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The Reliable Energy Efficient Routing Protocol Based on Cooperative and Non-Cooperative Repeated Game Theory in Wireless Sensor Networks

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ABSTRACT

Game theory is a field of applied mathematics for analysing complex interactions among entities. It is basically a collection of analytic tools that enables distributed decision process. Game theory (GT) provides insights into any economic, political, or social situation that involves individuals with different preferences. GT is used in economics, political science and biology to model competition and cooperation among entities, and the role of threats/penalties in long term relations. Contemporary social science is based on game theory, economics, and psychology in which mathematical logic is applied.

Keywords : Game theory, transferable utility, non-transferable utility, TU, Saad, NTU

I. INTRODUCTION

The formation of coalitions and non-coalitional or alliances is omnipresent in many applications. For example, in political games, parties, or individuals can form coalitions and non-coalitional for improving their voting power. Recently, computer science and engineering have been added to the list of scientific areas applying GT. While in optimization theory the goal is to optimize a single objective over one decision variable, game theory studies multi-agent decision problems. In social sciences and economics, the focus of game is the design of right motivations/payoffs; in engineering it comes to efficiency – how to design efficient decentralized schemes that take into account incentives. However, there are still similarities when applying game theory to different disciplines. A a measurement allocation framework for localization in wireless networks, based on the idea to allocate more measurements to the nodes which contribute more, mimics a capitalist society where the gains are mostly reinvested where more profit is expected. It also replicates the concept of natural selection in population genetics. In general, a game consists of a set of players (decision makers), while each player has its strategy, whereby utility (payoff) for each player measures its level of satisfaction. Each player's objective is to maximize the expected value of its own payoff (Myerson, 1997). (Srivastava V.2005) proposed a mapping of network components to game components according to the following table: 1

Network component	coalitional and non-coalitional Game component
Nodes	Players
Available adaptations	Achievement set
Performance metrics	Utility purpose

Table 1. Classification of coalitional and non-coalitional games

Game theory can be applied to communication networks from several aspects: at the physical layer, link layer and network layer. However, there a certain challenges when applying game theory principles to wireless networks. For example, GT assumes that the players act rationally, which does not exactly reflect real systems. Furthermore, realistic scenarios necessitate complex models, yet the main challenge is to select the appropriate utility function, due to a lack of analytical models that would map each node's available actions to higher layer metrics.

Coalitional and non-coalitional games – background

Coalitional and non-coalitional games in characteristic form are classified into two types based on the distributing of gains among users in a coalition and non-coalitional:

i. A transferable utility (TU) game where the total gain achieved can be apportioned in any manner between the users in a coalition and non-coalitional subject to feasibility constraints, and
ii. A non-transferable utility (NTU) game where the apportioning strategies have additional constraints that prevent arbitrary apportioning. Each payoff is dependent on joint actions within coalition and non-coalitional.

In TU games, the cooperation and non-cooperation possibilities of a game can be defined by a characteristic function *v* that assigns a value *v*(S) to every coalition and non-coalitional S. Here *v*(S) is called the value of coalition and non-coalitional S, and it characterizes the total amount of transferable utility that the members of S could gain without any help from the players outside of S. In general, we use the term coalition and non-coalitional structure to refer to any mathematical structure that describes which coalitions and non-coalitional (within the set of all 2n – 1 possible coalitions) can effectively negotiate in a coalitional and non-coalitional game.

$$V(s_1 \cup s_2) \geq V(s_1) + V(s_2);\ \text{for all } (s_1),(s_2) \in N, (s_1) \cap (s_2) = \emptyset \ \ldots\ldots(1)$$

In other words, a TU game is superadditivity if cooperation and non-cooperation is always rewarding. Thus, grand coalition and non-cooperation, i.e., the coalition comprising all sensors, is beneficial. The most notable solution concept for the coalition and non-coalitional formation in superadditivity games is the core; other solutions include Shapley value, kernel, and Nucleolus.

The superadditivity concept can be extended to NTU games, by:

$$\{x/((x_i)_{i\in s_i}) \in V(s_1), (x_j)_{j\in s_i} \in V(s_2)\} \subseteq V(s_1 \cup s_2) \ \ldots\ldots(2)$$

In case of TU games, goal is to find a coalition and non-coalitional structure that maximizes the total utility, while in NTU games it is the structure with Pareto optimal payoff distribution. A centralized approach can be used, but it is generally NP-complete. The reason is that finding an optimal partition requires iterating over all the partitions of the player set N. The number of partitions grows exponentially with the number of players in N. For example, for a game where N has 10 elements, the number of partitions that a centralized approach has to go through is 115,975 (easily computed through the Bell number (Saad W. 2009c). Therefore, using a centralized approach for finding an optimal partition is, generally, computationally complex and not very practical. Nevertheless, many applications require the coalition centralized approach has initiated a growth in the coalition formation literature, with the goal to find low complexity and distributed algorithms for establishing coalitions centralized approach has initiated a growth in the coalition formation literature, with the goal to find low complexity and distributed algorithms for establishing coalitions. A novel classification of coalitional games has been proposed in (Saad W.2009c). Games are grouped into three types: canonical games, coalition formation games and coalitional graph games. Their properties are shown in the following table.. A novel classification of coalitional games has been proposed in (Saad W.2009c). Games are grouped into three types: canonical games, coalition formation games and coalitional graph games. Their properties are shown in the following table. formation process to take place in a distributed manner, so that the players have autonomy on the decision whether or not to join a coalition. Indeed, the complexity of the centralized approach has initiated a growth in the coalition formation literature, with the goal to find low complexity and distributed algorithms for establishing coalitions. A novel classification of coalitional games has been proposed in (Saad W.2009c). Games are grouped into three types: canonical games, coalition formation games and coalitional graph games, Non-coalitional graph game. Their properties are shown in the following table;2

II. METHODS AND MATERIAL

Table 2. Properties of coalitional Non-coalitional graph game theory

Canonical form of game	**Formation of game**	**Coalitional graph game**	**Non-coalitional graph game**
Grand coalition or non-coalitional is the optimal structure	Resulting coalition or non-coalitional structure depends on gains and costs	Interaction of players depends on communication graph structure	Non-Interaction of players depends on communication graph structure
Goal :stabilize the grand coalition or non-coalitional	Goal: form appropriate coalition or non-coalitional structure	Goal: stabilize grand coalitional or form network game into account communication graph	Goal: stabilize grand non-coalitional or form network game into account communication graph

In this chapter we will focus on coalition and Non-coalitional graph formation games. A generalized approach to coalition and Non-coalitional graph formation has been proposed in (Apt & Witzel, 2006). The notion of stable partition is used when there does not exist any other partition that would improve the total gain. In order to illustrate the coalition formation procedure, an abstract preference operator ► has been introduced, and coalition's Non-coalition graph is being transformed using merge and split rules.

1. Applications to communication networks

From the communication networks perspective, there is the need for developing distributed and flexible wireless networks, where the units make independent and rational strategic decisions. In addition, low complexity distributed algorithms are required, to capably represent collaborative scenarios between network entities. Cooperative and Non-cooperative games have been mainly applied for applications such as spectrum sharing, power control or resource allocation – mainly settings that can be seen as competitive scenarios. On the other hand, cooperative game theory provides analytical tools to study the behaviour of rational players in cooperative and non-cooperative scenarios. In particular, coalitional games show to be a very powerful tool for designing fair, efficient and robust cooperation and non-cooperation strategies in communication networks. In order to highlight an expanding application field, in the following section we will give some examples on use of cooperative and Non-cooperative game theory for communication networks, and specifically for localization purposes.

Physical layer security has been studied via coalitional Non-coalition games in (Saad 2009a), (Saad W., 2009b). In a distributed way, wireless users organize themselves into coalitions (see Figure 1.) while maximizing their secrecy capacity - maximum rate of secret information sent from a wireless node to its destination in the presence of eavesdroppers (Saad W 2009a). This utility maximization is taking into consideration the costs occurring during information exchange. On the other hand, (Saad W2009b) introduces a cooperation and non-cooperation protocol for eavesdropper (attacker) cooperation. Here the utility function is formulated to capture the damage caused by the attackers, and the costs in terms of time spent for communication among the eavesdroppers. In both cases, independent disjoint coalitions will form in the network, as the grand coalition and non-coalition would involve various communication costs.

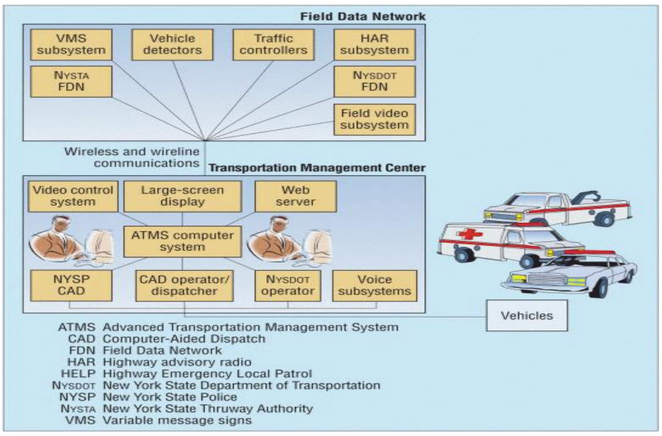

Figure 1. Wireless users organized into coalitions

(Mathur S 2006) and (Mathur S. 2008) consider coalition and non-coalition structures in wireless

network where users are permitted to cooperate, while maximizing their own rates. Here both transmitter and receiver cooperation in an interference channel is studied. Several models have been analysed: a TU and an NTU model, and with perfect and partial cooperation and nom-cooperation. In (Mathur S., 2006), the feasibility and stability of the grand coalition and non-coalition for all cases was evaluated, while the work in (Mathur S, 2008) is focused on stable coalition and non-coalition structures. In (Saad W., et all, 2008) a game theoretical framework for virtual MIMO has been proposed, where single antenna transmitters self-organize into coalitions and non-coalition. The utility function denotes the total achieved capacity, and also includes the power constraint to account for the costs.
In (Hao X., et all, 2011) the multi-channel spectrum sensing problem is formulated as a coalitional game, where players are secondary users that cooperatively sense the licensed channels of primary users. The utility of each coalition reflects the sensing accuracy and energy efficiency. Distributed algorithms have been proposed to determine a stable coalition structure, maximizing the overall utility in the system. More game theory based solutions for spectrum sensing in cognitive radio have been proposed in (Khan Z, 2010) and (Saad W.2009c).

A network-level study using coalition and non-coalition formation has been performed in (Singh C., 2012), considering a scenario where service providers are cooperating in order to enhance the usage of the available resources. Particularly, different providers may serve each other's customers and thereby increase the throughput and reduce the overall energy consumption. The model supports multi-hop networks and is not limited to stationary users and fixed channel conditions. A cooperative and non-cooperative game theory based framework is used to determine optimal decisions and a rational basis for sharing the aggregate utility among providers. The optimal coalition and non-coalition structure can be obtained by means of convex optimization Other applications of cooperative and non-cooperative game theory include packet forwarding in ad hoc networks, distributed cooperative and non-cooperative source coding, routing problems, and localization algorithms, which will be more elaborated in the next chapter.

2. Scenario

We propose the use of cooperative non-super additive games for modelling localization algorithms. As stated in the previous section, a typical localization process consists of the ranging phase, where nodes estimate the distances to their neighbours, and a second phase where nodes use the ranging information and the known anchor position to calculate their coordinates. In a dense network one can assume a large number of available anchor nodes. However, transmitting and processing all the obtainable information would consume immense power, without necessarily leading to better localization performance. This is due to the fact that not all the anchors provide reliable measurements, what leads to erroneous distance estimates. Furthermore, the geometry of selected reference nodes shows to have significant impact on localization accuracy, what will be extensively elaborated in our work. Assuming that at each time instant a target has several neighbouring anchor nodes in near vicinity, and different coalitions can be formed, the considered scenario is illustrated in Fig.2.

Figure 2. (a). Scenario

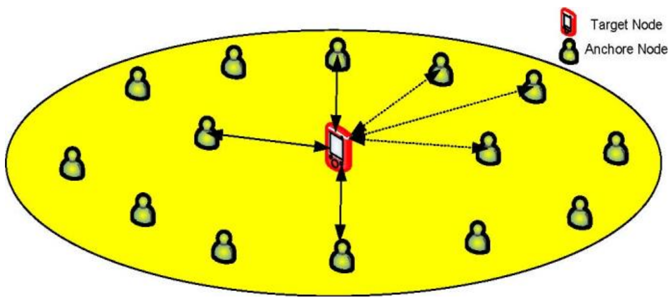

Figure 2. (b). Scenario

We propose an algorithm for reference node selection based on coalitional games. We model the localization process as a cooperative and non-cooperative game, and formulate the corresponding utility function. We define the node selection optimization as one that maximizes the accuracy subject to constraints given by nodes' limited processing capacity. Position estimates are obtained using the linearized least squares algorithm (trilateration).

3. Use of game theory in localization algorithms

Recently cooperative and non-cooperative game theory has been applied in localization algorithms, mainly for modelling the cost-performance trade-off and for selection of reference nodes. The work in (Ghassemi F. & Krishnamurthy V., 2008a) applies cooperative and non-cooperative game theory for sensor network localization, namely for measurement allocation among reference nodes localizing the target. The localization process has been modelled as cooperative and non-cooperative game belonging to the class of weighted-graph games. For such a representation, the vertices correspond to the players and the coalition and non-coalition value can be obtained by summing the weights of the edges that connect a pair of vertices in the coalition and non-coalitional with self-loop edges only considered with half of their weights. A weighted-graph game can therefore be well represented by $\frac{N(N-1)}{2} + N$ weights, in contrast to 2N numbers which are usually required to represent a cooperative and non-cooperative game. Basic idea is to allocate more measurements to nodes that contribute more to the localization process. The allocation algorithm has been integrated into a Bayesian estimator. In (Ghassemi F. & Krishnamurthy V., 2008b), utility is defined as information gain from a node, i.e. the mutual information between the prior density of target position and the measurement. Additionally, a price for transmission is included to account for the current energy level in the nodes, and the energy needed for data transmission. The algorithm proposed in (Moragrega A., 2011) assumes a number of static anchor nodes, strategically placed to guarantee coverage to all unknown nodes. Anchors transmitting with lower energy can provide coverage to a smaller number of nodes; aim is to minimize power consumption at the anchor nodes, while assuring desired localization accuracy. The metric for positioning quality is the GDOP. The problem has been formulated as a cooperative and non-cooperative game, using Nash equilibrium as solution concept

In (Bejar B., 2010) the coalition and non-coalition formation within the set of neighbouring anchors helps reduce communication costs. Using only a subset of available reference nodes does not necessarily degrade the accuracy, since some of them provide redundant information. In some situations it might be even useful to discard ranging information from some reference nodes, after they have been identified as unreliable due to biases in the measurements. This paper the localization problem has been defined as a coalition and non-coalition NTU game, where coalitions are formed based on the merge and split procedure. The utility function is defined to account for both a quality and cost indicator. While the quality function accounts for inconsistencies between each node's measured distance and the final joint estimated distance within the coalition, the cost function is related to communication costs. The target tracking task based on coalition formation has been implemented using a Kalman filter. For the coalition formation approach a higher mean estimation error has been observed than for grand coalition, i.e., when all nodes contribute to the tracking process. Nevertheless, in terms of communication costs the proposed scheme provides significant savings.

(Ghareshiran O. N. & Krishnamurthy V., 2010) proposes a dynamic coalition and non-coalition formation algorithm used for energy saving in multiple target localization. Assuming that nodes in sleep mode do not record any measurements and thereby save energy in both sensing and transmitting data, the optimization problem is formulated to maximize the average sleep time of all nodes in the network, assuring that targets are localized with desired accuracy. An important contribution is exploitation of spatial correlation of sensor readings. Accuracy metric used is the determinant of the Bayesian Fisher information matrix (B-FIM). The characteristic function is formulated in a way that larger coalitions of sensors do not necessarily lead to longer sleep times. This is mainly due to the fact that the B-FIM, depending on both relative angles and distances of sensors to the target, does not automatically increase as the number of sensor nodes in a coalition goes up. The trade-off between performance and average sleep time allocated in the network is demonstrated via Monte Carlo simulations.

4. Utility function

The following parameters are relevant for reference node selection: number of references, quality of range estimates and geometry. Therefore we propose a node selection mechanism based on the Cramer Rao Lower Bound. Since the CRLB gives the upper bound on accuracy, the utility function has to be inversely proportional to the CRLB. Besides the quality indicator, utility function also has to reflect the cost. Cost is related to the energy spent for message exchanges between nodes, and is proportional to the distances of target node to reference nodes. Having in mind the energy consumption if all reference nodes were used for localization, the grand coalition and non-coalitional is not optimal. Therefore we define the problem as a nonsuperaditive cooperative and non-cooperative game. Since least square localization is not possible for less than three reference nodes, we set the value of all coalitions containing less than three nodes to zero. For the remaining non-cooperative is ones, the coalition and non-coalition value of each chosen subset of nodes S will be of the form:

$$V(s) = \frac{1}{CRLB_{i\in s}} - \sum_{i\in s} \frac{d_{i,t}}{R} \text{.---------------- (3)}$$

Where $CRLB_{i\in s}$ is the CRLB for the coalition and non-coalition S, $d_{i,t}$is the distance from node i ∈ S to the target *t*, and *R* is the transmission range, used to normalize the cost function. In order to illustrate the performance of coalition and non-coalition formation based node selection, we will perform an exhaustive search over all possible coalition and non-coalition sets containing three nodes.

Definition .1. Repeated game

Each node i has a von Neumann-Morgenstern utility function defined over the outcomes of the stage game G, as $u_i: A \rightarrow R$ where A is the space of action profiles. Let G be played several times and let us award each node a payoff which is the sum of the payoffs it got in each period from playing G. Then this sequence of stage games is itself a game, called a repeated game. Here,

$$u_i^t = \alpha r_i^t - \beta c_i^t \text{…………………. (4)}$$

Where r_i^t is the gain of node I's reputation, c_i^t is the cost of forwarding a packet for the node $\alpha$and β are weight parameters. We assume that we call a packet. Packet all has the same size. The transmission cost for a single packet is a function of the transmission distance. In particular we assume $c_i^t = c' d^{\mu}$, where c'a constant that includes antenna characteristics d I the distance of the transmission μ is the path loss exponent.

Definition .2. Finitely Repeated Games

These games represent the case of a fixed time horizon *T* <∞. Repeated games allow players to condition their actions on the way their opponents behave in previous periods. We begin the one of the most famous examples, the finitely repeated Prisoner's Dilemma. The stage game is shown in below

Let $R\in(0, 1)$ be the common discount factor, and *G (R, T)* represents the repeated game, in which the Prisoner's Dilemma stage game is played *T* periods. Since we want to examine

$$\begin{bmatrix} \mathbf{2, 2} & \mathbf{0, 3} \\ \mathbf{3, 0} & \mathbf{1, 1} \end{bmatrix}$$

The Stage Game: Prisoner's Dilemma.

How the payoffs vary with different time horizons, we normalize them in units used for the per-period payoffs.

The average discounted payoff

$$R_i = \frac{1-R}{1-R^{T+1}} \sum_{t-0}^{T} R^t G_i(A^t) \text{………………(5)}$$

To see how this works, consider the payoff from both players cooperating for all *T* periods.
The discounted sum without the normalization is

$$\sum_{t=0}^{T} R^t = \frac{1-R^{T+1}}{1-R} \text{…………..(6)}$$

While with the normalization, the average discounted sum is simply.

Definition 3. Infinitely Repeated Games

These games represent the case of an infinite time horizon *T* = ∞ and are meant to model situations where players are unsure about when precisely the game will end. The set of equilibrium of an infinitely repeated game can be very different from that of the corresponding finitely repeated game because players can use self-enforcing rewards and punishments that do not unravel from the terminal date. In particular, because there is no fixed last period of the game, in which both players will surely defect, in the Repeated Prisoner's Dilemma (RPD) game players may be able to sustain cooperation by the threat of "punishment" in case of defection. While in the finitely repeated games case a strategy can explicitly state what to do in each of the T periods, specifying strategies for infinitely repeated games is trickier because it must specify actions after all possible histories, and there is an infinite number of these.

Definition.4. The payoffs $(v_1, v_2 \ldots \ldots v_n)$ is feasible in the stage game G if they are a convex combination of the pure-strategy payoffs in G. The set of feasible payoffs is

$$V = \text{convex hull } \{v / \ni a \in A \text{ with } g(a) = v\} \ldots\ldots\ldots\ldots (7)$$

Definition.5. Player i's reservation payoff or minmax value is

$$\underline{v_i} = \min_{\alpha_{-i}} \max_{\alpha_i} g_i(\alpha_i, \alpha_{-i}) \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Definition.6. The set of feasible strictly individually rational payoffs is the set

$$\{v \in \frac{V}{v_i} > \underline{v_i} \text{ for all } i\} \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Theorem.1. (Folk Theorem).

For every feasible strictly individually rational payoff vector v, there exists an R < 1 such that for all R ∈ (R, 1) there is a Nash equilibrium of G(R) with payoffs v.

Proof. Assume there is a pure strategy profile a such that $g(a) = v^8$ Consider the following strategy for each player i: "Play a_i in period 0 and continue to play a_i as long as

(i) The realized action profile in the previous period was a, or

(ii) The realized action in the previous period differed from *an* in two or more components. If in some previous period player i was the only one not to follow profile a, then each player j plays $m_{i,j}$ for the rest of the game." Can player i gain by deviating from this profile? In the period in which he deviates, he receives at most $\max_a g_i(a)$ and since his opponents will minimax him forever after, he will obtain v_i in all periods thereafter.

Thus, if player i deviates in period t, he obtains at most

$$(1 - R^T)v_i + R^T(1 - R)\max_a g_i(a) + R^{T+1}\underline{v_i} \ldots\ldots\ldots (10)$$

To make this deviation unprofitable, we must find the value of δ such that this payoff is strictly smaller than the payoff from following the strategy, which is v_i:

$$(1 - R^T)v_i + R^T(1 - R)\max_a g_i(a) + R^{T+1}\underline{v_i} < v_i.$$

$$(1 - R)\max_a g_i(a) + R^{T+1}\underline{v_i} < R^T v_i.$$

$$(1 - R)\max_a g_i(a) + R\,\underline{v_i} < v_i \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

For each player i we define the critical level R_i by the solution to the equation

$$(1 - R_i)\max_a g_i(a) + R_i\underline{v_i} = v_i \ldots\ldots\ldots\ldots\ldots (12)$$

Because $\underline{v_i} < v_i$, the solution to this equation always exists with $R_i < 1$. Taking $R = \max R_i$ completes the argument. Note that when deciding whether to deviate, player i assign probability 0 to an opponent deviating in the same period. This is what Nash equilibrium requires: Only unilateral deviations are considered.

Theorem .2. (Friedman, 1971).

Let α^* be a static equilibrium with payoffs e. Then for any v ∈ V with $v_i > e_i$ for all players i, there is an R< 1 such that for all R> $\underline{R}$ there is a subgame perfect equilibrium of G(R) with payoffs v.

Proof. Assume there is a strategy profile a such that $g(\hat{a}) = v^9$ Consider the following strategy profile: "In period 0 each player i plays a_i Each player i continue to play a_i as long as the realized action profiles were a in all previous periods. If at least one player did not play according to a, then each player plays a_i^* for the rest of the game." This strategy profile is a Nash equilibrium for R large enough that

$$(1\text{-R})\max_a g_i(a) + R\,e_i < v_i$$

This inequality holds strictly at R = 1, which means it is satisfied for a range of R < 1. The strategy profile is sub game perfect because in every sub game off the equilibrium path the players play α^* forever, which is a Nash equilibrium of the repeated game for any static equilibrium α^*.

5. Pure NE and Evolutionary Stability

1) Pure Nash Equilibrium:

We prove that our evolutionary routing game has two pure Nash Equilibrium strategies.

Proposition.1.

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

Proof: Suppose two nodes are picked randomly from two large populations of sensor nodes in the network. These nodes are supposed to select one of the two strategies; each competes against the other, in order to transmit the packet. In Table I, assume the row and the column are the two players from populations A and B, respectively. These players select strategy pairs (s_r, s_t) and (s_t, s_r). The payoffs of the selection are $\frac{1}{R_{ar}}, \frac{1}{R_{bt}}$ and $\frac{1}{R_{at}}, \frac{1}{R_{br}}$ respectively. Let us say that the players select strategy pairs (s_r, s_t) and (s_t, s_r) 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_r because of the penalty of reducing the payoff according to equation 1. As a result we can say that strategy pairs (s_r, s_t) and (s_t, s_r) are not profitable deviations. According to the NE definition the strategy pairs (s_r, s_t) and (s_t, s_r) are a pure NE for this game.

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

Proposition.2.

Our mixed strategy NE (s_r, s_t) is a two-species evolutionary stable strategy.

Proof: First, we define the replicator equations, which are ruling the behaviour of the system over time based on the strategy pair (s_r, s_t). 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:

$$\bar{P} = p[\left(\frac{1-q}{C_{A_r}}\right) - (\left(\frac{p[1-q]}{C_{A_r}}\right) + \left(\frac{q[1-p]}{C_{A_t}}\right))] = p(1-p)(\left(\frac{[1-q]}{C_{A_r}}\right) + \left(\frac{q}{C_{A_t}}\right)) \text{--------------- (9)}$$

$$\bar{q} = q[\left(\frac{1-q}{C_{B_r}}\right) - (\left(\frac{q[1-p]}{C_{B_r}}\right) + \left(\frac{p[1-q]}{C_{B_t}}\right))] = q(1-q)(\left(\frac{[1-p]}{C_{B_r}}\right) + \left(\frac{p}{C_{B_t}}\right)) \text{---------------------- (13)}$$

Second, we need to find the stable fixed point for the two replicator equations. We have the MSNE point, which we calculated in V-B1. We proved how this point is a fixed point under the two replicator equations (12) and (13). Since we already have a stable point (s_r, s_t) 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 $\left(\frac{[1-q]}{C_{A_r}}\right) - \left(\frac{q}{C_{A_t}}\right)$ and $\left(\frac{[1-p]}{C_{B_r}}\right) - \left(\frac{p}{C_{B_t}}\right)$ in equations (11) and (13), respectively, should equal zero. Therefore, if we substitute the values of p and q from equations (9) and (10) with these last parts, we will get zero. As result, (s_r, s_t) is a asymptotically stable fixed point for the replicator dynamic. Based on asymmetric ESS our mixed strategy NE (s_r, s_t) s a two-species evolutionary stable strategy.

III. RESULTS AND DISCUSSION

As we mentioned before, much of the prior investigation into multipath routing in wireless networks has focused on providing multiple node-disjoint paths for routing between a source and a destination node. It is intuitive that a forward-k strategy results in greater number of node-disjoint paths ask increases. Figure 3 shows how the number of node disjoint paths varies for the various schemes. It is noteworthy that the flooding is particularly effective as far as this metric is concerned. We now turn to our robustness metric P_H the probability that the source is able to send information to the sink in the presence of uniform random node failures. Figures 5 and 6 show how this metric varies with the transmission radius for failure rates of 5% and 20% respectively. We make two observations from these figures. The first is that for a given transmission radius, the single path routing mechanism does indeed provide much lower robustness than the multipath routing schemes. The second is that for low failure rates, the three multipath routing mechanisms all provide nearly the same level of robustness. In essence the additional redundancy provided by having more than 2 node-disjoint paths results in negligible gains in robustness for low levels of node failures. At the failure rate of 20% there is slightly greater differentiation between the different multipath routing schemes but one can again see the law of diminishing returns at play - flooding provides only negligibly greater robustness than the forward-3 routing protocol.

Thus far we have ignored one critical aspect: the energy expenditure. While the multipath routing schemes provide greater robustness for a fixed value of the transmission radius, they do, of course, do so at the cost of a greater number of transmissions. This can be seen in figure 4. Flooding requires an order of magnitude higher number of transmissions than even forward-3, showing it are clearly not an energy-efficient mechanism for providing robustness to node failures. This is still far from a clear picture of the energy-robustness trade-offs. We have two parameters that we can tune to increase the energy and robustness metrics: one is the value of k, which in effect changes the routing structure without affecting the underlying topology. By increasing k, we apply energy in the form of greater number of transmissions in order to realize robustness gains through multiple paths. The second tenable parameter is the transmission radius: even if we stick to single path routing, increasing this parameter increases the robustness to node failures because it decreases the number of hops, leaving fewer possible failure modes. Hence we plot the robustness metric with respect to the energy metric $E_H = m_H R^{\alpha}$ which incorporates both the transmission radius R as well as the number of transmission m_H . This is shown as scatter plots in figures 7 and 8 for failure rates of 5 and 20 % respectively, for $\alpha = 2$

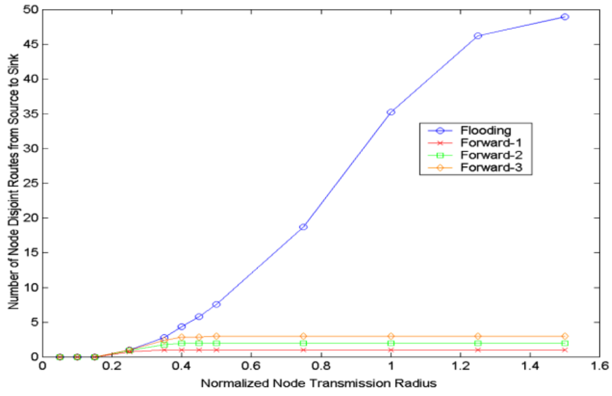

Figure 3: Number of Node Disjoint Source Sink Routes with respect to the Transmission Radius

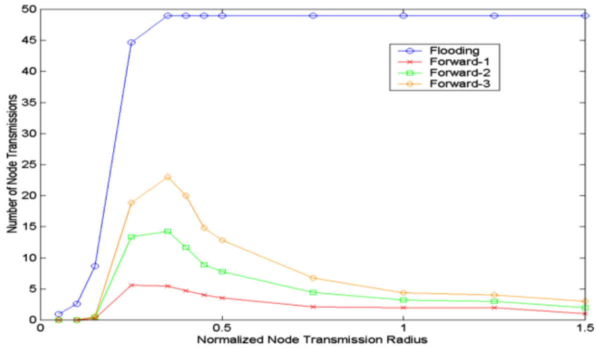

Figure 4: Number of Nodes Transmitting with respect to Transmission Radius

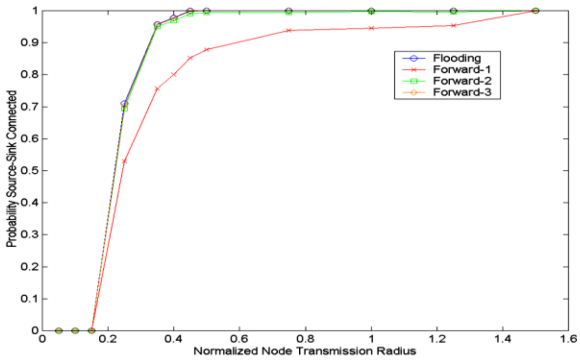

Figure 5: Probability that a route exists with respect to Transmission Radius (5 % failure rate)

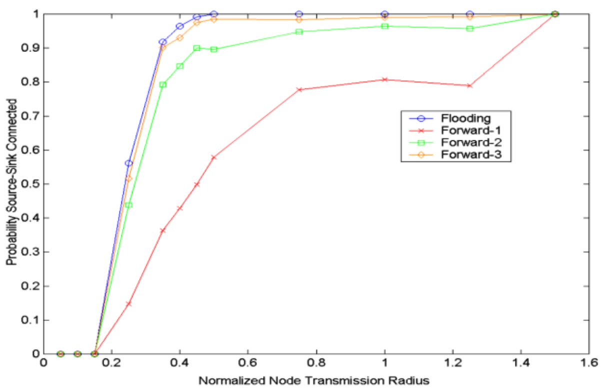

Figure 6: Probability that a route exists with respect to Transmission Radius (20 % failure rate)

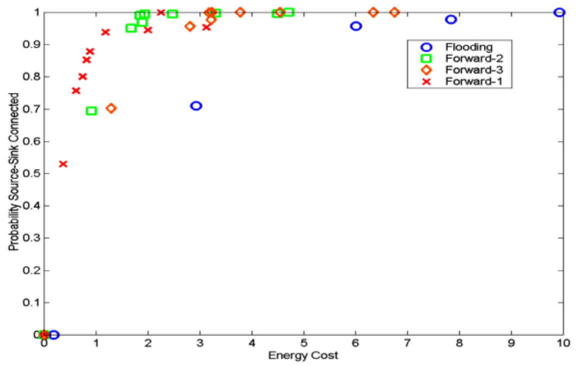

Figure 7: Probability that a route exists with respect to normalized energy cost (5 % failure rate)

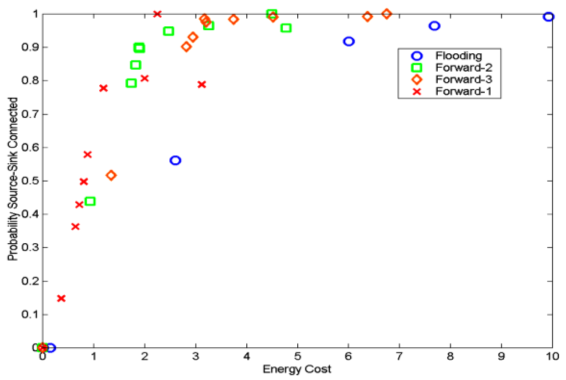

Figure 8: Probability that a route exists with respect to normalized energy cost (20 % failure rate)

IV.CONCLUSION

A cooperative and non-cooperative game theoretic model with for power control taking into account the residual energy of the nodes in a homogeneous sensor network considering various deployment schemes have been analysed in this paper. The connectivity is taken into consideration and the existence and uniqueness of the reliable energy efficient routing protocol based on cooperative and non-cooperative repeated game theory in wireless sensor networks and clustering are studied for the game model. The utility of nodes without residual energy and with residual energy are compared for all the deployment schemes. The maximum utility is obtained at minimal transmission power scheme. With the inclusion of the interference among the nodes due to the optimizing behaviour of a particular node is suppressed. Further the sensor nodes by requiring lesser transmit power and thereby extends the network security efficiently.

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