Evolution of Cooperation in Multi-Class Wireless Sensor Networks

Garth V. Crosby, Niki Pissinou
Florida International University,
College of Engineering and Computing,
Telecommunications and Information Technology Institute
Miami, Florida
garth.crosby1@fiu.edu ,pissinou@fiu.edu

***Abstract*-Cooperation among nodes is essential for the reliable routing of packets in large scale wireless sensor networks from nodes to base station. Most of the previous works have assumed a single governing authority with full cooperation among nodes. The assumption of node cooperation, however, cannot be applied to wireless sensor networks (WSNs) with more than one governing authority. In this paper, we introduce the concept of multi-class wireless sensor networks where each class is governed by a different authority. We study the evolution of cooperation in static and mobile multi-class wireless sensor networks using Evolutionary Game Theory which has, to the best of our knowledge, never been attempted before. We then propose a novel localized distributive algorithm we call the Patient Grim Strategy (PGS), and demonstrate that it provides a Nash equilibrium solution to the game theoretic problem of cooperation in multi-class static wireless sensor networks. Our simulation results show that in static multi-class WSNs populations playing the prisoner's dilemma, significant propensities to cooperate can evolve.**

Keywords-wireless sensor network; cooperation; evolutionary game theory; muti-class; patient grim strategy.

I. INTRODUCTION

Wireless sensor nodes are miniature communication, sensing and data processing devices. Their application include military, factory instrumentation, climate control, environmental monitoring, and building safety [1, 2]. We foresee a future where sensor networks will go beyond the boundaries of a single authority, where groups of people/institutions with common interest collaborate. In such situations, negotiations need to take place to prevent the nodes of one user from being depleted of power while the other users' networks remain relatively intact, and their nodes with ample battery power. If we assume that all the users are rational and thus act in their own best interest, then they may drop all the packets originated and destined to other networks that they are asked to relay. This would lead to a breakdown in cooperation and a significant decrease in throughput. To sustain cooperation, rational users must stand to benefit more than they stand to lose in interactions that require cooperation, unless cooperation is enforced via a global policy. If a global policy exists, then users that deviate from the rules would be punished more severely than any loss they would incur in cooperating; thus they would choose to cooperate. However, in this context, the distributive nature of wireless sensor networks, that is, the lack of centralized administration, and the multi-governing authorities make this very challenging, if not infeasible.

Recently, game theoretical analysis and modeling of ad hoc networks have attracted an increasing number of researchers [3, 4] . Classical game theory, however, relies on several assumptions that do not seem appropriate for ad hoc and sensor networks. In particular, players are assumed to have complete information about the game and also about the behavior of opponents. In addition, the players are assumed to be rational. For sensor networks this would imply that the nodes do a fair bit of computing to calculate and store all the possible strategies and actions of themselves and other nodes. Alternatively, if the processing is done by the more powerful sink then each node would be required to frequently communicate with the sink. Either way, this would be impractical given the limited memory and power capacities of wireless sensor nodes.

We believe that a more appropriate model can be developed using Evolutionary game theory [5]. In this approach the assumption of rationality, knowledge of game, and complete information of opponents' behavior are relaxed. Only local information is required. The main assumption is that players learn how to perform well in the game by experience or by being preprogrammed with a 'set of actions to perform'. Over time, the players have the chance to maximize their personal benefit by reacting to simple observation.

In this paper, we study a finite but large population of multi-class wireless sensor networks. We define a model and use the prisoner dilemma game to study the evolution of cooperation in static and mobile multi-class WSNs. Our contributions are: (i) we determined some conditions under which spatially dispersed multi-class wireless sensor networks exhibit tendencies to cooperate, and (ii) we propose a localized distributed and scalable algorithm we call the Patient

0742-1303/07 $25.00 © 2007 IEEE
DOI 10.1109/LCN.2007.149

Grim Strategy (PGS), which enforces cooperation in wireless sensor networks.

The remainder of the paper is organized as follows. In the next section, we discuss related works focusing our attention on mechanisms that stimulate cooperation. In section 3, we present our model and our main assumptions. This is followed by our game in section 4. In section 5, we present some analytical results. Our Patient Grim Strategy is presented in section 6. We then present our simulation in section 7. We draw some conclusions in section 8.

II. RELATED WORK

The operation of ad hoc networks depends on the cooperation of participating nodes. Since nodes have limited resources, in particular battery power, cooperation may come at a significant expense. In addition, since in many applications each node is governed by a different authority (user) cooperation cannot be assumed to exist. It is reasonable to assume that each node has the goal of strategically maximizing its own benefit by utilizing network services while simultaneously minimizing its contribution to the network. This has encouraged researchers to use game theory as a tool in modeling cooperation among nodes in wireless ad hoc networks as strategic interactions among rational players.

While the topic of cooperation in wireless ad hoc networks has been addressed in several works only a few attempts to address the issue in wireless sensor networks. Our work is closest in nature to [6] . In [6], Felegyhazi *et al.* introduced the concept of multi-domain sensor networks. The authors proposed a game-theoretic model to investigate the impact of cooperation and show the conditions under which cooperation is the best strategy. Our work differs in several ways. Firstly, we used evolutionary game theory to investigate cooperation in multi-class sensor networks, which we believe was, to the best of our knowledge, never considered before. Secondly, we investigate the effect of mobility versus a fixed network topology on cooperation among nodes. Finally, we propose a novel localized cooperation enforcement protocol, Patient Grim Strategy. Our protocol belongs to the class of enforcement protocol that discourages uncooperative behavior through punishment.

A.. Mechanisms to Motivate Cooperation

There are generally two approaches to motivate cooperation among network nodes: (i) punishment mechanisms and (ii) incentive mechanisms. Works that have employed punishment generally use a reputation mechanism to detect selfish or misbehaving nodes and to deny these nodes future network services. Incentive mechanism schemes include methods that reward cooperative nodes with some form of payment. In addition, a few works have explored the possibility of spontaneous cooperation, that is, cooperation that emerges without any incentive or punishment. Following is an overview of these approaches.

Marti *et al.* [7] proposed mechanisms to consider an ad hoc network with misbehaving or un-cooperating nodes that initially agree to forward packets but fail to do so. The authors proposed two mechanisms to mitigate this problem. The first, called *watchdog*, identifies misbehaving nodes, and the other, called *pathrater*, helps routing protocols avoid these misbehaving or uncooperative nodes. However, their solution fails to punish misbehaving nodes, and therefore presents no incentive for nodes to cooperate. In addressing this shortcoming, Buchegger *et al.* [8] proposed a reputation based system where nodes observe the behavior of each other and store the information locally. Periodically, this information is distributed in reputation reports. According to their results, nodes are able to selectively deny forwarding packets from misbehaving or uncooperative nodes; thus facilitating the punishment of un-cooperative nodes.

A reputation-based framework for wireless sensor network that utilizes Bayesian formulation and beta distribution is proposed in [9]. Watchdog mechanism resides in the middleware of each node and collects observable information. Second hand information is also included in the statistical computation of reputation. This information is gathered from nodes in the neighborhood. Direct observation and second hand information together facilitates a decentralized reputation based systems. A trust based system is developed using reputation that facilitates punishment of non-cooperating (malicious) nodes by denying them access to network resources.

Levin [10] proposes a new mechanism: punishment via channel jamming. The author argues that isolation does not always ensure cooperation. On the other hand, jamming, though seemingly malicious, is a viable means by which to enforce cooperation of each node in the system, even when there are neighbors acting in a collusive manner by communicating only with one another. As the author himself points out, the price of jamming, if not engineered in a careful manner can be high, resulting in a significant loss of system efficiency.

Mahajan *et al.* [11] proposed *Catch*, a protocol that uses anonymous messaging to detect free riders, i.e. nodes that send their own packets but do not forward packets from others, and disconnect them from the rest of the network. *Catch* uses an existing majority of cooperative nodes to collectively discourage a minority of selfish nodes from free riding. According to the authors, *Catch* assures that cooperation is an evolutionary stable strategy.

Incentive mechanisms to stimulate cooperation are proposed in [12-14]. In these mechanisms if a node wants to send its own packets, it has to pay. However, if a node forwards a packet for the benefit of another node, it is paid. These schemes rely on a trusted central authority or tamper-proof hardware to ensure the integrity of the virtual currency, and to redistribute wealth so that even nodes that are not in a position to forward for others can send their packets. A major drawback of these schemes is that incentives fail to encourage forwarding in nodes that have very little data of their own to send. This can lead to a disconnected network when light-senders are located at strategic points in the topology of the network. Another drawback is that further research is needed to develop trusted and efficient mechanisms to ensure the generation of high integrity virtual currencies.

Spontaneous cooperation is investigated by Srinivasan et al [3]. This work focuses on the energy-efficient aspects of cooperation without any incentive mechanism. Urpi et al [15] propose a general framework for cooperation without incentive. Felegyhazi et al [4] concentrated on the connection between the network topology and the possible existence of cooperation. They proposed a model based on game theory and graph theory to investigate equilibrium conditions of packet forwarding strategies. We agree with their conclusion that in static ad hoc networks- where the relationships between the nodes are likely to be stable- cooperation needs to be encouraged.

III. MODEL ASSUMPTIONS

We consider a large scale deployment of a wireless sensor network with n classes, where n >>1. We define *class* as follows: *a homogenous group of wireless sensor nodes that have localized control, total cooperation among nodes, and a single governing authority*. Let us denote a single class as c_i and the set of all classes by C, i.e. $C=\{c_1, c_2, c_3, ...c_n\}$. We assume the network to be an arbitrary, connected graph, $G=(V, E)$, of selfish classes, where each vertex corresponds to a class in the network. By *selfish* we mean that any $c_i \in C$ will act strategically to maximize its benefit over time. Edge(c_i, c_j) is in E if, and only if, c_i and c_j are one hop neighbors. We consider two classes as one hop neighbors if any two nodes, one from each class, are within transmission range.

In our model G is strongly connected, that is, any two non-neighboring classes $c_i, c_j \in C$ can communicate via multi-hop routing. This means that packets from the source to the destination are forwarded by intermediate nodes. We assume that each class $c_i \in C$ knows its active connections and acts strategically to optimize goodput across these connections.

In dealing with interclass relaying, that is, data-forwarding between classes, the class either cooperate or defect. A class cooperates if it relays the packets in response to a data forwarding request. If it drops the packets, then it defects. We limit our study to the forwarding of packets between classes in a multi-class wireless sensor network.

We assume that all communication packets are equal in size. In transmitting or retransmitting packets, the classes expend battery power equivalent to a disincentive in the amount β and gain an incentive for cooperation in the amount γ. If classes refuse to cooperate (retransmit) they gain ϕ and there is no cost to them. We ignore the power used up in receiving and listening. Ignoring these should have no effect on our model if we assume that these losses are equally distributed in our population. The following inequality holds: $\gamma > \beta > 0$

We assume that the sensor nodes in a *class* all operate in the promiscuous mode and are able to determine the response of neighboring *classes* in all interactions through monitoring techniques such as watchdog [7]. We assume that the communication channel is bidirectional and no loss occurs due to noise. Therefore, any loss of packet is as a result of defection. A class is considered inactive on the depletion of the battery of its first wireless sensor node.

We investigate two scenarios: (i) *scenario 1*: packet forwarding between mobile classes, and (ii) *scenario 2*: packet forwarding between spatially dispersed stationary classes. We then examine our PGS algorithm.

IV. GAME

Motivated by the iterated prisoner dilemma game, we develop two games; one for each of the scenarios that were previously mentioned. Firstly, we present the common parameters of both games. We then discuss the games separately.

Evolutionary game theory [5] provides an appropriate tool to model strategic decision situations. In our system, the authorities have to decide, whether to cooperate or not in the forwarding of packets between classes of wireless sensor nodes. We model this as a non-cooperative iterated N-player game g $=(P, S, U)$, where P denotes the set of players, S the set of strategies and U is the set of utility functions or payoff. We assume that the game is infinite, this can be approximated if there is a very small probability the game may end in any round. In other words, the players are unaware of the ending of the game. The game ends when only two classes remain active. This is so because we are concerning ourselves with packet forwarding between classes, which is only necessary in a network with more than two classes.

We assume time is divided into time units called *time slots*. Once per time slot t the sensors of each class send packets to be forwarded to a neighboring class. In each time slot, the players decide whether to cooperate or defect. We assume that each time slot is long enough to facilitate the delivery of all the packets, and the decision making processes.

For consistency with commonly used notation, we develop our payoff matrix as follows. For mutual cooperation, each player gets the reward R, where R= γ-β. For mutual defection each player gets the punishment P, where P=0. If one player cooperates and the other defects, the cooperator is left with the suckers payoff, S, where S= -β while the defector gets away with the temptation to defect T, where T=γ. It is clear that T>R>P>S. We assume that 2R> T + S i.e. in repeated encounters mutual cooperation returns the highest collective payoff.

		Class c_j	
		Cooperate	Defect
Class c_i	Cooperate	(R, R)	(S, T)
	Defect	(T, S)	(P, P)

Figure 1. Payoff matrix for wireless sensor classes c_i and c_j, where $i \neq j$ and $c_i, c_j \in C$

If we let cooperate be denoted by a_1 and defect by a_2 then the action set is $A=\{a_1, a_2\}$. Theoretically, players could seek several combination of action over time. However, we limit our study to either of the following two strategies.

i) $S_1=\{a_1, a_1, a_1, ...\}$ *i.e. a*lways cooperate

ii) $S_2=\{a_2, a_2, a_2, ...\}$ *i.e. a*lways defect

Since we are primarily using Evolutionary game theory in our investigation we assume that the sensors in all the classes are preprogrammed with one of these strategies.

A.. Scenario 1: Packet Forwarding between Mobile Classes

In this scenario, the game modeled is the iterated N player prisoner dilemma game. We note the following assumptions:

(i) the game is infinite

(ii) players randomly interact with other players

(iii) the game is symmetrical, i.e. players have mutual interest in having their packet forwarded by the other

B. Scenario 2: Packet Forwarding between Spatially Dispersed Stationary Classes

The iterated N-player prisoner dilemma game is an effective model for many situations that involve strategic decision making. Like most N-player game it is based on the following assumptions:

(i) players randomly interact with other players

(ii) the game is symmetrical

However, these assumptions may not apply to many ad hoc packet forwarding games. We can appropriately modify these games to be suitable for networking conditions by the inclusion of additional parameters [16]. In this respect, we extend our game and redefine it as g=(P,S,U, G) where G, the additional parameter, denotes the graph G= (V,E). This means that games are only played between a pair of classes c_i and c_j if $(c_i, c_j) \in E$ i.e. if c_i and c_j are neighbors. For comparative purposes with our previous scenario we maintain the assumption of symmetry. Nonetheless, we note that in ad hoc and sensor networks some neighbors' interests may be asymmetric.

V. ANALYSIS

We now investigate the evolution of cooperation in a large population of wireless sensor classes with cooperators and defectors.

A.. Scenario 1: Packet Forwarding between Mobile Classes

Since the population is large, the replicator dynamics can be used to model the population playing the iterated N-player prisoner dilemma. In this case, we can represent the state of the population by noting what proportion follows each strategy. Let p_c and p_d denote these proportions. Also, let us denote the average fitness (payoff) of cooperators and defectors by F_C and F_D, respectively, while $\overline{F}$ denote the average fitness of the entire population. Let $\Delta F(s_c,s_d)$ denote the change in fitness for a class following strategy s_c (COOPERATE) against an opponent following strategy s_d (DEFECT). Suppose that each class in the population has an initial fitness of F_0. Then the expected fitness of Cooperating and Defecting can be expressed as:

$$\begin{aligned} F_C &= F_0 + p_c\Delta F(s_c,s_c) + p_d\Delta F(s_c,s_d) \\ &= F_0 + p_cR + p_dS \end{aligned} \tag{1}$$

and

$$\begin{aligned} F_D &= F_0 + p_c\Delta F(s_d,s_c) + p_d\Delta F(s_d,s_d) \\ &= F_0 + p_cT + p_dP \end{aligned} \tag{2}$$

Since in the payoff matrix for the prisoner dilemma game $T>R$ and $P>S$, it follows that $F_D>F_C$ and hence $F_D> \overline{F} > F_C$. Therefore,

$$\frac{F_D - \overline{F}}{\overline{F}} > 0 \text{ , and} \tag{3}$$

$$\frac{F_C - \overline{F}}{\overline{F}} < 0 \tag{4}$$

The strategy frequencies for Defect and Cooperate in the next generation are given by

$$p_d / dt = p_d . \frac{F_D - \overline{F}}{\overline{F}} \tag{5}$$

and,

$$p_c / dt = p_c . \frac{F_C - \overline{F}}{\overline{F}} \tag{6}$$

respectively. Thus, it is clear that over time the proportion of the population choosing the strategy COOPERATE eventually becomes extinct. The only stable strategy is DEFECT.

B. Scenario 2:Packet Forwarding between Spatially Dispersed Stationary Classes

In this scenario, we use simulation to validate our findings. Our results, which are discussed in detail in section VII part B, show that significant propensities to cooperate can evolve among spatially dispersed stationary wireless sensor classes. In spatial settings wireless sensor classes with a greater willingness to cooperate can thrive by forming clusters among themselves, and thus reducing exploitation by less cooperative classes.

VI. PATIENT GRIM STRATEGY

We now introduce our Patient Grim Strategy. We consider a spatially dispersed large population of stationary wireless sensor classes playing the prisoner's dilemma with the payoff matrix as shown in figure 1. We assume that time is slotted and each slot is independent of all others. The payoff to each is the sum of the payoffs over all periods, weighted by a discount factor δ, with 0< δ <1. We assume that each class is playing our Patient Grim Strategy. The Patient Grim Strategy is defined as follows: *cooperate and continue cooperating until the other player defects n times (* $n \geq 0$ *), then defect forever*. This is an adaptation of the popular Grim Strategy. We propose that this strategy can enforce cooperation in spatially dispersed wireless sensor classes playing the iterated N-player prisoner's dilemma.

Theorem: The cooperative solution can be achieved as a Nash Equilibrium of the infinite repeated game if δ is sufficiently close to unity and each player uses the Patient Grim Strategy.

Proof: We use the fact that for any discount factor δ with 0< δ <1,

$$1 + \delta + \delta^2 + \dots\dots\dots = 1/(1-\delta) \qquad (7)$$

This follows from

$$\begin{aligned} x &= 1 + \delta + \delta^2 + \dots\dots\dots \\ &= 1 + \delta(1 + \delta + \delta^2 + \dots\dots) = 1 + \delta x \end{aligned} \qquad (8)$$

We can simplify by considering the interaction between a pair of classes. Since all classes play the Patient Grim Strategy then, the payoff to each is R/(1-δ). Suppose a player uses another strategy. This must involve cooperating for a number (possibly zero) of periods, then defecting forever. Once a player defects *n* times, where 0< n < ∞, his opponent defects forever, therefore, the player gets at most zero payoff in all the following rounds. His best response would therefore be to also defect forever. Since the game is infinite this is a significant loss of potential payoffs.

Consider the game from the time *t* at which the first player defects. Let that be at *t*=0. The node's maximum payoff from defection is *n* * T, afterwards the nodes receive at most 0 payoff forever. Thus, the cooperate strategy is Nash if R/(1-δ) ≥ *n*T, i.e. the payoff for cooperation is greater than or equal to the temptation to defect.

The implication of this proof is that players can be encouraged to cooperate with the threat that if they defect a certain number of times (adjustable according to networking conditions) then they would be punished forever. This punishment is a denial of future network services. Our PGS requires only local information, namely, a history of interactions with neighbor. This makes it ideal for distributive networks. It is also scalable, since its performance is independent of the number of neighbors.

VII. SIMULATIONS

In this section, we present the simulation results for the two scenarios we investigated, namely, packet forwarding between mobile classes and between spatially dispersed stationary wireless sensor classes. Also, we present the simulation results we obtained for PGS.

A.. Scenario 1: Packet Forwarding between Mobile Classes

We simulated an evolutionary prisoner's dilemma model. Our simulation model is an extension of Wilensky's model [17]. In our simulation model, it is assumed that an increase in the number of classes that cooperate will increase proportionately the benefit for each cooperating player. For those that do not cooperate, we assume that their benefit is some factor α multiplied by the number of nodes that cooperate. How much cooperation is stimulated is dependent on the value of α. As a consequence of this, the dynamics of the evolution in cooperation in our simulation model may be observed.

		Class c_j	
		Cooperate	Defect
Class c_i	Cooperate	(1,1)	(-0.5, α)
	Defect	(α, -0.5)	(0,0)

Figure 2. Payoff matrix for wireless sensor classes c_i and c_j, where $i \neq j$ and $c_i, c_j \in C$

We use the payoff matrix in figure 2 in our simulation. We arbitrarily select α to be 1.53. The following two strategies were implemented:

(i) Cooperate at all times
(ii) Defect at all times

Classes are allowed to wander about the spatial domain and randomly interact with the other classes. All classes have an initial energy of 10,000 units. If all the energy of a class is used up it dies. For mutual cooperation both classes gain 1 unit; for mutual defect both classes gain nothing. If one class defect while the other cooperate it gains 1.53 units while the other gain -0.5 units. We do not consider the energy used up in wandering. We vary the initial proportion of the population that cooperate and monitor the evolution of cooperation over time.

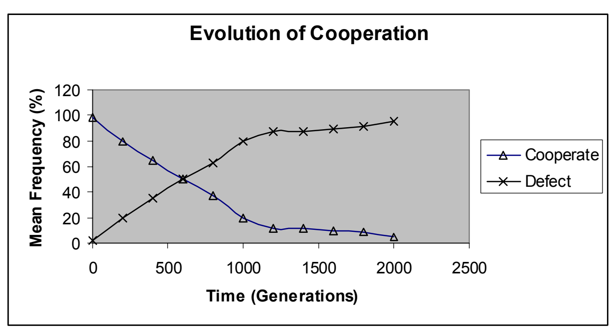

Figure 3. The mean frequencies of the Cooperate and Defect strategies of a population of randomly interacting mobile wireless sensor classes. The initial mean frequency of cooperators is 98%.

Figure 3 shows how the fitness of the Cooperate and Defect strategies varies over time, and the proportion of the population that employs each. Initially, the proportion of the population playing the Cooperate strategy is 98%. This result validate our analytical solution and clearly demonstrate that the Cooperate strategy is not evolutionary stable, that is, as time proceeds the mean frequency of the population using that strategy approaches zero.

B. Scenario 2: Packet Forwarding between Spatially Dispersed Stationary Classes

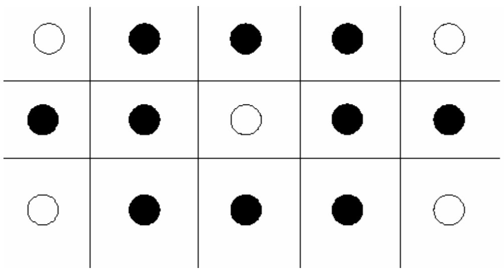

Figure 4. The spatial layout of stationary classes of cooperators and defectors.

In this simulation the classes are positioned at the center of a square grid (see figure 4). Each class is played against its eight neighboring classes iteratively and the scores are averaged. Strategies replicate by comparing the current mean scores of each class with its eight surrounding classes. The strategy with the highest mean is replicated. Mean values are initialized at the end of each generation. We use the same values for the payoff matrix as in the previous simulation. In addition, similar to the previous simulation, the classes initial energy value is 10,000 units.

Figures 5a and 5b show the mean frequency and the mean payoff of the population, respectively, using the two strategies. In addition, figure 5b also shows how these strategies compare to the mean payoff of the population average. Initially, 98% of the population is using the COOPERATE strategy and 2% of the randomly distributed population is employing the DEFECT strategy. The figures show that the mean frequency and payoff of the population using COOPERATE stabilizes over time.

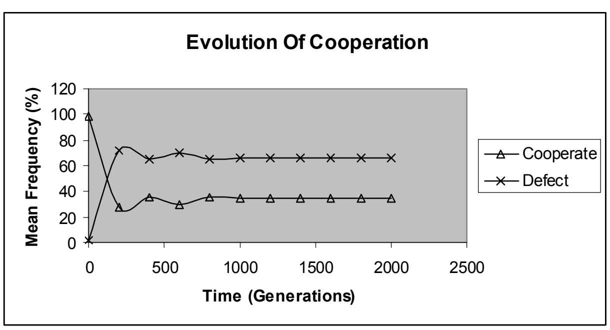

Figure 5a. The mean frequencies of the Cooperate and Defect strategies of a population of spatially dispersed stationary wireless sensor classes. The initial mean frequency of cooperators is 98%.

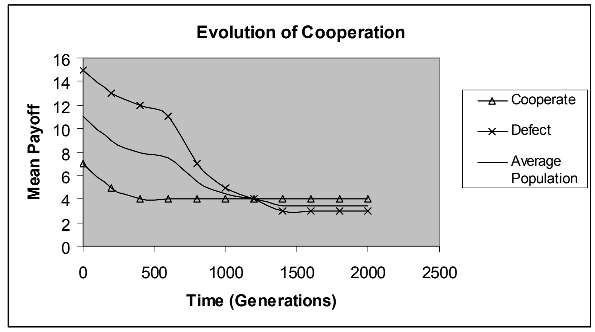

Figure 5b. A comparison of the mean payoff of the Cooperate and Defect strategies with the population average, of a population of spatially dispersed stationary wireless sensor classes.

This is because in stationary spatially dispersed populations cooperators are able to survive by forming clusters and thereby reducing exploitation by defectors. This contrasts with our previous results for mobile classes with random interactions, where defectors outperform cooperators and drive the latter to extinction. In stationary spatially dispersed classes defectors are limited to exploiting only the cooperators on the edge of the clusters. However, we note that the results presented were dependent on the value of our payoff matrix. We observed that, if α is large then cooperators are forced into extinction.

C. Patient Grim Strategy in Spatially Dispersed Stationary Classes

Our simulation setup is similar to that of scenario 2 with the following exceptions.

(i) Instead of adapting to cooperate or defect based on the neighboring classes with the highest score, classes decide whether to cooperate or defect based on the history of cooperation and defection of their neighbors.

(ii) We introduce PGS as a third strategy with varying initial proportions of COOPERATE and DEFECT.

In Figure 6, we present the average of 100 simulation runs with varying initial proportions of the population using the COOPERATE, DEFECT and PATIENT GRIM strategies. Our result shows that our PGS delivers the highest mean

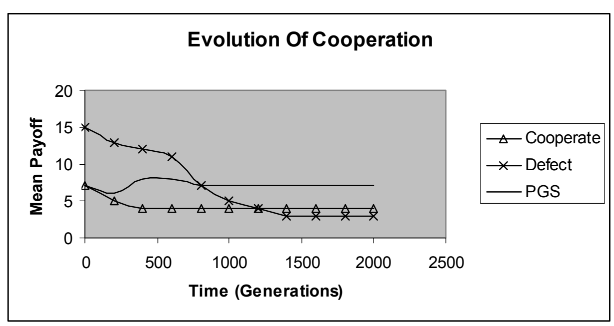

Figure 6. A comparison of the mean payoff of the Cooperate, Defect and PGS strategies in a population of spatially dispersed stationary wireless sensor classes.

payoff over time. This is because this strategy punishes defectors after a certain number of interactions by permanently defecting in all future interactions. This makes it impossible for defectors to exploit them continuously. In addition, it stimulates the creation of clusters of cooperators and those employing PGS.

VIII. CONCLUSION AND FUTURE WORK

We have presented an evolutionary game theory approach to investigate the conditions for cooperation in multi-class wireless sensor networks. Because of the complexity of the problem we have restricted ourselves to packet forwarding and not network flow. We have also focused on two topologies, namely, random and static topologies. We derived an analytical proof to demonstrate that cooperation is not evolutionary stable in populations playing the iterated N-player prisoner's dilemma. This is further validated with simulation results. However, we show that in the case of stationary classes there is some possibility for cooperation to emerge without any incentive. Finally, we presented our PGS protocol that enforces cooperation by punishment and proved that it is a Nash equilibrium of our problem. Our PGS protocol is scalable and requires only local information.

The main focus of our future work is to develop an evolutionary model that incorporates network flow with players with different interests, and lightweight strategies that enforce cooperation.

ACKNOWLEDGMENT

This research was partially funded by grants from the U.S. Department of Defense, the U.S. Department of Transportation and the National Science Foundation.

REFERENCES

[1] I. F. Akyildiz, W.Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless Sensor Networks: A Survey," *Computer Networks*, vol. 38, pp. 393-422, 2002.

[2] R. Anderson, H. Chan, and A. Perrig, "Key Infection: Smart Trust for Smart Dust," presented at The 12th IEEE International Conference on Network Protocols (ICNP'04), Berlin, Germany, October 2004.

[3] V. Srinivasan, P. Nuggehalli, C. F. Chiasserini, and R. R. Rao, "Cooperation in Wireless Ad Hoc Networks," presented at the IEEE Conference on Computer Communications (INFOCOM '03), San Francisco, U.S.A., March 30-April 3, 2003.

[4] M. Felegyhazi, J.-P. Hubaux, and L. Buttyan, "Nash Equilibria of Packet Forwarding Strategies in Wireless Ad Hoc Networks," *IEEE Transactions on Mobile Computing*, vol. 5, May 2006.

[5] H. Gintis, *Game Theory Evolving: A Problem-Centered Introduction to Modeling Strategic Behavior*. Princeton: Princeton University Press, 2000.

[6] M. Felegyhazi and J.-P. Hubaux, "Cooperative Packet Forwarding in Multi-Domain Sensor Networks," presented at Pervasive Computing and Communications Workshops (Percom 2005 Workshops), 2005.

[7] S. Marti, T. J. Giuli, K. Lai, and M. Baker, "Mitigating Routing Misbehavior In Mobile Ad Hoc Networks," presented at The 6th Annual International Conference on Mobile Computing and Networking (MobiCom), Boston, Massachusetts, United States, August 2000.

[8] S. Buchegger and J.-Y. L. Boudec, "Nodes Bearing Grudges: Towards Routing Security, Fairness, and Robustness in Mobile Ad Hoc Networks," presented at the Tenth Euromicro Workshop on Parallel, Distributed, Network-based Processing, Canary Islands, Spain, January 2002.

[9] S. Ganeriwal and M. B. Srivastava, "Reputation-based Framework for High Integrity Sensor Networks," presented at ACM Workshop on Security of Ad Hoc and Sensor Networks (SASN '04), Washington, D.C., USA, October 25, 2004.

[10] D. Levin, "Punishment in Selfish Wireless Networks: A Game Theoretic Analysis," presented at First Workshop on the Economics of Networked Systems (NetEcon), Ann Arbor, Michigan, USA, June 2006.

[11] R. Mahajan, M. Rodrig, D. Wetherall, and J. Zahorjan, "Sustaining Cooperation In Multi-Hop Wireless Networks," presented at 2nd Symposium on Networked System Design and Implementation (NSDI), Boston, Massachusetts, May 2005.

[12] L. Buttyan and J.-P. Hubaux, "Stimulating Cooperation in Self-Organizing Mobile Ad Hoc Networks," *ACM/Kluwer Mobile Networks and Applications (MONET) Special Issue on Mobile Ad Hoc Networks*, vol. 8, October 2003.

[13] B. Raghavan and A. C. Snoeren, "Priority Forwarding in Ad Hoc Networks with Self-interested Parties," presented at Workshop on Peer-to-Peer Systems, June 2003.

[14] S. Zhong, Y. Yang, and J. Chen., "Sprite: A Simple, Cheatproof, Credit-based System for Mobile Ad Hoc Networks," presented at IEEE INFOCOM, March 2003.

[15] A. Urpi, M. Bonuccelli, and S. Giordano, "Modeling Cooperation in Mobile Ad Hoc Networks," presented at WiOpt'03: Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, INRIA Sophia-Antipolis, France, March 2-3, 2003.

[16] E. Altman, T. Boulogne, R. El-Azouzi, T. Jimenez, and L. Wynter, "A Survey on Networking Games in Telecommunications," *Computers and Operations Research*, vol. 33, February 2006.

[17] U. Wilensky, "NetLogo PD Basic Evolutionary model," http://ccl.northwestern.edu/netlogo/models/PDBasicEvolutionary. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, 2002.