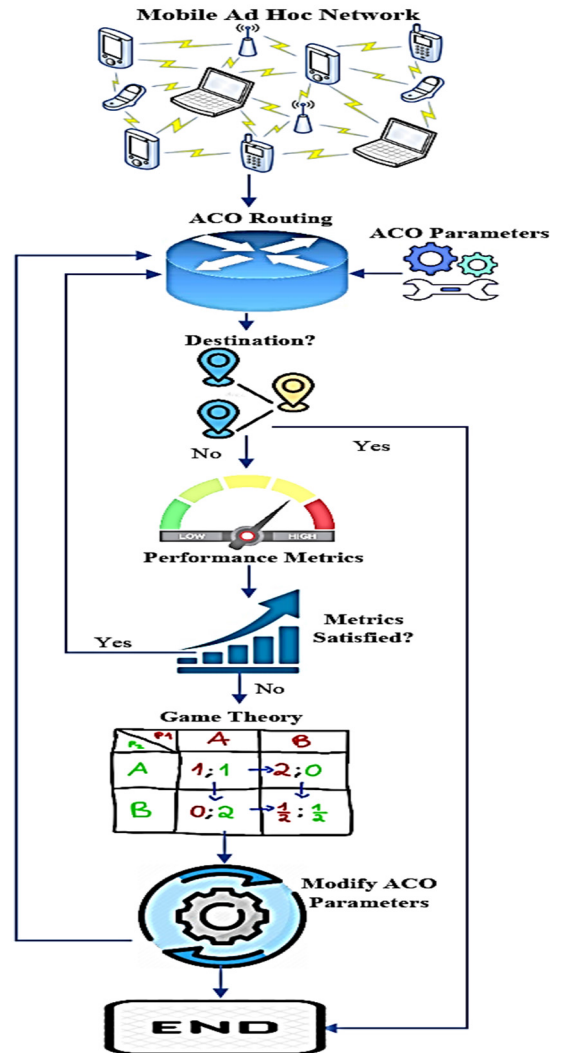


FIGURE 3. The flowchart of the proposed algorithm.

maximize the same parameter. The Exploration player aims to let more ants explore the network rather than utilizing the best-known routes marked by high pheromone values in the pheromone table T^i . To achieve this target, it tries to reduce the parameter’s value to make a great reliance on the new incoming information (τ_d^i) carried by the BANTS in updating the pheromone table’s value. In this case, we consider that the pheromone evaporation is high. On the other hand, the Exploitation player aims to maximize the parameter to get the most benefit from the existing value in the routing table and relies less on the new incoming value with the BANTS.

In Eq. (2), the value of γ is between 0 and 1. In our implementation, we give the freedom to the Exploration player to set a value γ_1 for γ between 0 and γ_{Limit} and the freedom to the Exploitation player to set a value γ_2 for γ between γ_{Limit} and 1. That is:

$$0 \leq \gamma_1 \leq \gamma_{Limit} \leq \gamma_2 \leq 1 \quad (5)$$

TABLE 1. Setting the strategies for the players.

PLAYER'S ASSOC. METRIC RANGE	STRATEGIES OF EXPLORATION PLAYER		STRATEGIES OF EXPLOITATION PLAYER	
	LOW	$s_1: \gamma_{1L} = 0$	$s_1: \gamma_{2L} = \gamma_{Limit}$	
	MODERATE	$s_2: \gamma_{1M} = \frac{\gamma_{Limit}}{2}$	$s_2: \gamma_{2M} = \frac{1 + \gamma_{Limit}}{2}$	
	HIGH	$s_3: \gamma_{1H} = \gamma_{Limit}$	$s_3: \gamma_{2H} = 1$	

γ_{Limit} is an arbitrary value between 0 and 1, that is the maximum value the Exploration player can assign to γ and, at the same time, is the minimum value that the Exploitation player can assign to γ . The decision taken by every player is based upon one QoS metric, the BANTs carry the metric measurement through their journey from the destination node back to the sender node. We associated the Signal to Noise Ratio (SNR) metric with the Exploration player and the End-to-End Delay (EED) metric with the Exploitation player. Other player-metric associations can be utilized in different environments. The definitions of SNR and EED can be found in [32] and [33]. The raw measurements of both QoS metrics are transformed into Low, Moderate, and High categories, and then a strategy is chosen by the associated player as shown in Table 1. The boundaries between the Low, Moderate, and High categories are arbitrary and are metric-environment specific. For a video streaming environment, for example, the numerical boundaries for the categories of the EED metric in Table 1 may be set differently from a MANET environment used for a text exchange application.

The strategy chosen by the player k is either $s_1 = \gamma_{kL}$, $s_2 = \gamma_{kM}$ or $s_3 = \gamma_{kH}$ for the Low, Moderate, and High metric measurements respectively, $k \in \{1, 2\}$. The strategy is determined as the corresponding third of the allowed range for the player to set the γ parameter r . Since we have only one value for the γ parameter to be set in (2) at the node level, the final γ value is determined according to Table 2 as follows:

TABLE 2. Value of γ parameter based on players' contribution.

		PLAYER2: EXPLOITATION (BASED ON: EED)		
		STRATEGY	s_1 : LOW QUALITY	s_2 : MODERATE QUALITY
PLAYER1: EXPLORATION (BASED ON SNR)	s_1 : LOW QUALITY	$\frac{\gamma_{1L} + \gamma_{2L}}{2}$	$\frac{\gamma_{1L} + \gamma_{2M}}{2}$	$\frac{\gamma_{1L} + \gamma_{2H}}{2}$
	s_2 : MODERATE QUALITY	$\frac{\gamma_{1M} + \gamma_{2L}}{2}$	$\frac{\gamma_{1M} + \gamma_{2M}}{2}$	$\frac{\gamma_{1M} + \gamma_{2H}}{2}$
	s_3 : HIGH QUALITY	$\frac{\gamma_{1H} + \gamma_{2L}}{2}$	$\frac{\gamma_{1H} + \gamma_{2M}}{2}$	$\frac{\gamma_{1H} + \gamma_{2H}}{2}$

3) THE UTILITY FUNCTIONS

The utility function of player 1 (Exploration player) is the average SNR measurement of the next three generations of the BANTs after setting the new value of the γ parameter in Table 2. Similarly, the EED measurement is the utility function for player 2 (Exploitation player). So, $SNR(\gamma)$ and $EED(\gamma)$ are the utility functions of the two players correspondingly. Each of which is a QoS function measured from the MANET environment and is based on a single variable (γ) from the point of view of each player. In other words, after setting the γ parameter from Table 2, we send FANTs according to the modified pheromone table, then wait for the BANTs carrying the SNR and EED information from the environment for 3 successive generations, and average the results.

4) EQUILIBRIUM POINT

We consider the equilibrium is reached if the $SNR(\gamma)$ and $EED(\gamma)$ functions satisfy the following conditions: (1) the metric category is elevated from Low to Moderate or from Moderate to High, and (2) the metric category remains constant for the next 3 consecutive generations. In this case, the equilibrium equation (3) is satisfied by reaching the point that there is no reason to change the strategy to obtain more benefits in the utility functions $SNR(\gamma)$ and $EED(\gamma)$. If no stability is reached, then the current measurements of SNR and EED are utilized to initiate another game and change the γ parameter again, then testing for the equilibrium till it is reached.

5) GAME THEATER

Any communicating node can initiate the game after detecting a degradation in the performance of the incoming QoS measurements carried by the BANTs with a minimum pre-determined threshold. In our experiments, we considered detecting a 30% degradation in the used QoS metrics as a trigger to initiate the game.

The game is played locally at every node, and the local pheromone table is updated according to the new value given to the γ parameter that indicates pheromone evaporation rate.

IV. RESULTS AND DISCUSSION

A. SIMULATION ENVIRONMENT

Experiments are implemented using the NS2.34 simulator [34]. Simulation environment is a PC Intel core i3 CPU with 8 GB RAM. The experiments are performed by varying the number of communicating nodes from 20 to 100. Other environmental settings are listed in Table 3. The proposed algorithm is compared with the AntHocNet and the AODV algorithms regarding the effect of the network size on the average EED, the Packet Loss Ratio, and the Throughput metrics. The AODV is a reactive routing algorithm that is discussed in section II. In the first three experiments, we compare the proposed algorithm against AntHocNet and AODV in terms of EED, Packet Loss Ratio, and Throughput in

TABLE 3. Chosen parameters for the simulation environment.

SIMULATION DURATION	100 SECONDS
MOBILITY MODEL	RANDOM WAY POINT
SPEED OF THE NODES	100 M/S
RADIO-PROPAGATION MODEL	TWO RAY GROUND
MAC TYPE	802.11
INTERFACE QUEUE TYPE	CMU PRIQUEUE
LINK LAYER TYPE	LL
MAX PACKET IN IFQ	50
ANTENNA TYPE	ANTENNA/OMNIANTENNA
SIMULATION AREA	1000 M×1000 M
PAUSE TIME	20 s

multiple simulation sessions using different numbers of nodes in each session. In these sessions, we fixed the parameters $\gamma = 0.7$ and $\beta = 20$ for the AntHocNet as stated in the original work. The proposed algorithm starts initially with $\gamma = 0.7$ and then modifies it according to the network conditions as described in the algorithm. In the proposed algorithm and the other two compared algorithms, 20% of the nodes are moving. The fourth experiment demonstrates the effect of varying the γ_{Limit} parameter on the proposed algorithm’s performance in terms of EED.

B. COMPARING THE PROPOSED ALGORITHM AGAINST ANTHOCNET AND AODV IN END-TO-END DELAY METRIC

The End-to-End delay metric is defined as the average time taken for packets to travel from a source node to a destination node in a network. It gathers all types of delay for a certain packet from its source till it reaches its destination. If we are tracing the packet delay from a sender node i to a destination node j , we denote the delay from i to j as $D_{i,j}$ as follows [32]:

$$D_{i,j} = P_i + Q_i + P + \frac{B}{b} + Q_j + P_j \quad (6)$$

P_i, P_j are the processing delays at nodes i and j , and Q_i, Q_j represent the queue delays at nodes i and j , respectively. P is the propagation delay, B is the bandwidth of the channel, and b is the size of the packet (measured in bits). B/b represents the transmission delay.

Fig. 4 shows that the proposed algorithm starts with a higher EED value than the AntHocNet till approximately the number of nodes =50. For a number of nodes greater than 50, the proposed algorithm outperforms the AntHocNet in terms of EED. The difference between the proposed algorithm and the AntHocNet in terms of End-to-End delay reaches 0.2 ms at a number of nodes=100 nodes. The reason for the advantage of the proposed algorithm over the AntHocNet for larger networks is that AntHocNet sets $\gamma = 0.7$, which gives an advantage to the Exploitation process over the Exploration process. In our algorithm, we give the two concepts the freedom to reach an equilibrium that leads to dynamicity in

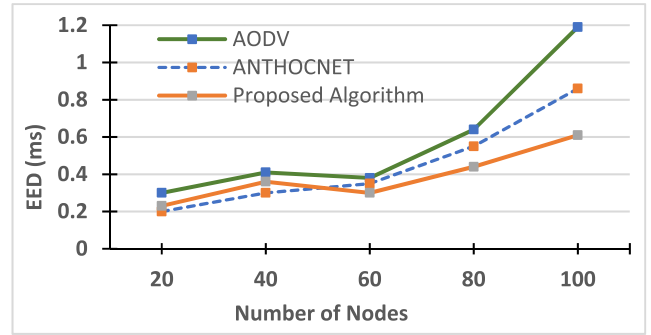


FIGURE 4. The EED metric for the proposed algorithm vs. AntHocNet and AODV.

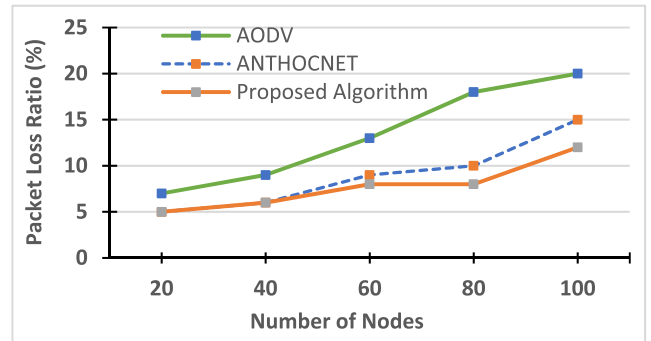


FIGURE 5. The packet loss ratio metric for the proposed algorithm vs. AntHocNet and AODV.

route selection that is reflected upon delay time. The AODV algorithm has a greater delay compared with the proposed algorithm and the AntHocNet.

C. COMPARING THE PROPOSED ALGORITHM AGAINST ANTHOCNET AND AODV IN PACKET LOSS RATIO

The packet loss ratio metric measures the ratio of the number of lost packets to the total number of sent packets. As shown in Fig. 5, the proposed algorithm is relatively equivalent to AntHocNet for a number of nodes of less than 60, and then it outperforms AntHocNet in terms of the Packet Loss Ratio for larger networks up to 100 nodes. The reason is that our algorithm gives the nodes the flexibility to search more routes or retain the best-known routes according to the network conditions. This route selection flexibility reduces the packet loss. The two algorithms are nearly equivalent for small number of nodes as there is no many alternative routes to explore in case of bad performance. In larger networks (>50 nodes), the proposed algorithm’s notion of giving the Exploration player more freedom is reflected in the performance metrics. Both of the proposed algorithm and AntHocNet outperform the AODV algorithm in terms of packet loss ratio.

D. COMPARING THE PROPOSED ALGORITHM AGAINST ANTHOCNET AND AODV IN THROUGHPUT

The throughput metric is the rate at which information is sent successfully through the network [35]. Fig.6 shows the throughput of the proposed algorithm against AntHocNet and AODV. Both of the proposed algorithm and AntHocNet

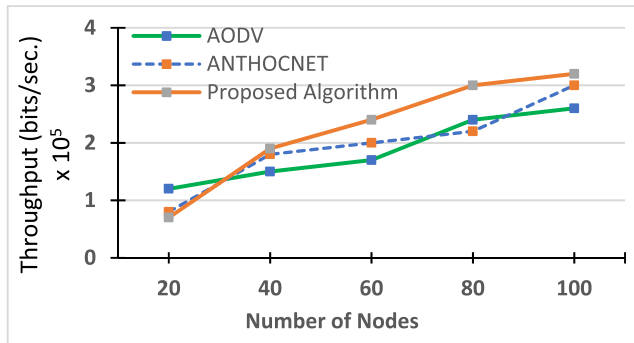


FIGURE 6. The packet loss ratio metric for the proposed algorithm vs. AntHocNet and AODV.

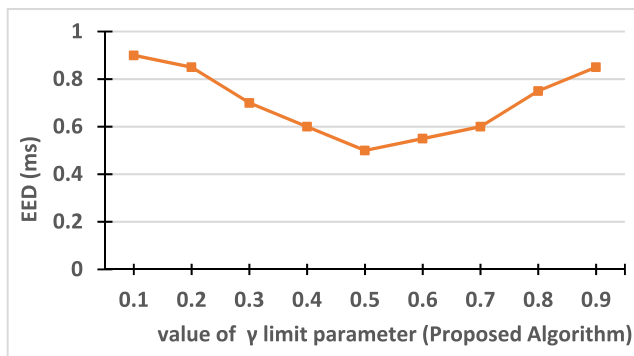


FIGURE 7. Effect of γ_{Limit} parameter on the EED metric for the proposed.

outperform the AODV algorithm in terms of throughput for a number of nodes greater than 20. The proposed algorithm outperforms the AntHocNet for a number of nodes greater than 40 and up to a number of nodes of 100 nodes.

E. THE EFFECT OF THE γ_{Limit} PARAMETER UPON THE PROPOSED ALGORITHM'S EED METRIC

The γ_{Limit} parameter is the boundary between the maximum value that the Exploration player can assign to γ and the lower value that the Exploitation player can assign to it. In Fig.7, we test the impact of changing γ_{Limit} upon the EED metric. It is obvious that giving equal chances to the Exploration and Exploitation players by setting $\gamma_{Limit} = 0.5$ pours in the benefit of the EED metric. On the other hand, forcing the algorithm to give one player an advantage over the other player -either by increasing or decreasing γ_{Limit} - is harmful to the overall performance.

V. CONCLUSION AND FUTURE WORK

This paper introduced a game theoretic approach to optimize online the γ parameter in the AntHocNet routing algorithm. This parameter controls the contribution share of the exploration notion and the exploitation notion in calculating the amounts of pheromone in the pheromone table. Parameters in the AntHocNet are tuned offline, which gives some rigidity to the algorithm. The proposed algorithm uses the notion of game theory and considers two semantic players, who are the Exploration and Exploitation players. The two players have contradictory plans towards the γ parameter. The Exploration

player aims to lower it in order to increase pheromone evaporation, while the Exploitation player aims to increase the parameter and decrease the evaporation rate. The proposed algorithm introduces an equilibrium between the two players to tune the parameter. Experimental results show that the proposed algorithm is competitive with the AntHocNet in relatively small networks and outperforms it in large networks. Future work is intended to conduct more experimental results and perform more QoS metrics associations with the game players.

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MARWAN A. HEFNAWY received the B.Sc. degree in mathematics and physical oceanography and the double M.Sc. degree in physical oceanography from the Faculty of Science, Alexandria University, Alexandria, Egypt, in 1994 and 2006, respectively, and the M.Sc. degree in information technology from the Institute of Graduate Studies and Research, Alexandria University, in 2013, where he is currently pursuing the Ph.D. degree in information technology with the Institute of Graduate Studies and Research. He is also working as the IT Director at Health Insurance Organization, Ministry of Health and Population, Alexandria. He is the coauthor of research paper that won the Best Paper Award, in 2013, International Conference of Data Mining and Knowledge Engineering ICDMKE'13, London, U.K.



SAAD M. DARWISH received the B.Sc. degree in statistics and computer science from the Faculty of Science, Alexandria University, Egypt, in 1995, the M.Sc. degree in information technology from the Department of Information Technology, Institute of Graduate Studies and Research (IGSR), Alexandria University, in 2002, and the Ph.D. degree from Alexandria University, for a thesis in image mining and image description technologies. Since June 2017, he has been a Professor with the Department of Information Technology, IGSR. He is the author or coauthor of more than 100 papers publications in prestigious journals and top international conferences. He has supervised around 60 M.Sc. and Ph.D. students. His research and professional interests include image processing, optimization techniques, security technologies, database management, machine learning, biometrics, digital forensics, and bioinformatics. He received several citations. He has served as a reviewer for several international journals and conferences.



AMR A. ELMASRY received the B.Sc. and M.Sc. degrees in computer engineering from the Faculty of Engineering, Alexandria University, Alexandria, Egypt, in 1991 and 1995, respectively, and the Ph.D. degree in computer science from the Computer Science Department, Rutgers University, NJ, USA, in 2001. He worked as a Senior Researcher with the Max-Planck Institute for Informatics and a Full Professor at the University of Copenhagen.

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