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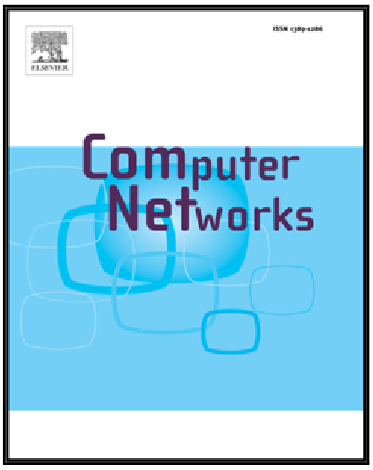

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An Evolutionary Routing Game for Energy Balance in Wireless Sensor Networks

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Abstract

In a Wireless Sensor Network (WSN), the sensor nodes rely on each other to forward packets from the origin to the base station via some routes. Computation of a desirable route is challenging. Some of the routes can be better than others, which might lead to an imbalance in contention for disparate routes as one route may be congested more frequently or exhausted quicker than the others. Since each node's self-interest is to save its own energy due to the limited energy resource, it can lead to congestion resulting in higher delays and additional packet collisions– which may eventually result in quicker energy depletion along such routes and shorten the lifespan of the network. In this paper, we analyze this issue from a game theoretic perspective and model the route selection problem in a WSN as an evolutionary anti-coordination routing game. We derive the evolutionary stable strategy (ESS) of the game and prove that the derived incumbent strategy cannot be invaded by a greedy strategy i.e., mutant strategy. Furthermore, we derive the replicator dynamic of the proposed game in order to show the behavior of the sensors in selecting the paths. The mechanism of the replicator dynamics also shows how the nodes learn from their strategic interactions and modify their strategies at every stage of the game until reaching a stable strategy (ESS). Furthermore, the evolutionary game can be implemented in a distributed manner. Finally, in order to achieve increased lifetime, we analyze the fairness of the proposed equilibrium solution under the selfish node behavior by utilizing Jain's fairness index. The results show that the proposed system is successful in converging the strategy choices to ESS even under dynamic conditions.

Keywords: Wireless Sensor Networks, Energy Efficient, Evolutionary Game Theory, Congestion, Stable Strategy, Fairness

1. Introduction

With the rapid advancements in wireless technology, Wireless Sensor Networks (WSNs) are being widely deployed. A WSN consists of hundreds or even thousands of heterogeneous

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small devices that sense various physical or environmental conditions and communicate with each other in order to transmit the sensed data to the destination for further analysis. A unique challenge of these networks is that they usually have very limited resources, especially energy.

A multi-path routing protocol improves the reliability and load balancing in WSNs, where it provides heterogeneous paths to choose from. Thus, some paths in this mechanism could be considered to be better than others. The rational choice of sensor nodes will be forwarding through the best path (in terms of energy consumption, transmission delay, etc.), which intuitively results in future congestion on the same path used by multiple data transmission connections. The congestion, which is one of the main causes of energy waste, will seriously degrade the overall performance of **a** sensor network. In some cases, especially in emergency or disaster monitoring where the sensor networks are deployed in extreme environmental conditions, high reliability and energy efficiency are extremely important because a slight transition failure could cause unpredictable damages. However, without any centralized mechanism to balance the traffic load across heterogeneous paths, it is challenging to achieve long-term dynamic traffic load balance and hence alleviate congestion to improve the network lifetime. In this paper, we deal with this challenge and present a new distributed mechanism of forwarding data packets in order to achieve fair long-term routing of WSNs.

1.1. Problem Definition

Most WSN routing algorithms attempt to route packets to the base station via the most efficient route [1]. However, utilizing the same shortest or the same most efficient path by multiple data sources to the destination could result in congestion and increased delays.

The heterogeneity of the paths can be in the sense that each path is associated with different costs according to the various routing metrics. Paths with lower cost in terms of transmission energy are more attractive for sensor nodes as compared with higher cost paths. However, if every node tries to select the shortest path to its target, it will result in collisions and lead to quick energy depletion among nodes. Thus, forwarding packets through the lowest energy-consumed path may not always be optimal for the network lifetime. As a result, nodes are expected to have a clear preference over a set of available paths and every sensor node should have an incentive for altruism to avoid the overheads of retransmitting dropped packets due to a collision, which can cause more depletion of the energy. In this paper, we address the challenges that raise due to the absence of a centralized enforcement mechanism and present an evolutionary routing congestion game that would ensure long-term routing with a fair distribution of heterogeneous paths among sensor nodes.

1.2. Our Contribution

Our aim in this paper is to optimize the energy consumption of the sensor nodes so as to increase the lifetime of a WSN by reducing congestion and optimally distributing data traffic among multiple heterogeneous paths under a game theoretic framework. The process of selecting a path to transmit the packets in our game will continue until the destination node is reached. We establish an evolutionary routing anti-coordination game and present a stable strategy as a solution that is robust under dynamic network conditions as well as distributing the data transmission task on all possible routes in a fair manner. Our major contributions are as follows:

- We have formulated an incentive based game model of the sensor nodes for forwarding packets. We have derived the game's Pure Strategy Nash Equilibria (PSNE) and Mixed Strategy Nash Equilibria (MSNE).
- We have analyzed the stability of the game's solutions and showed that MSNE in the game is an Evolutionary Stable Strategy (ESS), where there are no other strategies except this ESS dominating the population, and it is robust under dynamic network conditions.
- We have derived dynamic replicators of the proposed evolutionary routing game, which describes a dynamic selection process. The players learn from their payoff outcomes with each strategy's interaction until they reach a stable state.
- In addition, as fairness in path selection strategies is highly important, we have proposed a fairness analysis of our evolutionary routing game by utilizing Jain's fairness index [2].

The rest of the paper is structured as follows: In Section 2, we provide a survey of the existing work on different solutions for routing issues using game theory. System model and assumptions of the evolutionary routing game are proposed in Section 3. Section 4 presents the formulation of our proposed game along with the derived replicator dynamics while Section 5 presents the fairness analysis of the game. The simulation model and results are discussed in Section 6. Section 7 concludes the paper.

2. Related Work on Game Theoretic Applications to WSNs

2.1. Basics of Game Theory

Game theory is a powerful mathematical tool that models strategic interaction and analysis of competition, conflict, or cooperation with multiple entities [3]. Fundamentally, it is the study of decision-making and analysis of the behavior of two or more participants in a situation involving rewards or punishments. Players may be either cooperative or non-cooperative while aiming to maximize their outcomes according to their preference (utility function). The utility in any game is expressed by the motivation of the players.

Nash Equilibrium (NE) is one of the most common solutions that describes a steady state condition of the game; no player can benefit by changing her/his strategy while the other players keep their strategies unchanged. Evolutionary game theory is another elegant means in game theory which models and studies the evolution of the population, and the interaction among rational agents, towards the optimal strategies that evolve over time by focusing more on the dynamics of strategic change (i.e., strategy adaptation over time).

2.2. Related Work

Game theoretic techniques have been applied to numerous areas of wireless communication for analyzing and predicting the rational behaviors of agents that have also proven very useful in the design of wireless sensor networks [4]- [5]. Important and essential issues in WSNs, including routing protocol design, energy saving, packet forwarding, security, and other sensor management tasks, have been modeled and described by the game theoretic approaches for efficient solutions that maximize the network lifetime. Finding optimal routes is one of the most interesting research topics in communication networks. Various research tools have been proposed to investigate this issue, including game theory. This paper provides a game theoretic model, with utility functions, considering forwarding and routing. In this section, we provide an overview of some previous works in the domain of WSNs, and some of the game theoretic solution concepts used in WSNs.

Furthermore, in [6], the authors proposed a detailed study of different energy efficiency trade-off mechanisms in green communication in all network layers including routing. Establishing and maintaining a successful wireless communication link to simultaneously achieve the objectives of having high Quality of Service and Quality of Expectation becomes challenging since the energy consumption requirements of the user and network are different for different objectives. The effect of energy efficiency trade off in the network has been discussed and classified based on each protocol layer. Several approaches should be considered to enhance user as well as network performance along with the energy efficiency. Therefore, the authors provide several studies of the inter-dependencies of different standoffs, which could be varied with different applications objectives. In [7], the authors presented the fundamental issue on exploring electronic vehicles (EVs)s mobility to balance power demand among districts in the smart grid. A dynamic complex network model of Vehicle-to-grid mobile energy networks is proposed with considering the fact that EVs travel across multiple districts, and hence EVs can be acting as energy transporters among different districts. The authors of [8] provide trade-offs between application requirements and lifetime extension that arise when designing wireless sensor networks. A new classification of energy-conservation schemes is presented as found in the recent literature. Severals techniques applied in WSNs to achieve a trade-off between multiple requirements are discussed.

The pricing and payment model is presented as a cooperative game in [9]. 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 cooperate in the game. Buttyan and Hubaux [10] proposed Nuglets, which is virtual currency in the system, to stimulate the cooperation of the nodes participating in forwarding packets in mobile ad hoc networks. Furthermore, a reliable length-energy constrained routing scheme in WSNs has been presented in [11], 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 WSNs has been addressed in [12]. 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 has emerged as a robust tool to investigate and solve dynamic networking issues. An evolutionary game theory was applied in [13] 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 [14], a joint duty cycle scheduling and energy aware routing approach (DREG) is presented based on evolutionary game theory. The solution for this game is proposed as evolutionary equilibrium. The authors aimed to prolong the network lifetime in WSNs by finding an optimal wakeup/sleep scheduling policy, based on a trade-off between network throughput and energy efficiency for each sensor. The issues of duty cycle scheduling and energy conservation are modeled as a multi-agent non-cooperative game, and the game is repeated until a steady state is reached. Authors of [15] have also applied the evolutionary game theory to solve the routing problem in a general network topology. The authors consider the link costs that are linear in the link flow.

Furthermore, authors of [16] model the evolutionary game to study the dynamic cooperative behavior of selfish nodes under AODV routing. In the game, packet-forwarding is repeated, and includes two distinct modes, in order to learn and predict the neighbors' node behavior to improve network performance. The first mode is deterministic to analyze the behavior of the network for standard strategic patterns. Random mode is the second one that applies a genetic algorithm to predict the best strategy randomly. Proposed in [17] is an adaptive and distributed routing algorithm for correlated data that gathers and exploits the data correlation between nodes based on a game theoretic framework. Specifically, the issue of effective energy minimization is addressed and a routing solution is presented. The energy metric, interference awareness and opportunity for multi-hop partial data aggregation are considered. The authors formulate the game by incorporating a general multi-hop data aggregation model into the problem definition to describe data reduction in a congestion game.

A reliable delivery routing issue in WSNs is addressed in [18] through the game theoretic framework. The authors aim to ensure stable cooperation among nodes for delivering the packet and minimizing the routing cost as well. The proposed reliable coalition formation routing protocol (RCFR) is presented using a coalitional game theory, which selects the route according to the principle of lowest cost. In order to introduce a fair allocation method for payoff division, a characteristic function is designed by leveraging performance metrics. RCFR protocol is elaborated by extending the AODV protocol, where the path with minimum cost will be selected to transmit packets, and route maintenance is achieved by adding route residual energy ratio monitoring.

In our paper, we leverage concepts from evolutionary game theory and model the routing decisions in a WSN as an anti-coordination evolutionary game. We provide detailed analysis of the system stability and fairness of the solution as well. 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. We study the behavior of the population and induce the equilibrium even under dynamic network conditions.

3. System Model and Assumptions

3.1. System Model

We consider an anti-coordination routing game where there is a set of $\mathcal{N}$ homogeneous sensors (i.e., players) that are randomly distributed in a designated area. Each player has to select a path to transmit packets. We model the set of next hops that are available for a node $\mathcal{R} = \{1, 2, 3, ..r\}$. We consider a routing game where each packet's path is controlled independently by a rational player in order to minimize the cost of transmission and latency. Furthermore, each node takes its own decision to transmit a packet without cooperation with other nodes. Each selected hop (i.e., hop r) has a specific cost C_r which is related to the distance between the transmitter and receiver (different hops sustain diverse transmission energy costs). For example, if the distance between the next hop and the transmission node is increased, 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 received signals correctly. Players are assumed to be non-cooperative and rational, i.e., they are interested in minimizing their own cost of transmission and they do not share a common goal to cooperate with each other. The energy model will determine the transmission cost C and payoff u for selecting a specific hop, which will be introduced in the following subsection. As demonstrated subsequently, the evolutionary game is concerned with *the evolution of the strategies, payoffs, and stability* [19]. Thus, the number of sensor nodes is not significant in the game model.

3.2. Cost Model

Most of the sensors' energy is used during packet forwarding. Many energy models [20, 21] have been used for energy consumption in WSNs. In our model, the total cost C of forwarding a packet consists of two parts: i) the energy spent for transmitting the packet and ii) the energy consumed for receiving the packet. Thus,

$$C = C_{tx}(d) + C_{rx} \tag{1}$$

where $C_{tx}(d)$ is the cost of transmitting the packet to another over distance d, and C_{rx} is the cost of receiving it. C_{tx} is defined as:

$$C_{tx}(d) = e_{(tx-elec)} + e_{amp} \cdot d^{\alpha} \tag{2}$$

where $e_{tx-elec}$ is the energy consumption of the transmission circuit, and e_{amp} is the transmit amplifier dissipation in order to achieve the required signal level. α represents the propagation loss exponent (i.e., typically $\alpha = 2$ for free space). The cost of receiving the packet is:

$$C_{rx} = e_{(rx-elec)} \tag{3}$$

where $e_{(rx-elec)}$ is the receiving circuitry dissipation. In our game model, it is noteworthy that any other positive value for the cost of packet forwarding derived from other energy models can be used in the game without affecting our analysis and the outcome.

3.3. Assumptions and Notations

The assumptions of the incentive game model are as following:

- *Populations:* All sensor nodes are grouped into several populations according to their geographical positions, and we model the game as an asymmetric routing game between two populations (i.e., $\upsilon = \{\mathcal{A}, \mathcal{B}\}$). All nodes in each population have the same strategy set and payoff matrix. In an evolutionary game, the number of nodes does not play any role in the game model, where the payoff of a strategy depends on the strategy adopted by the others, but not on who is playing the strategy [22].
- *Strategy space:* Each node has a set of available actions/strategies represented as $\mathcal{S} = \{s_r | r \in \mathcal{R}\}$, where $\mathcal{R}$ is the set of next hops available in the game.
- *Payoffs and cost:* Obtaining the nearest hop will result in a lower transmission cost and thus a higher payoff. Similarly, selecting a farther hop will result in a higher transmission cost and a lower payoff. The next hops selected by different players simultaneously may interfere with each other, raising the contention situation, and wasting the transmission energy of all nodes in question. Each selected hop for either node will incur a specific amount of energy that is the cost of transmitting the packet. This cost is denoted by C (as was defined in equation (1)). As an example, selecting r as the next hop to transmit the packet individually from population $\mathcal{A}$ will cost $C_{\mathcal{A}r}$.
- *Non-cooperative behavior:* All sensor nodes are independent as they do not cooperate with each other for a common goal. Nodes are expected to have a clear preference of selecting the best paths over a set of available choices, and the nodes are always interested in transmitting packets through the route with the least possible minimum cost (i.e., the minimum value of C). Each node needs to recognize its neighbor nodes, the distances, and the cost of the packet transmission through each available route. Therefore, if many nodes take this same routing strategy, this rational behavior of sensor modes will intuitively result in further congestion and lead to energy depletion of the nodes along those paths.

For reader's convenience, we list the main mathematical notations and acronyms in Table 1.

4. An Evolutionary Routing Game

In this section, we first provide some basic concepts of evolutionary game theory as well as the structure of our routing game. Then, we derive the equilibrium state for the game as a solution for 2-hop scenario, followed by extension for multi-hop scenario by driving the so-called Replicator Dynamics of the game.

The incentive anti-coordination routing game proposed in this paper is a non-cooperative repeated game with perfect information, where the nodes have perfect knowledge about the utility function, which is common information to all nodes. The nodes are able to know other

Notation	Definition
NE	Nash Equilibrium
ESS	Evolutionary Stable Strategy
PSNE	Pure Strategy Nash Equilibrium
MSNE	Mixed Strategy Nash Equilibrium
$\mathcal{R}$	Set of available hops in the game
$\mathcal{S}$	Strategy space, (set of actions that are available for the players ($S = \{s_r \| r \in R\}$))
$\mathcal{U}$	Set of hops' utilities
s_r	Strategy of selecting hop r
u_r	Utility/payoff for selecting hop r.
$u(s_r, s_t)$	The utility/payoff for playing strategy s_r and s_t when competing against each other
s_i	Strategy played by player i
s_i^*	Strategy of player i which is the best response to s_i^*
s_{-i}^*	Best strategy played by player other than player i
$\upsilon \in \{A, B\}$	Population
$C_{\upsilon r}$	Transmission cost of the packet through hop r
$C_{\upsilon t}$	Transmission cost of the packet through hop t
$\hat{P}$	Probability distribution over set of of pure strategies for any player (collection of wights in MSNE)
$(\grave{p}, \grave{q})$	Incumbent strategy/ESS probability distribution over set of hops (MSNE)
$(\hat{p}, \hat{q})$	A mutant strategy that is greedier than ESS
$EU_\upsilon(s_r)$	Expected Utility from selecting hop r

Table 1: List of Notations and Acronyms

nodes' selection and their payoffs in the past. Furthermore, each node in WSNs behaves rationally and selfishly in order to obtain the best route to forward his own packets with minimum cost of energy consumption (maximizing the own utility).

4.1. An Evolutionary Game Theory

The evolutionary game provides an effective modeling tool to describe and analyze models of population behavior as well as design efficient strategies in communication networks. The difference compared with a classical game theory is that evolutionary game theory focuses more on the dynamics of strategy change, where the decision processes can be seen as the strategy evolution over time. An evolutionary stable strategy is a behavior that, when adopted by a population of players, cannot be invaded by an alternative strategy. In this paper, we consider the action of selecting a specific hop as nodes' strategy in our routing game. We need to provide the evolutionary stability analysis of Pure Strategy Nash Equilibrium (PSNE) and Mixed Strategy Nash Equilibrium (MSNE) in the game in order to seek a fair and stable solution for the long term. In addition, we prove that MSNE can not be invaded by a greedier strategy (i.e., mutant strategy).

4.2. Routing Game Structure

The evolutionary routing game is represented as $\mathcal{G} =< \mathcal{R}, \mathcal{S}, \mathcal{U} >$, where $\mathcal{R}$ represents the set of next hops available in the game; $\mathcal{S} = \{s_r | r \in \mathcal{R}\}$ 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 $u(s_r, s_t) \in \mathcal{U}$ 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 always preferred to be low, which will increase the payoff and prevent energy wastage. Thus, we define the payoff as:

$$u(s_r, s_t) = \begin{cases} (\frac{1}{C_{\upsilon r}}, \frac{1}{C_{\upsilon t}}) & \text{when} \quad r \neq t, \quad \upsilon \in \{\mathcal{A}, \mathcal{B}\} \\ (0, 0) & \text{when} \quad r = t \end{cases} \tag{4}$$

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

We define the routing game as a strategic matrix shown in Table 2 with a player set composed of players that comprise $\upsilon = \{\mathcal{A}, \mathcal{B}\}$ populations. The payoff for players playing strategies s_r and s_t, which are competing against each other, is denoted by $u(s_r, s_t)$. For the sake of clarity in analysis and without loss any generality, we assume that $u_r > u_t$ regarding the variety of the available routes in the network, and transmitting the packet by using the strategy s_r will cost less than transmitting the packet by using strategy s_t according to the distance between the nodes. Thus, it is 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 cause a collision, and hence, the payoff will be zero (see Eqn. 4).

	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

Table 2: Strategies competition form of evolutionary routing game (i.e., strategies s_r and s_t)

In addition, we initially consider a 2-available hop game i.e., we show competition between the two strategies s_r and s_t as a demonstration to clarify and analyze the performance of the game besides deriving its PSNE and MSNE. Later, we utilize the same technique in the case of multiple hops, as will be presented in the experimental results in Section 6. The players in our game adopt one of the two available hops (i.e., r or t). We analyze the payoff based on Table 2, and employ the same game formulation to answer the fundamental questions as: 1) What does a strategy s_r gain as a payoff when it meets another same strategy s_r or another different strategy s_t? 2) How does the equilibrium solution make the player satisfy and respect the other's choices? As we consider the players in our game are to be rational, all players would maximize their payoff by minimizing the cost of energy consumption and all players' interest to not end up selecting the same strategy.

4.3. Pure Strategy Nash Equilibrium and Evolutionary Stability for the Game

In this subsection, we derive the PSNE as first potential solutions for our evolutionary anti-coordination routing game. Then, we analyze its evolutionary stability.

4.3.1. Pure Strategy Nash Equilibrium

According to definition 1, we prove that our evolutionary routing game has two pure Nash Equilibrium strategies.

Definition 1: A Pure Nash Equilibrium [3] of the routing game is a strategy profile $s^* \in \mathcal{S}$ of actions, such that:

$$u({s^*}_i, {s^*}_-i) \geq u(s_i, {s^*}_-i), \forall i \in \mathcal{N} \tag{5}$$

In other words, the strategy ${s^*}_i$, to be pure NE, must satisfy the above condition. This condition means that no player i has an incentive to deviate to another strategy to gain a higher payoff than the one who is playing ${s^*}_i$, given that the other players' strategies remain the same ${s^*}_-i$.

Lemma 1: In the evolutionary routing congestion anti-coordination game, strategy pairs (s_r, s_t) and (s_t, s_r) are pure strategy 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 2, assume the row and the column are the two players from populations $\mathcal{A}$ and $\mathcal{B}$, respectively. These players select strategy pairs (s_r, s_t) and (s_t, s_r). The payoffs of the selection are $\frac{1}{C_{\mathcal{A}r}}, \frac{1}{C_{\mathcal{B}t}}$ and $\frac{1}{C_{\mathcal{A}t}}, \frac{1}{C_{\mathcal{B}r}}$, 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 4. 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 PSNE definition 1, the strategy pairs (s_r, s_t) and (s_t, s_r) are a pure strategy NE for this game. □

4.3.2. Evolutionary Stability of the Game's PSNE

We examine the PSNE evolutionary stability of the routing game according to definition 2 as follows:

Definition 2: In a symmetric game, the strategy s is evolutionary stable ESS in pure strategies if:

1. $u(s, s)$ is NE; $u(s, s) > u(\acute{s}, s)$ for all $\acute{s}$ and

2. if $u(s, s) = u(\acute{s}, s)$, then $u(s, \acute{s}) > u(\acute{s}, \acute{s})$

That means the players will play (s, s), which is a symmetric Nash equilibrium (NE). The symmetric Nash equilibrium is an equilibrium where all players use the identical strategy. Strategy s is called evolutionary stable if a small group playing different strategy, mutant strategy $\acute{s}$, would be less and less as time evolves. Eventually, it will not be played at all.

4.4. Mixed Strategy Nash Equilibrium and Evolutionary Stability for the Game

In this subsection, we derive the MSNE as a second potential solution for our evolutionary anti-coordination routing game, and we analyze its evolutionary stability.

4.4.1. Mixed Strategy Nash Equilibrium

Definition 3: The Mixed Strategy Nash Equilibrium [23] of the routing game is a probability distribution $\hat{P}$ (collection of weights) over the set of pure strategies $\mathcal{S}$ for any player such that:

$$\hat{P} = (p_1, p_2, p_3, ..., p_r) \in \mathbb{R}^{\mathcal{R}} \geq 0, \quad \text{and} \quad \sum_{t=1}^{\mathcal{R}} p_t = 1 \tag{6}$$

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 Nash Equilibrium are equal.

In our game, let $\grave{p} = \{p, 1-p\}$ denotes the proportions of the population $\mathcal{A}$ adopting s_r and s_t strategies, respectively, and $\grave{q} = \{q, 1-q\}$ denotes the proportion of the population $\mathcal{B}$ adopting s_r and s_t strategies, respectively. In a 2-hop scenario, player 1, who belongs to population $\mathcal{A}$, plays strategy s_r with probability p and strategy s_t with $1-p$ probability. Player 2, who belongs to population $\mathcal{B}$, 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 3.

	Prob.$(s_r) = p$	Prob.$(s_t) = 1-p$
Prob.$(s_r) = q$	0 , 0	$\frac{1}{C_{Ar}}$, $\frac{1}{C_{Bt}}$
Prob.$(s_t) = 1-q$	$\frac{1}{C_{At}}$, $\frac{1}{C_{Br}}$	0 , 0

Table 3: Strategies competition form of evolutionary routing game with probability distribution $\hat{p}$ over the pure strategies (i.e., strategies s_r and s_t).

According to Mixed Nash definition 3, the expected utility from playing strategy s_r is equal to the expected utility for playing strategy s_t for any player as follows:

$$EU_\upsilon(s_r) = EU_\upsilon(s_t), \quad \upsilon \in \{\mathcal{A}, \mathcal{B}\} \tag{7}$$

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

$$EU_{\mathcal{A}}(s_r) = q \cdot 0 + (1-q)\frac{1}{C_{\mathcal{A}r}} \tag{8}$$

$$EU_{\mathcal{B}}(s_r) = p \cdot 0 + (1-p)\frac{1}{C_{\mathcal{B}r}} \tag{9}$$

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

$$EU_{\mathcal{A}}(s_t) = q\frac{1}{C_{\mathcal{A}t}} + (1-q) \cdot 0 \tag{10}$$

$$EU_{\mathcal{B}}(s_t) = p\frac{1}{C_{\mathcal{B}t}} + (1-p) \cdot 0 \tag{11}$$

Setting (8) and (10) equal as in (7), then solve it to find the probability distribution $\grave{p} = \{p, 1-p\}$. Similarly, setting (9) and (11) equal as in (7), then solve it to find the probability distribution $\grave{q} = \{q, 1-q\}$ such as:

$$p = \frac{C_{\mathcal{A}t}}{C_{\mathcal{A}t} + C_{\mathcal{A}r}}, \quad 1-p = \frac{C_{\mathcal{A}r}}{C_{\mathcal{A}t} + C_{\mathcal{A}r}} \tag{12}$$

$$q = \frac{C_{\mathcal{B}t}}{C_{\mathcal{B}t} + C_{\mathcal{B}r}}, \quad 1-q = \frac{C_{\mathcal{B}r}}{C_{\mathcal{B}t} + C_{\mathcal{B}r}} \tag{13}$$

The players from $\mathcal{A}$ and $\mathcal{B}$ 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.

4.4.2. Analysis Evolutionary Stability of the Game's MSNE

Previously, we proved that the game solution is a Mixed Strategy Nash Equilibrium $(\grave{p}, \grave{q})$. Here, we analyze the evolutionary stability of Mixed Strategy Nash Equlibrium (MSNE) (i.e., $(\grave{p}, \grave{q})$) in our asymmetric routing game according to definition 4 of asymmetric evolutionary stable strategy [24] such as:

Definition 4: Defines $(\grave{p}, \grave{q})$ as a two-species evolutionary stable strategy [24] 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 Nash equilibrium $(\grave{p}, \grave{q})$ is a two-species evolutionary stable strategy.

Proof. First, we define the replicator equations, which are ruling the behavior of the system over time [25], 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:

$$\begin{aligned}\dot{p} &= p[(\frac{1-q}{C_{\mathcal{A}r}}) - (\frac{p(1-q)}{C_{\mathcal{A}r}} + \frac{(1-p)q}{C_{\mathcal{A}t}})] \\ &= p(1-p)(\frac{1-q}{C_{\mathcal{A}r}} - \frac{q}{C_{\mathcal{A}t}})\end{aligned} \tag{14}$$

$$\begin{aligned}\dot{q} &= q[(\frac{1-p}{C_{\mathcal{B}r}}) - (\frac{q(1-p)}{C_{\mathcal{B}r}} + \frac{(1-q)p}{C_{\mathcal{B}t}})] \\ &= q(1-q)(\frac{1-p}{C_{\mathcal{B}r}} - \frac{p}{C_{\mathcal{B}t}})\end{aligned} \tag{15}$$

Second, we need to find the stable fixed point for the two replicator equations. We have the MSNE point (i.e., equations (12) and (13)), which we calculated in 4.4.1. We proved how this point is a fixed point under the two replicator equations (14) and (15).

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., $(\frac{1-q}{C_{\mathcal{A}r}} - \frac{q}{C_{\mathcal{A}t}})$ and $(\frac{1-p}{C_{\mathcal{B}r}} - \frac{p}{C_{\mathcal{B}t}})$) in equations (14) and (15), respectively, should equal zero. Therefore, if we substitute the values of p and q from equations (12) and (13) with these last parts, we will get zero. As a result, $(\grave{p}, \grave{q})$ is a asymptotically stable fixed point for the replicator dynamic. Based on asymmetric ESS [24], our mixed strategy NE $(\grave{p}, \grave{q})$ is a two-species evolutionary stable strategy. □

4.4.3. Numerical Analysis of Evolutionary Stability for the Game's MSNE

For the sake of certainty, we will analyze the ESS for the proposed MSNE solution by satisfying the condition of the following theorem [24] numerically in this part.

Theorem[24]: $(\grave{p}, \grave{q})$ 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 interspecies interaction.

In our routing game, suppose two sensor nodes are picked randomly from two population (i.e., $\mathcal{A}$ and $\mathcal{B}$), 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 2 as: $C_{\mathcal{A}t} = 4, C_{\mathcal{A}r} = 2, C_{\mathcal{B}t} = 8$, and $C_{\mathcal{B}r} = 6$. 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. It is supposed that 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, it is assumed 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 [24], 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.

4.5. R-Hop Scenario and Replicator Dynamics

In this subsection, we provide a dynamic way to achieve the equilibria and extend our analysis to the R-Hop scenario for our evolutionary routing game according to the concept of replicator dynamics. We introduce the replicator dynamic model in order to show how the players, who repeatedly play the routing game, evolve their behavior at every stage of the game. The populations learn with each strategy's interaction until they reach a stable state. Replicator dynamics describe the populations' behavior of sharing associated with different strategies, that evolve over time [25]. In the following equations, we derive the replicator dynamics of our routing game framework with r hops.

In the following, we introduce fitness defined by our replicator dynamic equations. From the above sections 4.4, let's consider two populations of interacting nodes. Each time nodes from one population (row players $\mathcal{A}$) are randomly paired with nodes from the other population (column players $\mathcal{B}$). All players have a set of hops $\mathcal{R}$, and strategy $s_r \in \mathcal{S}$ 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 proportions equals to 1 (i.e., $\sum_{i=1}^{r} p_i = 1$ and $\sum_{i=1}^{r} q_i = 1$) as described in section 4.4. 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 $\mathcal{U} = \{u_1, u_2, u_3, ...u_r\}$ 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 ($\mathcal{A}$) is given by:

$$u_r = u_0 + \sum_{t=1}^{|R|} q_r u(s_r, s_t), \quad \forall r, t \in \mathcal{R} \tag{16}$$

The payoff of selecting hop r strategy s_r for column player ($\mathcal{B}$) is given by:

$$u_r = u_0 + \sum_{t=1}^{|R|} p_r u(s_r, s_t), \quad \forall r, t \in \mathcal{R} \tag{17}$$

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

$$\overline{u_{\mathcal{A}}} = \sum_{y=1}^{r} p_y(q_y u_y), \quad \forall y \in \mathcal{R} \tag{18}$$

$$\overline{u_{\mathcal{B}}} = \sum_{y=1}^{r} q_y(p_y u_y), \quad \forall y \in \mathcal{R} \tag{19}$$

Algorithm: Replicator Dynamics

```
Results: Converge the startegy of selection hops to ESS;
Initialization: Set the available hops 𝓡 and their related utilities
(payoffs) 𝓤, intial fitness u_0, population distribution p_r and q_r, hop
utilities u_r ;
begin
    for evrey time slot of the game do
        At current time caculate:
            1. average payoff of selecting hop r for sensors
               population (i.e.,𝓐 and 𝓑) at current time
               (equations (16-17))
            2. Calculate average fitness ū for entire sensor
               nodes population (equations (18-19))
            3. Calculate hop selection startegies for next time
               slot (equations (20-21)) ;
    end
end
```

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

$$\check{p_r} = p_r + \frac{q_r(u_r - \overline{u_{\mathcal{B}}})}{\overline{u_{\mathcal{B}}}} \tag{20}$$

$$\check{q_r} = q_r + \frac{p_r(u_r - \overline{u_{\mathcal{A}}})}{\overline{u_{\mathcal{A}}}} \tag{21}$$

The proportion of sensors selecting hop r in the next time slot will be either increased or decreased according to the 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. Algorithm shows the summary of the proposed replicator dynamics. The time complexity of the proposed algorithm is $\mathcal{O}(n)$.

5. Fairness Analysis

Fairness is an important performance criteria in routing protocols for resource sharing. Janin's fairness index [2] is one of the efficient measurements to determine the fair share of the system's resources. In our proposed game, we analyze the fairness of both pure and mixed solutions of the Nash Equilibria, and consider the case of 2-hop scenario of the routing sharing game for the sake of clarity. Furthermore, the same concept will be applied in the case of R-hop scenario. Measuring of the fairness of the derived Nash equlibria, and the guaranteeing of the provision of the same utilities to all users, is achieved by following Jain's equation:

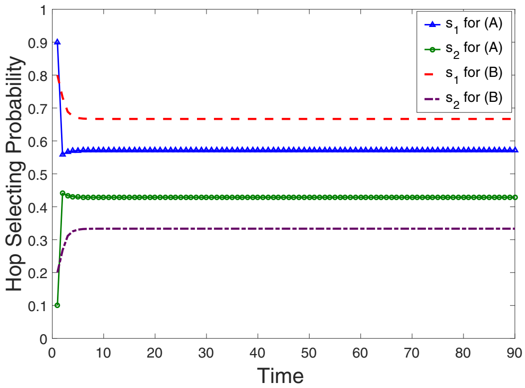
$$\mathcal{J}(u_1, u_2, u_3, ..., u_N) = \frac{(\sum_{i=1}^{\mathcal{N}} u_i)^2}{\mathcal{N} \cdot \sum_{i=1}^{\mathcal{N}} {u_i}^2} \tag{22}$$

where $\mathcal{N}$ is the number of sensor nodes and the utility of allocating the hops is given by u_i. The index of the equation are bounded between 0 (worst case and totally unfair system) and 1 (best case and perfectly fair system). We analyze the fairness of the solutions of the game as follows:

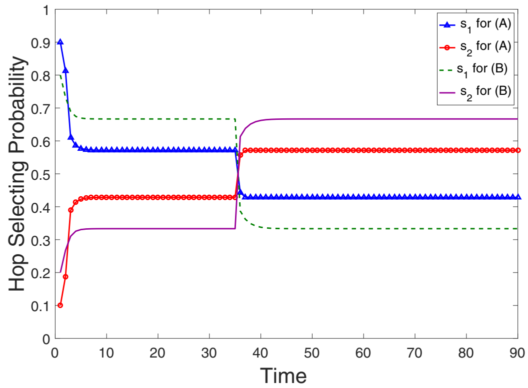
1. As we proved earlier that the Pure Strategy Nash Equilibrium (PSNE) for the evolutionary routing anti-coordination game is the pair of strategy (s_r, s_t) and (s_t, s_r). According to our previously named assumption for 2-hop scenario, transmitting the packet through hop r will provide a higher payoff than transmitting the packet through hop t. This means that $u_r \neq u_t$ and the distribution of payoffs for the ratio in equation (22) are unequal and less than 1. Also, one player in the game always gets a smaller payoff than the other. Thus, PSNE is not a fair solution because it does not result in equal payoff for all nodes.
2. Another finding for the game is that a Mixed Strategy Nash Equilibrium (MSNE) is the probability distribution $\grave{p}, \grave{q}$ (collection of weights) computed by equations (12) and (13). Based on definition 3 of MSNE, the expected utility of the strategies for all players are equal even though the costs of transmitting the packet through the hops are different, and that makes the opponents indifferent about their choice of strategy. Having equal payoffs u_i will maximize the value of the equation (22) which equals 1. As a result, the MSNE's resource distribution is fair.

6. Simulation Model and Results

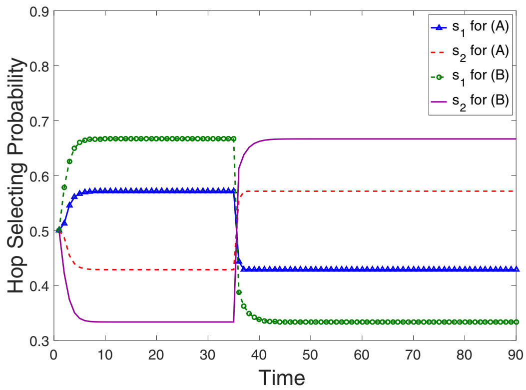
In order to analyze and study the effects of applying the proposed routing game model for multiple routes in a wireless sensor network, we have conducted simulation experiments. We study the behavior of selecting strategies when sensor nodes do not cooperate with each other, and how the hop selection strategies converge into evolutionary stable states. The empirical analysis of our evolutionary routing game consists of three aspects: First, we will demonstrate the results of our experiments in which sensor nodes have only two available hops to transmit the data packets, show the impact of implementing Replicator Dynamics, and how the strategies converge to an evolutionarily stable state. Second, we will present the results of simulation under dynamic network conditions, and show that the evolutionary game is able to converge to a new ESS. A diversity of wireless network conditions will result in different transmitting costs. Node failure due to changing conditions can occur for various reasons, such as uncontrolled environment, battery depletion, or a communication failure. Node failure will in turn result in the changes of the cost of routing paths. Also, the mobility of the nodes in a WSN is another possible cause for the dynamic changes of the cost of routing paths. Finally, we will provide several experimental results with multiple hops available (i.e., 3 and 4 heterogeneous hops) as well.



(a)



(b)

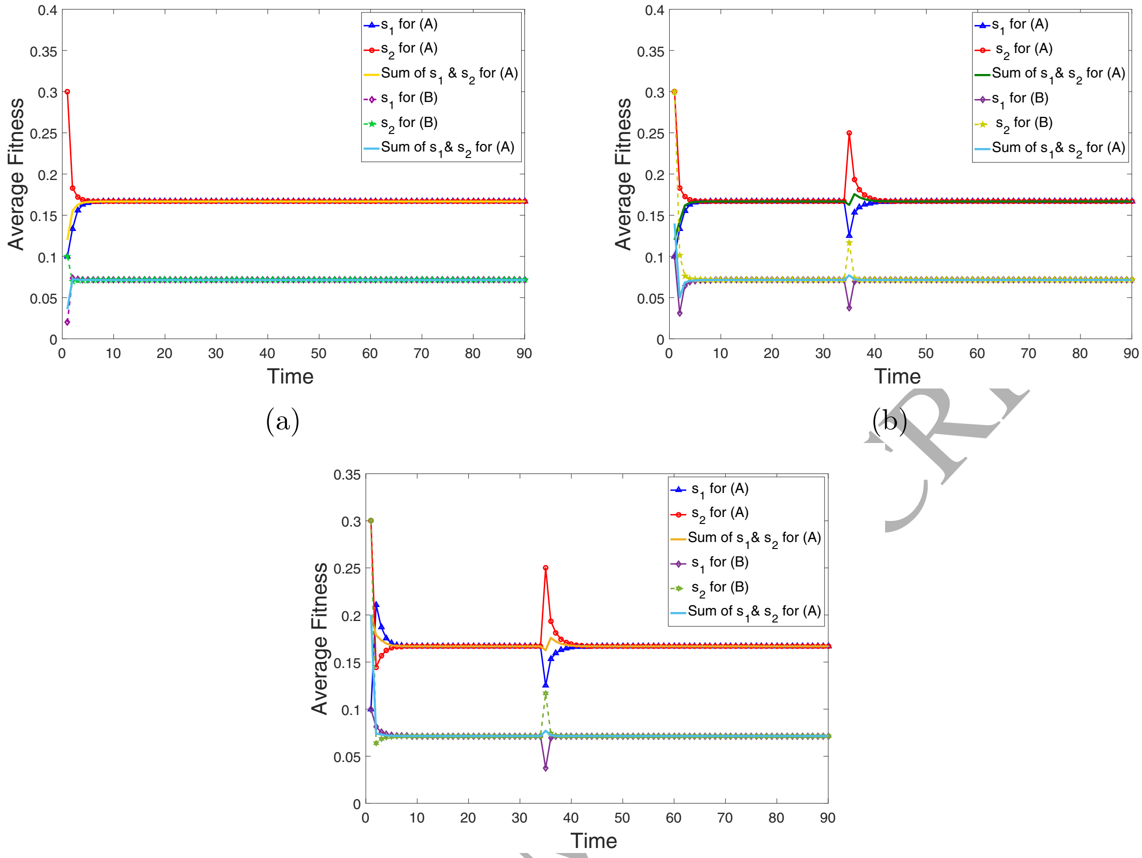


(c)

Figure 1: Proportion of selecting strategies for both population (i.e.,$\mathcal{A}$ & $\mathcal{B}$) when number of available hops for forwarding is $R = 2$. (a) Hop selecting probability when the initial probabilities are unequal. (b) Hop selecting probability when the initial probabilities under changing conditions, (i.e., cost of forwarding through hop 1 higher than hop 2 at t=350, when initial probabilities are unequal, and (c) when initial probabilities are equal.

6.1. Experiment Results

Figures 1 and 2 represent the scenario of having 2 hops available to forward the data packet. Figure 1a shows the behavior of selecting one of two available hops with some probability where a transmission through hop 1 produces a lower cost than a transmission through hop 2. The probabilities of selecting the hops are modified depending on average fitness, which is gained from strategic interaction in subsequent time slots as shown in Figure 2a. Moreover, in our simulation, any positive value for the utility function would be commutable and feasible. In Figures 1 and 2, the cost function of selecting the hops are assumed to be ($u_{1\mathcal{A}} = 0.5$ & $u_{2\mathcal{A}} = 0.25$) and ($u_{1\mathcal{B}} = 0.166$ & $u_{2\mathcal{B}} = 0.125$) for hops 1 and 2, respectively. MSNE is $\grave{p} = \{0.57, 0.43\}$ and $\grave{q} = \{0.66, 0.33\}$ for population $\mathcal{A}$ and $\mathcal{B}$, respectively.



(a) (b) (c)

Figure 2: Related Average fitness of selecting strategies in Fig. 1 for both population (i.e.,$\mathcal{A}$ & $\mathcal{B}$) when number of available hops for forwarding is $R = 2$. (a) Average and weighted sum of fitness when the initial probabilities are unequal. (b) Related average fitness under changing conditions (i.e., cost of forwarding through hop 1 higher than hop 2 at t=35) when initial probabilities are unequal, and (c) when initial probabilities are equal.

First, let us consider the scenario where some sensor nodes 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 Figures 1a and 2a. This is because forwarding through the lower cost hop by more nodes results in collisions and thus gains a zero payoff. As a result, the hop selecting probability of greedy nodes decreases in $time = 2$ (as shown in Figure 1a and their payoff increases at that time, which is still less than the average payoffs of the entire population as shown in Figure 2a). In a similar yet opposite scenario, 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 is modified until the system becomes stable

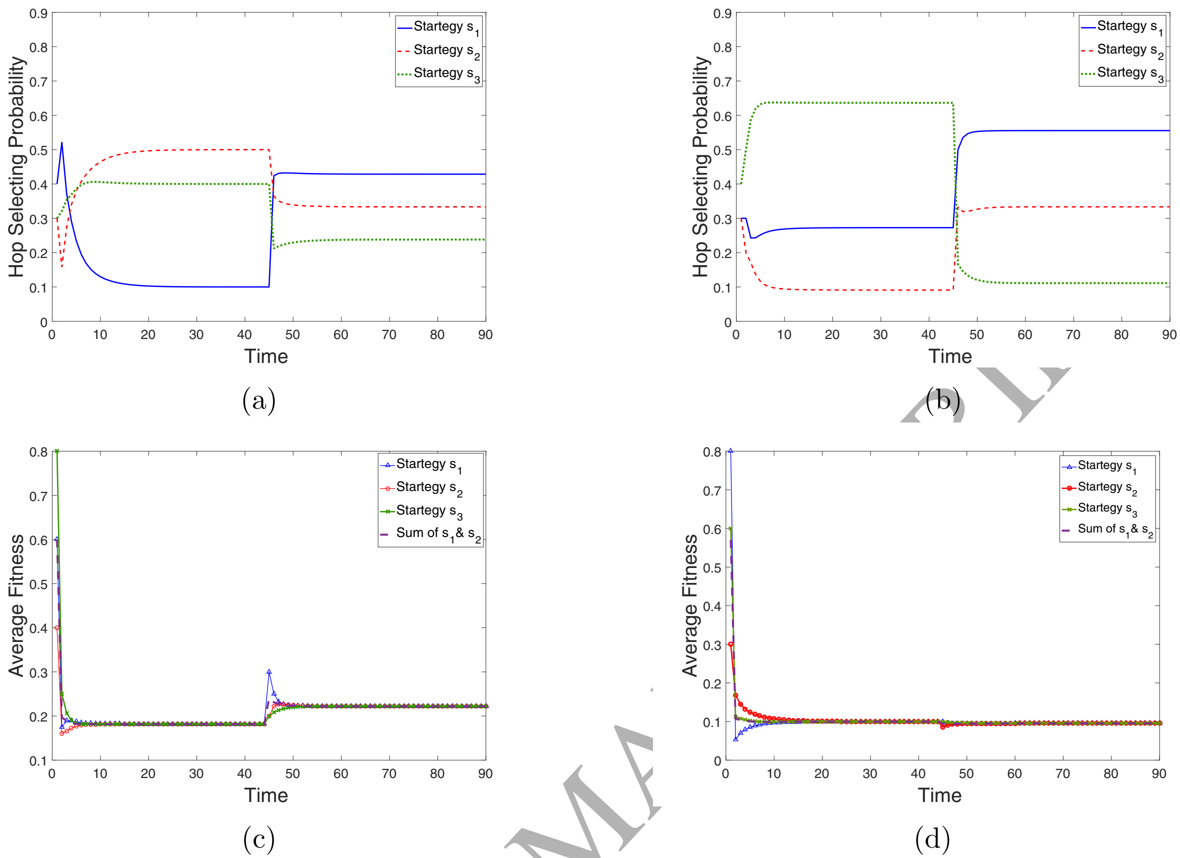


Figure 3: Proportion of selecting strategies and related average fitness for both population (i.e.,$\mathcal{A}$ & $\mathcal{B}$) when number of available hops for forwarding is $R = 3$. (a) and (b) Hop selecting probability when under changing conditions and initial probabilities are unequal for population $\mathcal{A}$ and $\mathcal{B}$, respectively. (b) and (d) Related average.

and reaches the ESS, (i.e., time=10 in the case of figure 1a). The amount of time taken to converge to ESS is important in determining energy wastage in sensor networks due to the collision and loss of data.

Figures 1b and 2b demonstrate the case of changing network conditions, where the cost of transmitting through hop 2 becomes less than through hop 1, and hop 2 becomes more preferable to be selected from the nodes at $t = 35$. The hop selecting probability still converges to a new ESS. Similar observations of convergence to ESS can be found in the case where initial hop selection probabilities are equal and the network conditions are changed as shown in Figures 1c and 2c.

The previous experiment (i.e., figures 1 and 2) demonstrated that the fairness of probability distribution of selecting the two hops are achieved only when the probability of selecting the two hops equals $p_1 = 0.57, p_2 = 0.43, q_1 = 0.66$, and $q_2 = 0.33$ as in figure 1a, for both population, respectively, which is the game's MSNE as well as the ESS. Next, in order to present the robustness of our game, we conduct the experiment under changing network

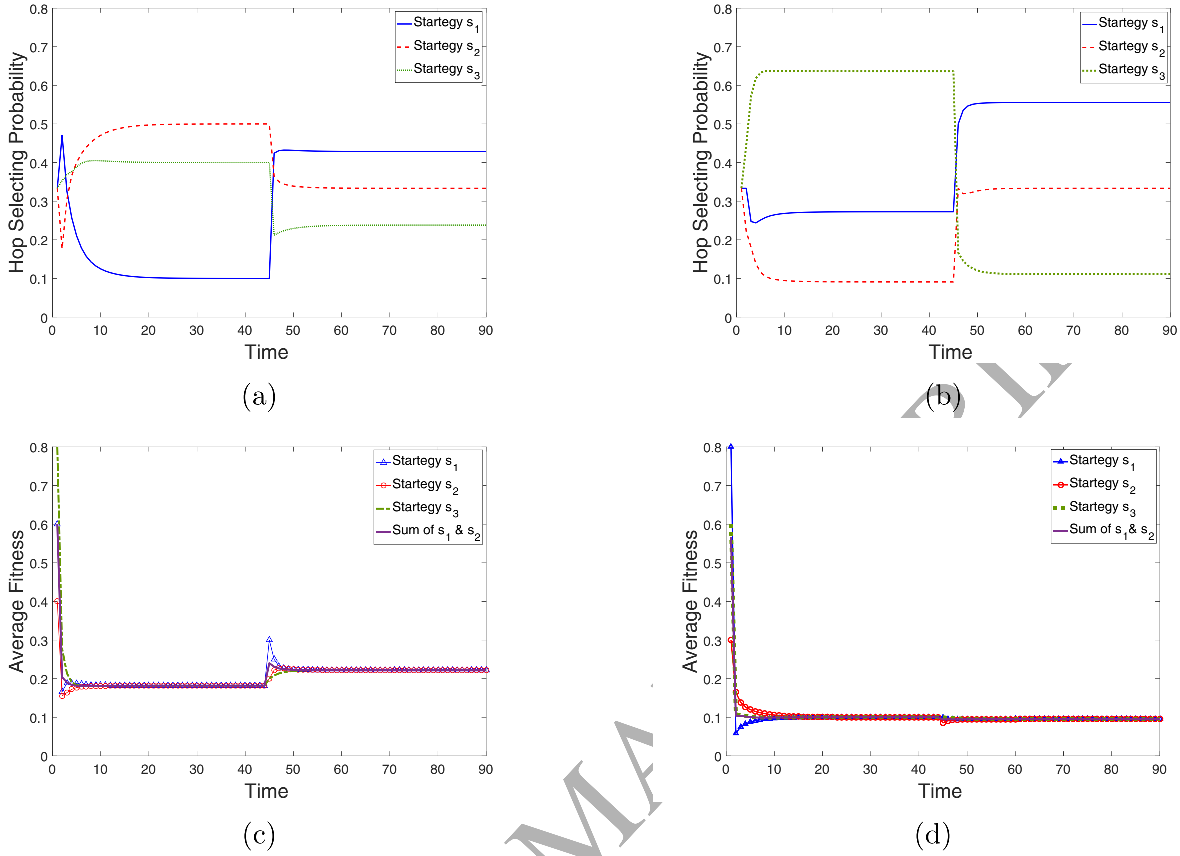


Figure 4: Proportion of selecting strategies and Related Average fitness for both population (i.e.,$\mathcal{A}$ & $\mathcal{B}$) when number of available hops for forwarding is $R = 3$. (a) and (b) Hop selecting probability when the initial probabilities under changing conditions and initial probabilities are equal for population $\mathcal{A}$ and $\mathcal{B}$, respectively. (b) and (d) Related average.

condition and with equal and unequal initial probabilities for the player as well. The results show that the strategies are still able to converge to ESS as shown in figures 1b,2b,1c and 2c.

Figures 3 and 4 exhibit the performance of the system and the convergence of hop selection probabilities to ESS in case of multi-hops (i.e., 3 hops), where each hop has a different transmitting cost for each population ($\mathcal{A}$ and $\mathcal{B}$). Moreover, Figures 3 and 4 show the behavior of nodes when the network conditions changed (i.e., changed at the time $t = 45$) in our proposed evolutionary game, and when the initial probabilities are unequal and equal, receptively. Figures 3a, 3c, 4a, and 4c show the convergence probabilities of selecting 3 hops to ESS and related average fitness by population $\mathcal{A}$. Figures 3b, 3d, 4b, and 4d show the convergence probabilities of selecting 3 hops to ESS and related average fitness by population $\mathcal{B}$. For example, at the beginning in figure 3a, the game converges to ESS for population $\mathcal{A}$ 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 are 0.2, 0.9 and 0.5, respectively. At $time = 45$, the network

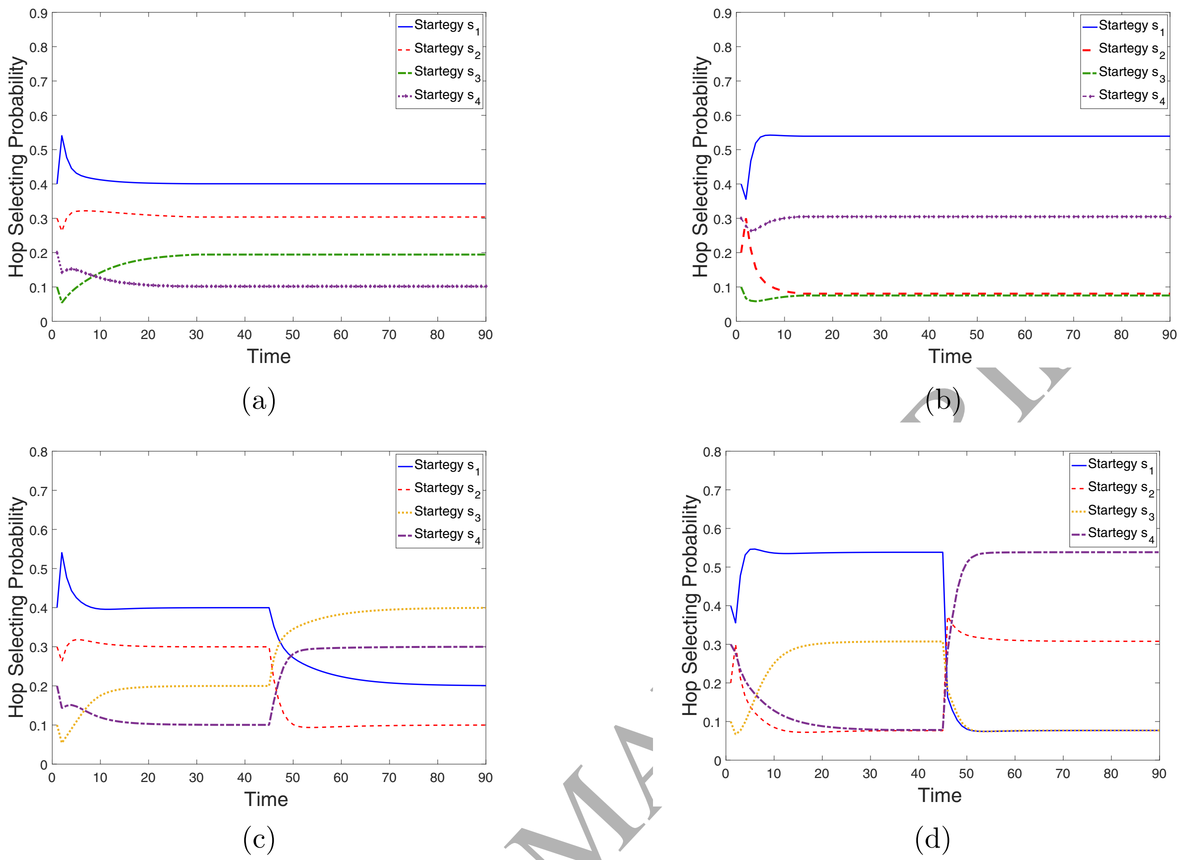


Figure 5: Proportion of selecting strategies for both population (i.e.,$\mathcal{A}$ & $\mathcal{B}$) when number of available hops for forwarding is $R = 4$. (a) and (b) Hop selecting probability for population $\mathcal{A}$ and $\mathcal{B}$, respectively. (b) and (d) under changing condition of network (i.e., $t = 45$).

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 are changed to 0.5, 0.3 and 0.2, respectively. Similarly in Figure 3b, the network conditions are 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.

Figure 5 shows the convergence of hop selection probabilities to ESS in case of having 4 hops available, and their utilities are varied according to transmitting cost. Figures 5a and 5b illustrate the converges to the ESS for population $\mathcal{A}$ and $\mathcal{B}$, respectively. We notice that the rate of convergence to ESS is affected by the number of hops, variety of the transmitting cost, and the initial access probabilities of players, where the convergence rate to ESS decreases when the number of hops increases. Figures 5c and 5d illustrate the converges to the ESS under new network conditions for population $\mathcal{A}$ and $\mathcal{B}$, respectively. As a result, the system will be able to reach stability with 2-hop and multi-hops of different transmitting costs, even under the changing of network conditions and with varied values of initial access probabilities.

7. Conclusion

The existence of a heterogeneous set of paths for sensor nodes in WSNs raises many technical issues related to data routing, where some routes become preferable for the nodes and lead to an imbalance in contention. Furthermore, some routes may be exhausted more quickly than others in long-term routing. In this paper, we designed an evolutionary routing game to reduce the load and avoid collisions on the most used routes in a distributed manner. We derived the equilibrium strategies of selecting the next hop in the routing game, and we proved that the Mixed Strategy Nash Equilibrium derived in the game is an Evolutionary Stable Strategy (ESS) and achieves fairness as well. In addition in our proposed new evolutionary game, we derived the mechanism of Replicator Dynamics, where the players learn and modify their strategies, based on the strategies' interaction in a given unit of time, in order to eventually achieve the solution.

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