An Evolutionary Game for Efficient Routing in Wireless Sensor Networks

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***Abstract*—One of the major challenges in a wireless sensor network (WSN) is to extend its lifetime by minimizing the energy consumption. One of the ways to do so is to reduce network congestion as it increases delays and introduces additional packet collisions– thus, adversely affecting network performance.**

In this paper, we analyze this issue in routing and take an evolutionary game theoretic approach to show how sensor nodes in a WSN could evolve their routing strategies to transmit data packets in an efficient and stable manner. We derive the equilibrium state for the routing game and prove that there is no mutant– an individual node which adopts another strategy to invade the evolutionary stable strategy (ESS). In addition, we introduce a replicator dynamic model to show that the behavior of nodes with various strategies over time. The proposed equilibrium solution aims to alleviate congestion and thereby improves the network lifetime. Simulation results show that the proposed system is successful in converging to the strategy choices to ESS even under dynamic network conditions.

I. Introduction

A wireless sensor network (WSN) typically consists of a large number of sensor nodes, which are capable of sensing, and communicating wirelessly to transmit the sensed data to the destination for further processing. As the sensor nodes have limited power resources, efficient energy management is very crucial. Phenomenon such as power control, medium access, and routing lead to energy depletion; thus efficient techniques are always sought. Routing is a specially challenging task as it involves energy depletion from all the nodes that lie on a given route for a source-destination pair. Thus, designing routing protocols in WSNs requires approaches that are not only energy efficient but are also able to extend the network lifetime by utilizing the sensors' limited battery as efficiently as possible [1]. With ever-increasing deployment of customized WSN applications, research is still being pursued that try to improve network capabilities and meet the quality-of service demands for the application in question.

Congestion is one of the vital issues in WSNs since it has a significant negative impact on network performance and energy consumption [2]. While transmitting packets toward their destinations, the nodes in a WSN have multiple paths to choose from. Each path can potentially have a different associated costs as per the various routing metrics. Such variation in the cost of energy through different routes would mean that some routes/paths could be considered to be "better" than the others. Therefore, nodes are expected to have a clear preference over a set of available paths. To avoid the overheads of retransmitting dropped packets due to collision, which can cause an additional drain on battery life, every node has an incentive to choose the path with the lowest cost while transmitting packets. When many nodes take this same routing strategy, this rational behavior of sensor nodes will intuitively result in further congestion on the same path and lead to energy depletion of the nodes along that path. A centralized mechanism will balance the traffic load across various paths. However, in the absence of a centralized mechanism, it is challenging to achieve long-term dynamic traffic load balance; this paper seeks to address this challenge.

Though the route selection problem in a WSN is a well investigated problem, we are motivated to explore further where the objective is to alleviate energy consumption and collisions through a game theoretic framework. Among the various models of computation in game theory, evolutionary game provides a powerful modeling tool to i) study the behavior of populations and ii) design efficient strategies in communication networks.

In this paper, we leverage concepts from evolutionary game theory and model the routing decisions in a WSN as a non-cooperative evolutionary game. We prove that the mixed strategy Nash Equilibrium (NE) in our routing game is the evolutionary stable strategy (ESS); where there are no other strategies except this ESS can dominate the population. The payoff for every node, also referred to as a player, is determined by the packet transmitting cost, which depends on the distance between the nodes. In the routing game, choosing the shortest distance between the source and the next neighbor hop is preferable for each player because it will consume least amount of energy for the transmission, thereby increasing the payoff. The players who transmit the packets through the shortest path will gain a higher payoff/lower cost compared with the players who transmit through longer paths. However, if every player tries to select the shortest path to the target, it will result in collisions and lead to energy depletion at the nodes. Thus, forwarding the packet through the lowest energy path may not always be the optimal for the network lifetime. To model the adaptation of the hop selection strategies and to show the behavior of the system over a period of time, we present the replicator dynamics of our game. We study how the sensor nodes improve their strategy selection over time until they converge to an evolutionary stable strategy. Furthermore, once the strategies converge to ESS, the population cannot be invaded by any other populations of the nodes, and the system will reach stability. The process of selecting the path to transmit the packets in our routing game will continue until the destination node is reached. The objective of the game is to reduce the load and avoid collisions on the most used routes by distributing the data transmission task on all possible routes.

The rest of the paper is structured as follows. Evolutionary games and routing related work is presented in the next section. System model and game structure are proposed in Section III and Section IV, respectively. We investigate the NE and ESS for the game solution in Section V. The simulation model and results are discussed in Section VI. Conclusions are drawn in the last section.

II. Related Work

Finding optimal routes have been some of the most interesting research topics in communication networks. Various research tools have been proposed to investigate these issues including game theory. Game theoretical methodologies have been successfully used in sensor networks [3]. This paper provides a game theoretic model with utility functions considering forwarding and routing in the presence of adversaries. In [4], a pricing and payment model is presented as a cooperative game. The goal of the game is to find an optimal path in a WSN by considering reliability, energy, and traffic load, where the nodes have incentives to cooperative in the game.

Buttyan and Hubaux [5] proposed nuglets, which are virtual currency in the system, to stimulate the cooperation of the nodes participating to forwarding packets in a mobile ad hoc networks. Furthermore, a reliable length-energy constrained routing issue in WSNs has been presented in [6], where a game-theoretic approach is utilized. In this approach, the sensors cooperate as rational agents in order to find the optimal route and maximize their payoffs in the game. Two different possible payoff models and utility functions were illustrated. The issue of energy efficiency in wireless sensor networks has been addressed in [7]. It provided a game theoretic adaptive algorithm in order to manage sensor behavior for achieving complete decentralized control in an energy-constrained sensor network.

Evolutionary game theory emerged as a robust tool to investigate and solve the dynamic networking issues. Evolutionary game theory was applied in [8] where the authors proposed a three-dimensional game theoretic energy balance (3D-GTEB) routing protocol to enhance the routing decisions and to decrease the overhead in a WSN. They addressed the unbalanced energy consumption problem by applying evolutionary and classical game theory at two levels of game theoretic decision making. The two levels were called wedge-level energy balance and node-level energy balance. In this paper, we formulated the routing problem by utilizing an evolutionary game to study the behavior of the population and induce the equilibrium even under dynamic wireless sensor network conditions.

III. System Model and Assumptions

In this paper, we study a non-cooperative routing game in wireless sensor networks. We model the set of next hops that is available for a node to transmit packets as a set of $R = \{1, 2, 3, ..r\}$ hops. The sensor nodes are independent, where each node takes its own decision to transmit the packet without cooperation with the other nodes. Transmitting the packets through different hops sustains diverse cost. This cost is related to the transmission energy cost which in turn depends on the distance between the transmitter and receiver. For example, if the distance between the next hop and the transmitting node is increased, then the cost of transmission will also increase. This is because, all receivers must have the signal to interference and noise ratio (SINR) above a certain threshold in order to decode signals correctly. Obtaining the nearest hop will result in a lower transmission cost and a higher payoff. Similarly, selecting farther hops will result in a higher transmission cost and a lower payoff. Furthermore, transmitting packets through the same hop simultaneously by two or more nodes will raise the contention situation and waste the transmission energy of all nodes in question.

For the sake of simplicity, we consider two nearby nodes that have packets to transmit to their potential next hop neighbors. As the distances to the next hop are diverse, so are the costs associated with the respective transmission. For this reason, the payoff of selecting a specific strategy for each node could be different. Consequently, we model the game as an asymmetric routing game between two populations (i.e., $\upsilon = \{A, B\}$) based on the distance between the nodes. In order to select the next hop, each node must have the same set of strategies S. $R = \{1, 2, 3, ..r\}$, as explained above, denotes the set of hops that are available to transmit the packet. Each selected hop for either node will incur a specific amount of energy that is the cost of transmitting the packet, and we denote it by C. As an example, selecting r as the next hop to transmit the packet individually from population A will cost C_{Ar}. Nodes are always interested in transmitting the packet through the hop with the least possible minimum cost (i.e., minimum value of C). As demonstrated, the evolutionary game is concerned with the evolution of the strategy, payoffs, and stability [9]. Thus, the number of sensor nodes is not significant in the game model.

IV. Game Structure

The routing game is represented as $<R, S, U>$, where R represents the set of available hops in the game; $S = \{s_r | r \in R\}$ is the strategy space, which is the set of actions that are available for the players. The payoff for playing strategy s_r and s_t is denoted by $u(s_r, s_t) \in U$ when competing against each other. This happens when the player who is adopting the strategy s_r meets another player who is adopting the s_t strategy. In our game, the cost of transmission is permanently preferred to be low, which will increase the payoff and prevent energy wastage. Thus, we define the payoff as:

$$u(s_r, s_t) = \begin{cases} (\frac{1}{C_{\upsilon r}}, \frac{1}{C_{\upsilon t}}) & when \quad r \neq t, \quad \upsilon \in \{A, B\} \\ (0, 0) & when \quad r = t \end{cases} \tag{1}$$

where $C_{\upsilon r}$ is the transmission cost of the packet through hop r, which either belongs to the population A, or belongs to the population B. For example, C_{Br} denotes the cost of selecting hop r by the player, who belongs to population B.

We define the routing game as a strategic matrix shown in Table I with a player set composed of players that comprise

TABLE I: Strategies competition form of evolutionary routing game (i.e., strategies s_r and s_t)

	s_r	s_t
s_r	$0\ ,\ 0$	$\frac{1}{C_{Ar}}\ ,\ \frac{1}{C_{Bt}}$
s_t	$\frac{1}{C_{At}}\ ,\ \frac{1}{C_{Br}}$	$0\ ,\ 0$

$\upsilon = \{A, B\}$ populations. The payoff for players playing strategies s_r and s_t, which are competing against each other, is denoted by $u(s_r, s_t)$. Without loss of generality, we assume that transmitting the packet by using the strategy s_r will cost less than transmitting the packet by using strategy s_t based on the distance between the nodes. Thus, it preferable for all the nodes to forward the packets through hop r, which produces a high payoff. In addition, transmitting the packet through the same hop (i.e., r or t) will raise the collision situation and the payoff will be zero (see eqn. 1).

We show the competition between the two strategies s_r and s_t as a demonstration to clarify and analyze the performance of the game. These players adopt one of the two available hops (i.e., r or t). We analyze the payoff based on Table I we employ the same to answer fundamental questions as: 1) What does a strategy s_r gain as a payoff when it meets another same strategy s_r or s_t? 2) How does the equilibrium solution make the player satisfy and respect the other's choices? In addition, we utilize the same technique in the case of having multiple hops, as will be presented later in the experimental results in Section **??**.

V. Equilibrium and Evolutionary Stability Strategies

In this section, we derive the equilibrium state for our routing game where the populations mix in the equilibrium state and there is no incentive to change the selection strategy and improve payoff. In this state, there are no mutant strategies that can invade the population who utilizes an incumbent strategy which is the ESS. Once the strategy reaches ESS, then the proportion will be stable and does not change over time. Next, we will provide the evolutionary stability analysis of our game in order to seek equilibrium solution.

A. Pure NE and Evolutionary Stability

1) Pure Nash Equilibrium: We prove that our evolutionary routing game has two pure Nash Equilibrium strategies [10].

Lemma 1: In the evolutionary routing game, strategy pairs (s_r, s_t) and (s_t, s_r) are pure NE.

Proof: Suppose two nodes are picked randomly from two large populations of sensor nodes in the network. These nodes are supposed to select one of the two strategies, each competes against the other, in order to transmit the packet. In Table I, assume the row and the column are the two players from populations A and B, respectively. These players select strategy pairs (s_r, s_t) and (s_t, s_r). The payoffs of the selection are $\frac{1}{C_{Ar}}, \frac{1}{C_{Bt}}$ and $\frac{1}{C_{At}}, \frac{1}{C_{Br}}$, respectively. Let us say that the players select strategy pairs (s_r, s_r) and (s_t, s_t) instead. Thus, the payoffs for those strategy pairs will be zero. This means that the player who is playing strategy s_r does not have an incentive to change the strategy to s_t because of the penalty of reducing the payoff according to equation 1. As a result we can say that strategy pairs (s_r, s_r) and (s_t, s_t) are not profitable deviations. According to the NE definition [10], the strategy pairs (s_r, s_t) and (s_t, s_r) are a pure NE for this game. ■

2) Evolutionary Stability: We will examine if the pure NE strategies (s_r, s_t) and (s_t, s_r) in the routing game are evolutionary stable or not. Consider a group of two populations playing the same strategy s, which is referred to as the incumbent strategy. That means the players will play (s, s), which is a symmetric NE. The strategy s is called evolutionary stable if a small group playing a different strategy, $\acute{s}$, which is referred to as the mutant strategy, would disappear with time. The ESS defined [10] as any evolutionary stable strategy must be a symmetric pure NE, where the performance of strategy s against itself is better than it does against a mutant strategy. However, if the strategy is not strictly Nash, it should satisfy the second condition of the evolutionary stability. The second condition defined as that the incumbent s must do strictly better against the mutant $\acute{s}$ than a mutant strategy does against a mutant. In this game, the pure strategies are not symmetric pure NE where the payoff of strategy s_r is different from the payoff of strategy s_t (i.e., $u(s, s) < u(\acute{s}, s)$). According to the definition of ESS, the pure strategy NE in our game is not evolutionary stable.

B. Mixed Strategy NE and Evolutionary Stability

1) Mixed Strategy Nash Equilibrium (MSNE): The mixed strategy Nash Equilibrium of the routing game is a probability distribution $\hat{p}$ (collection of weights) over the set of pure strategies S for any player [11]. The pure strategy will be available with certain probabilities where the payoffs from all opponents of their strategies are eventually equal. Thus, the expected payoffs given to strategies in a mixed NE are equal.

In our game, let $\acute{p} = \{p, 1-p\}$ denote the proportions of the population A adopting s_r and s_t strategies, respectively, and $\grave{q} = \{q, 1-q\}$ denote the proportions of the population B adopting s_r and s_t strategies, respectively. In a 2-hop scenario, player 1, who belongs to population A, plays strategy s_r with probability p and strategy s_t with $1-p$ probability. Player 2, who belongs to population B, plays strategy s_r with probability q and strategy s_t with $1-q$ probability. We calculate those probabilities using the mixed strategy algorithm and the payoff in Table I. According to Mixed Nash definition, the expected utility from playing strategy s_r is equal to the expected utility for playing strategy s_t for any player as follows:

$$EU_\upsilon(s_r) = EU_\upsilon(s_t), \quad \upsilon = \{A, B\} \tag{2}$$

The expected utility for playing strategy s_r for the player who belongs to A population and the player who belongs to population B, respectively, are:

$$EU_A(s_r) = q \cdot 0 + (1-q)\frac{1}{C_{Ar}} \tag{3}$$

$$EU_B(s_r) = p \cdot 0 + (1-p)\frac{1}{C_{Br}} \tag{4}$$

The expected utility for playing strategy s_t for the players in the two populations are:

$$EU_A(s_t) = q\frac{1}{C_{At}} + (1-q) \cdot 0 \tag{5}$$

$$EU_B(s_t) = p\frac{1}{C_{Bt}} + (1-p)\cdot 0 \tag{6}$$

Setting (3) and (5) equal as in (2), then solve it to find the probability distribution $\grave{p} = \{p, 1-p\}$. Similarly, setting (4) and (6) equal as in (2), then solve it to find the probability distribution $\grave{q} = \{q, 1-q\}$ such as:

$$p = \frac{C_{At}}{C_{At}+C_{Ar}}, \quad 1-p = \frac{C_{Ar}}{C_{At}+C_{Ar}} \tag{7}$$

$$q = \frac{C_{Bt}}{C_{Bt}+C_{Br}}, \quad 1-q = \frac{C_{Br}}{C_{Bt}+C_{Br}} \tag{8}$$

The players from A and B populations adopt the strategy s_r with probabilities (p, q), respectively, and the strategy s_t with probabilities $(1-p, 1-q)$, respectively. The players in the routing game mix their selections of the next hop to transmit the data packet with (p, q) and $(1-p, 1-q)$ probabilities. In addition, none of the players would change the strategy with an expectation of gaining a better payoff. The reason behind this behavior is that adopting the strategies in that manner will represent the same outcome.

2) Analysis Evolutionary Stability for MSNE: We analyze the evolutionary stability of mixed strategy NE (MSNE) (i.e., $(\grave{p}, \grave{q})$) in our asymmetric routing game according to asymmetric ESS [12]. Previously, we already proved that the game solution is a mixed strategy Nash Equilibrium $(\grave{p}, \grave{q})$.

Asymmetric ESS Definition [12]: Define $(\grave{p}, \grave{q})$ as a two-species evolutionary stable strategy if it is asymptotically stable under the two-dimensional equation whenever it is based on the strategy pair $(\grave{p}, \grave{q})$ and $(\hat{p}, \hat{q})$, when $(\grave{p}, \grave{q}) \neq (\hat{p}, \hat{q})$.

In other words, the two-species ESS with strategy pair $(\grave{p}, \grave{q})$ cannot be invaded by a mutant subsystem, which uses a different strategy pair $(\hat{p}, \hat{q})$.

Lemma 2: Our mixed strategy NE $(\grave{p}, \grave{q})$ is a two-species evolutionary stable strategy.

Proof: First, we define the replicator equations, which is ruling the behavior of the system over time [13], based on the strategy pair $(\grave{p}, \grave{q})$. In our routing game, we define the replicator equation such that the fraction of strategy s_r grows at a rate equal to its fitness minus the average fitness of the player. We have the following replicator equations:

$$\begin{aligned} \dot{p} &= p[(\frac{1-q}{C_{Ar}}) - (\frac{p(1-q)}{C_{Ar}} + \frac{(1-p)q}{C_{At}})] \\ &= p(1-p)(\frac{1-q}{C_{Ar}} - \frac{q}{C_{At}}) \end{aligned} \tag{9}$$

$$\begin{aligned} \dot{q} &= q[(\frac{1-p}{C_{Br}}) - (\frac{q(1-p)}{C_{Br}} + \frac{(1-q)p}{C_{Bt}})] \\ &= q(1-q)(\frac{1-p}{C_{Br}} - \frac{p}{C_{Bt}}) \end{aligned} \tag{10}$$

Second, we need to find the stable fixed point for the two replicator equations. We have the MSNE point, which we calculated in V-B1. We proved how this point is a fixed point under the two replicator equations (9) and (10).

Since we already have a stable point $(\grave{p}, \grave{q})$ in our model, we need to show that the point is fixed under the replicator equations. Therefore, we need to satisfy that the last part (i.e., $(\frac{1-q}{C_{Ar}} - \frac{q}{C_{At}})$ and $(\frac{1-p}{C_{Br}} - \frac{p}{C_{Bt}})$) in equations (9) and (10), respectively, should equal zero. Therefore, if we substitute the values of p and q from equations (7) and (8) with these last parts, we will get zero. As result, $(\grave{p}, \grave{q})$ is a asymptotically stable fixed point for the replicator dynamic. Based on asymmetric ESS [12], our mixed strategy NE $(\grave{p}, \grave{q})$ is a two-species evolutionary stable strategy. ■

3) Numerical Analysis of ESS for MSNE : For the sake of certainty, we will analyze the ESS for the proposed MSNE solution by satisfying the condition of the following theorem [12] numerically in this part.

Theorem [12]: $(\grave{p}, \grave{q})$ is a two-species ESS if and only if
either $\grave{p}\cdot(D\hat{p} + E\hat{q}) > \hat{p}\cdot(D\hat{p} + E\hat{q})$
or $\grave{q}\cdot(F\hat{p} + G\hat{q}) > \hat{q}\cdot(F\hat{p} + G\hat{q})$
for all strategy pairs $(\hat{p}, \hat{q})$ that are sufficiently close (not equal) to $(\grave{p}, \grave{q})$. D, E, F, and G are the payoff matrices for intra-specific interaction.

In our routing game, suppose two sensor nodes are picked randomly from two population (i.e., A and B), and these nodes are supposed to select one of the two strategies (i.e., s_r and s_t), which compete against each other in order to transmit the data packet. Assume that we have the payoff matrix values for Table I as: $C_{At} = 4, C_{Ar} = 2, C_{Bt} = 8$, and $C_{Br} = 6$. Based on those values, we calculate the MSNE and the rest of the elements as: $(\grave{p}, \grave{q}) = \begin{pmatrix} \frac{4}{7} & \frac{2}{3} \\ \frac{3}{7} & \frac{1}{3} \end{pmatrix}$, $D = \begin{pmatrix} 0 & \frac{1}{2} \\ \frac{1}{4} & 0 \end{pmatrix}$, and $E = \begin{pmatrix} 0 & \frac{1}{6} \\ \frac{1}{8} & 0 \end{pmatrix}$. D and E are the payoff matrices for interspecies interactions. Suppose there are small groups adopting a mutant strategy $(\hat{p}, \hat{q})$ instead, which is greedier than the incumbent strategy $(\grave{p}, \grave{q})$. Furthermore, assume that the mutant strategy selects the near hop r with higher probability (i.e., $p + \delta$, $q + \delta$) and selects the farther hop t with lower probability (i.e.,$(1-p) - \delta$, $(1-q) - \delta$), where δ is a small positive number (i.e., $\delta = 0.1$). Thus, $(\hat{p}, \hat{q}) = \begin{pmatrix} \frac{4}{7}+\delta & \frac{2}{3}+\delta \\ \frac{3}{7}-\delta & \frac{1}{3}-\delta \end{pmatrix}$. Then, by substituting those values in the first condition of the theorem [12], we have $\grave{p}.(D\hat{p} + E\hat{q}) > \hat{p}.(D\hat{p} + E\hat{q})$ (i.e., $0.23 > 0.22$). Accordingly, $(\grave{p}, \grave{q})$ cannot be invaded by the greedier mutation and is ESS.

C. Replicator Dynamics

Replicator dynamics describe populations' behavior of sharing associated with different strategies that evolve over time [13]. We introduce the replicator dynamic model in order to show how the players, who repeatedly play the routing game, evolve their behavior in every stage of the game. The populations learn with each strategies interaction until they reach a stable state. In the following equations, we derive the replicator dynamics of our routing game framework with r hops. Our replicator dynamic equations will define the fitness as follows:

Consider two populations of interacting nodes. Each time, nodes from one population (row players A) are randomly paired with nodes from the other population (column players B). All players have a set of strategies S, and strategy $s_r \in S$ are adopted. Let $\grave{p} = \{p_1, p_2, p_3, ..., p_r\}$ and $\grave{q} = \{q_1, q_2, q_3, ..., q_r\}$ denote the proportion of the two-population adopting $s_1, s_2, s_3, ..., s_r$ strategies, respectively, where summation of the proportion equal to 1 (i.e., $\sum_{i=1}^{r} p_i = 1$ and $\sum_{i=1}^{r} q_i = 1$) as described in section V-B1. Let $(\grave{p}, \grave{q})$ represent the incumbent strategy of selecting hop r with probability p_r,q_r. In addition, let the set of $U = \{u_1, u_2, u_3, ...u_r\}$ represent the average payoff of the players selecting hop r at a given stage of our game. Furthermore, let u_r denote the utility function of adopting strategy s_r. The payoff of selecting hop r strategy s_r for row player (A) is given by:

$$u_r = u_0 + \sum_{x=1}^{R} q_r u(s_r, s_t), \quad \forall r, t \in R \tag{11}$$

The payoff of selecting hop r strategy s_r for column player (B) is given by:

$$u_r = u_0 + \sum_{x=1}^{R} p_r u(s_r, s_t), \quad \forall r, t \in R \tag{12}$$

where u_0 is the initial fitness of every player, and $u(s_r, s_t)$ is the fitness of selecting hop r in pairwise competition against adopting hop t.

Let $\overline{u_A}$ and $\overline{u_B}$ denote the average fitness for entire population A, and B, respectively, which are given by:

$$\overline{u_A} = \sum_{y=1}^{r} p_y (q_y u_y), \quad \forall y \in R \tag{13}$$

$$\overline{u_B} = \sum_{y=1}^{r} q_y (p_y u_y), \quad \forall y \in R \tag{14}$$

For each next time slot, the probability $(\check{p_r}, \check{q_r})$, of selecting next hop r of the game is calculated by:

$$\check{p_r} = p_r + \frac{q_r(u_r - \overline{u_B})}{\overline{u_B}} \tag{15}$$

$$\check{q_r} = q_r + \frac{p_r(u_r - \overline{u_A})}{\overline{u_A}} \tag{16}$$

The proportion of sensors selecting hop r in the next time slot will be either increased or decreased according to comparison of the average fitness of selecting that hop to the overall fitness of the entire sensor population in the current time slot. According to our evolutionary replicator equations, the next particular hop will be selected more frequently in a subsequent time slot if the payoff of selecting that hop is higher than the average overall fitness of the entire sensor network.

VI. Simulation Model and Results

To demonstrate the effectiveness of the proposed routing game, we conducted extensive simulation experiments. The results show the behavior of selecting strategies when sensor nodes do not cooperate with each other and demonstrate how our evolutionary routing game converges to ESS. First, we present the results when there are two hops available to transmit the data packet for all populations. We consider the diversity of wireless network conditions that result in different transmitting costs. For example, a sensor node will fail either because of an uncontrolled environment, battery issues, or a communication failure. Thus, in the case of a node failure, the cost of paths in routing networks will be changed. Mobility of the nodes in a WSN is another cause for diversity of the cost paths. In our simulation, we show how the nodes behave with multiple hops available and converge to ESS. Moreover, we show the results of experiments under dynamic network conditions.

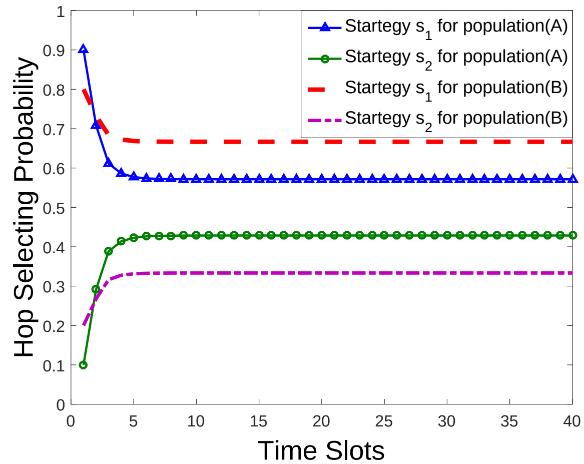

Fig. 1: Proportion of selecting strategy 1 and strategy 2 (i.e., transmitting to hops 1 and 2), Stability of the system occurs at $t = 10$.

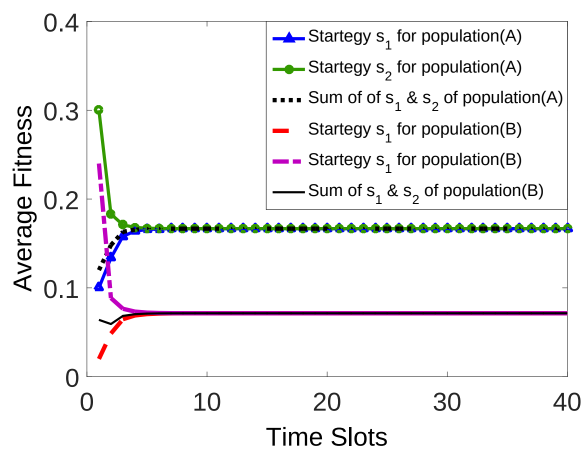

Fig. 2: Related average and weighted sum of fitness for both populations (i.e., A & B). Stability of the system occurs at $t = 10$..

Figures 1 and 2 represent the behavior of selecting one of two available hops for the two populations in order to transmit the packet during every time slot. We assume different costs of transmission for different hops, where a transmission through hop 1 produces a lower cost than a transmission through hop 2. The figures show how the probabilities of selecting the hop are modified according to average fitness, which is gained from strategic interactions. Let us consider the sensor nodes from population A become greedier and transmit the packet with a lower cost through hop 1. Thus, the payoff for those nodes who adopt strategy s_1 at $time = 1$ is less than the payoff for selecting hop 2, as demonstrated in Figure 2. As a result, the hop selecting probability of greedy nodes decreases in $time = 2$ (as shown in Figure 1) and their payoff increases at that time, which is still less than the average payoffs of the entire population as shown in Figure 2. In contrast, the nodes that are less greedy and transmit through hop 2, which costs more for transmitting, receive a higher payoff at $time = 1$ than the nodes transmitting through hop 1. Moreover, this causes the hop selecting probability to increase in the following time for the less greedy nodes and decreases their payoffs. In a similar manner, the hop selecting probability for both populations (i.e., population A and B) are modified until the system becomes stable (i.e., time=10).

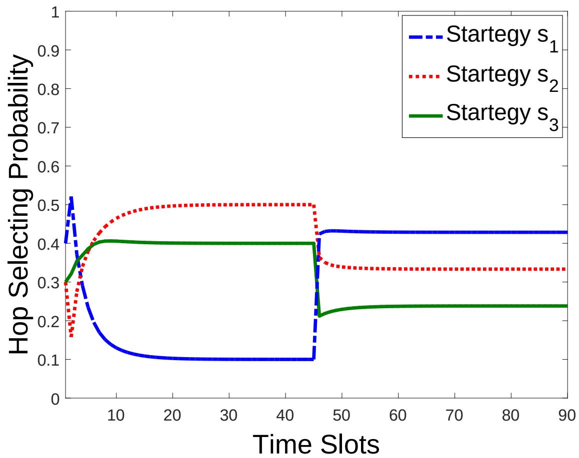

Fig. 3: Convergence probabilities of selecting 3 hops to equilibrium probabilities at $t = 63$ when network conditions change at $t = 45$ for population (A).

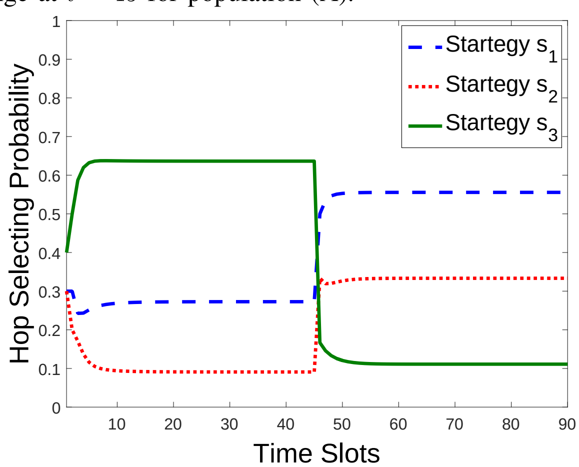

Fig. 4: Convergence probabilities of selecting 3 hops to equilibrium probabilities at $t = 63$ when network conditions change at $t = 45$ for population (B).

Figures 3 and 4 present the experimental results of playing our proposed evolutionary game with multiple hops (i.e., 3 hops) where each one has a different transmitting cost for each population. The convergence to ESS occurs at $time = 20$, which is slower than convergence to ESS with having two hops, as Figure 1 shows. Moreover, the figure shows the behavior of nodes when the network conditions changed in our proposed evolutionary game. Figure (3) shows the convergence probabilities of selecting 3 hops to ESS by population A. Figure 4 shows the convergence probabilities of selecting 3 hops to ESS by population B. For example, at the beginning in Figure 3, the game converges to ESS for population (A) (i.e., $time = 20$) when hop 2 is more preferable to be selected from the nodes and the initial values for utility of selecting s_1, s_2, and s_3 is 0.2, 0.9 and 0.5, respectively. At $time = 45$, the network conditions are changed: Hop 1 becomes more attractive for the sensors and adopting s_1 will produce higher payoff than selecting s_2 or s_3. The initial values for utility of selecting s_1, s_2, and s_3 were changed to 0.5, 0.3 and 0.2, respectively. Similarly in Figure 4, the network conditions were changed with different utility values for each strategy selection. The system reaches stability under new network conditions and converges to a different ESS for all populations at $time = 63$. As a result, the system will be able to reach stability with multiple hops of different transmitting costs, even under the changing of network conditions.

VII. Conclusions

Designing routing protocols that alleviate congestion in wireless sensor networks is a challenging problem. Absence of a centralized mechanism to select among available paths will unavoidably introduce extra collisions, resulting in reduction of the sensor network lifetime. This paper formulates the congestion routing issue in WSNs to seek equilibrium solutions and approaches the issue with an evolutionary game theoretical framework. We derived the equilibrium strategies of selecting the next hop in the routing game, and we proved that the mixed strategy Nash Equilibrium that was derived in the game is an evolutionary stable strategy (ESS). Moreover, we presented the replicator dynamic model to show how the populations improve their performance and converge their strategy selections to ESS over time based on payoff comparison as demonstrated in the experiment results.

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