OPTIMIZE THE POWER CONTROL AND NETWORK LIFETIME USING ZERO - SUM GAME THEORY FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

A wireless sensor network is one of the most attractive research fields in the communication networks. This will creates a great popularity regarding their potential use in a wide variety of applications like monitoring environmental attributes, intrusion detection, and various military and civilian applications. The main performance of these sensor networks is maintaining network life time while satisfying coverage and connectivity in the deployment region. In this paper, we look at the problem of maintaining energy level of the sensor node , reliable routing and multi-hop in WSN within a finite two-person zero-sum game theoretic approach. The game theoretic scheme is based on models that express the interaction among players, in this case, nodes, by modeling them as elements of a social networks in such a way that they act as to maintaining the maximum utility. Simulation results are shows the effectiveness of the proposed game with various path loss exponents and also the proposed games is able to maintain the energy level of the network life time.

Keywords: *Wireless Sensor Networks, Two-person zero-sum Game Theory, Routing, Life time*.

I. INTRODUCTION

Wireless Sensor networks is one of the most promising and interesting areas in the past years. This network consists of a large number of sense nodes. These nodes are able to gather the information and process it and send it to the relevant destinations. Also, these nodes form a network by communicating with each other either directly or through other nodes. One or more nodes among them will serve as sink(s) that are capable of communicating with the user either directly or through the existing wired networks. The primary component of the network is the sensor, essential for monitoring real world physical conditions such as sound, temperature, humidity, intensity, vibration, pressure, motion, pollutants etc. at different locations. The nodes are deployed in hostile environment it is not feasible to replace the batteries. Therefore energy conservation is very crucial for WSN's both for each sensor node and the entire network level operations to prolong the network lifetime.

Energy –constrained networks, such as Wireless sensor networks are composed of nodes typically powered by batteries, for which replacement or recharging is very difficult, if not impossible. With finite energy, we can only transmit a finite amount of information. Therefore, minimizing the energy consumption for data transmission becomes one of the most important design considerations for such networks **[1]**. One of the desired features of wireless sensors networks is their capability to function unattended in unkind environments and inaccessible terrains in which up to data monitoring schemes are unsafe, heavy-handed, and sometimes infeasible.

Now days, some research efforts have focused on establishing efficient routing paths for transmitting packets from a sensor node to a sink in WSN's. Routing means finding the best possible way for data transmission from source node to the destination node in the network by considering networks parameters. The other important factor that must be considered in the network is Load Traffic Distribution. Usually the traffic load in wireless sensor networks is unbalance. For example, sensors which are nearer to the source have more data load. Therefore, optimization of load distribution, called Load Balancing, is one of the important factors for improving the efficiency of the networks. Optimization of load traffic distribution in WSN could increase the lifetime of the network. Since, there is more power consumption in nodes with more traffic load then the data transaction in the network could be optimized.

Game Theory is based on models that express the interaction among players, in this case nodes, by modeling them as an element of a social networks in such a way that they act to maximize their own utility. This allows the analysis of existing algorithms and protocols for WSN's as well as the design of equilibrium-inducing mechanisms that provide incentives for individual nodes to behave in socially constructive ways. In this paper, by using Zero-Sum Game Theory approach for WSN, optimal route in WSN is found. In this approach, routing and sensor nodes are assumed to be the game and players respectively. All players want to increase their benefit. So we use a mixed strategy model as well as profit and loss calculation for each player.

II. RELATED WORKS

The main goal of routing in WSNs is to guarantee successful packet delivery from source to sink node under constraint requirements like energy consumption, end to end delay, packet delivery ratio and QoS etc. In addition to energy consumption, more challenges and design issues are pointed out **[1]**.

Lifetime is the one of main design issue in WSN and the lifetime of the sensor node is mainly depends on the battery energy level. Since WSN is composed of very small nodes, their energy resources are very limited this imposes tight constraints on the operation of sensor nodes. The transceiver is the element which drains most power from the node (**Fedora and Collier 2007**), thus the routing protocols will significantly influence the lifetime of the overall network.

Energy-aware Routing protocol (**Shah and Rabaey 2002**) is similar to directed diffusion with the difference is, it maintains a set of paths instead of or enforcing one optimal path. These paths are maintained and chosen by means of a certain probability, which will depend the energy consumption of each path. By selecting different routes at different times, the energy of any single route will not deplete so quickly, the network lifetime increases.

Data centric, hierarchical and location based routing protocols gives the importance on energy efficiency and increased network lifetime, with little concern on quality measures. This group of routing protocols in addition to the energy efficiency focuses on QoS metrics such as latency, bandwidth and efficiency. QoS based protocols emphasize on acknowledging the data at the right time, differentiating data based on priorities and propose reliable routing algorithms. These protocols are concerned on the network fault tolerance and resilience of the network on node failures or node malfunctioning.

III. MATHEMATICAL MODEL

Game Theory is a theory of decision making under conditions of uncertainly and interdependence. In the distributed sensor network the game equation has to be found, with application of a game strategy. It is assumed that all the nodes in the sensor networks are the same and that all nodes are in the interference range. The activity of all the nodes is at the same level and it increases with the increase of power level transmission.

A game has three components:

(i) ***a set of players*** *(ii)* ***a set of possible of actions for each player*** *and (iii)* ***a set of strategies***.

A player's strategy is a complete plan of actions to be taken when the game is actually played. Players can act selfishly to maximize their gains and hence a distributed strategy for players can provide an optimized solution to the game. In any game, utility represents the motivation of players. A utility function, describing player's preferences for a given player assigns a number for every possible outcome of the game with the property that a higher number implies that the outcome is more preferred.

A Zero-sum game is a mathematical representation of situation in which a participant's gain or loss of utility is exactly balanced by the losses or gain of the utility of the other participants. The present survey covers research on infinite zero-sum two-person games in normal form **[3]** .(i.e., zero-sum two-person games with infinite sets of player strategies in which the player strategies are elements of certain abstract sets. In this article we do not consider dynamic and differential games.

Definition: 3.1. *The zero-sum two-person game in normal form is formally defined as a triple* $\Gamma = \langle X, Y, P \rangle$ *in which* X *and* Y *are arbitrary infinite sets representing the sets of strategies of Players I and II respectively and* P *is a real function defined on the set* $X \times Y$ *of all situations and is called the payoff function or kernel of the game.* (If $P : X \times Y \to R$ is the payoff function of Player I. Player II's payoff in the situation (x, y) is $[-P(x, y)]$, where $x \in X$, $y \in Y$ the game being zero-sum)

Definition: 3.2 The existence of optimal ($\in -$ optimal) strategies for the opponents in a zero-sum two-person game is equivalent to satisfaction of the following equations:

$$\max_{x \in X} \inf_{y \in Y} P(x, y) = \min_{y \in Y} \sup_{x \in X} P(x, y) = \upsilon \quad \text{------------} \quad (3.1)$$

$$\sup_{x \in X} \inf_{y \in Y} P(x, y) = \inf_{y \in Y} \sup_{x \in X} P(x, y) = \upsilon \quad \text{------------} \quad (3.2)$$

The quantity υ is called the value of the game. Even in the simplest cases, however, equations (1) and (2) fall short of being satisfied. Their proof requires the imposition of rather stringent algebraic constraints on the strategy sets X , Y and the function P (such as concavity in x and convexity in y) as well as topological constraints (the sets X and Y are topological spaces, and the function P has properties of the continuity type).

It is reasonable, therefore, to extend the strategy sets of the players in such a way that the payoff function, now defined on a new extended set of situations, will satisfy the required constraints .The extended strategy sets must be convex and include the usual strategies.

Let χ be a certain $\sigma-$ algebra of subsets of X containing all one-element subsets, let γ be a $\sigma-$algebra of subsets of Y , and let the function P be bounded and measurable under the $\sigma-$algebra χ x γ . A probabilistic measure defined on χ (γ) is called a mixed strategy of Player I (II). If μ is a mixed strategy of Player I and ν is a mixed strategy of Player II, then the payoff function $P(\mu,\nu)$ under the conditions of the mixed situation (μ,ν) is defined by the integral $P(\mu,\nu) = \int_X \int_Y P(x,y) d\mu(x) d\nu(y)$.

If the set of pure strategies of a player is infinite (and especially if it is denumerable), then in the choice of his set of mixed strategies there is a certain arbitrariness, which rests on the particular choice of $\sigma-$algebra of subsets of the pure strategy set on which the probabilistic measure is defined**[2]** .Various randomizations of pure strategy sets have been investigated by ***Wald*** and ***Bieriein*** .Clearly, the sets of mixed strategies are convex and, if the ordinary, or so-called pure, strategies are regarded as corresponding degenerate measures, include all the pure strategies of the players. Under the conditions of mixed strategies the payoff function turns out be linear in each of the variables.

Theorems establishing the validity of equations (1) and (2) for an infinite game or its mixed extension are called existence theorems (or minimax theorems). The proof of existence theorem, (i.e.) the identification of classes of games for which a value of the game exists (or does not exist), is one the fundamental problems of the theory of infinite zero-sum two-person games **[4].**

A pair of optimal strategies of each player in a zero-sum two-person game (or the set of $\in$ – optimal strategies for each player) in conjunction with the process of finding those strategies is known as a solution of the game.

In the infinite game, as in any zero-sum two-person game $\Gamma\langle X, Y, P\rangle$ the principle of player's optimal behavior is the saddle point (equilibrium) principle.

Definition: 3.3. Saddle point

The point $(x*, y*)$ *for which the inequality*

$$P(x, y^*) \le P(x^*, y^*) \le P(x^*, y) \text{ ----------- } (3.3)$$

holds for all $x \in X$, $y \in Y$ *is called saddle point.*

This principle may be realized in the game Γ *if and only if* $\upsilon = \bar{\upsilon} = \underline{\upsilon} = P(x^*, y^*)$ *where*

$$\underline{\upsilon} = \max_{x\in X} \inf_{y\in Y} P(x,y) \text{ ------------------------ } (3.4)$$

$$\bar{\upsilon} = \min_{y\in Y} \sup_{x\in X} P(x,y)$$

(i.e) the external extreme of maximin and minimax are achieved and the lower value of the game $\underline{\upsilon}$ *is equal to upper value of the game* $\bar{\upsilon}$. *The game* Γ *for which the (4) holds is called* ***strictly determined*** *and the number* υ *is the value of the game.*

Definition: 3.4. $\in -$ **Saddle points**, $\in -$ **optimal strategies**

The point $(x_\in, y_\in)$ *in the zero-sum two-person game* $\Gamma\langle X, Y, P\rangle$ *is called the* $\in -$ ***equilibrium*** *point if the following inequality holds for any strategies* $x \in X$ *and* $y \in Y$ *of the Players I and II, respectively:*

$P(x, y_\in) - \in \leq P(x_\in, y_\in) \leq P(x_\in, y) + \in$ ------------ (3.5).

The point $(x_\in, y_\in)$ *for which equation (5) holds, is called the* $\in -$ ***Saddle point*** *and the strategies* $x_\in$ & $y_\in$ *are called* $\in -$ ***optimal strategies*** *for the players I and II, respectively.*

NOTE:

Compare the definitions of the saddle point equation (3) and the $\in -$ Saddle point equation (5), A deviation from the optimal strategy reduce the player's payoff where as a deviation from the $\in -$ optimal strategies may increase the payoff by no more than $\in$.

In conclusion we will point out a special class of zero-sum two-person game in which $X = Y = [0, 1]$. In these games, situations are the pairs of numbers (x, y), where $x, y \in [0,1]$ such games are called the ***games on the unit square***. The class of the games on the unit square is basic in examination of infinite games.

Example 1:

Suppose each of the players I and II chooses a number from the open interval (0,1). Then Player I receives a payoff equal to the sum of the chosen numbers. In the manner we obtain the game on the open unit square with the payoff function $P(x, y)$ for Player I.

$P(x, y) = x + y$, $x \in (0,1)$, $y \in (0,1)$ --------(3.6).

Here the situation (1,0) would be equilibrium if 1 and 0 were among the players' strategies, with the game value υ being $\upsilon = 1$ Actually the external extreme in (4) are not achieved but in the same time the upper value is equal to the lower value of the game. Therefore $\upsilon = 1$ and Player I can always receive the payoff sufficiently close to the game value by choosing a number $1-\in$,

$\in > 0$ as a sufficiently small number (close to 0), Player II can guarantee that his loss will be arbitrarily close to the value of the game.

The following theorem yields the main property of $\in -$ **optimal strategies.**

Theorem1: *For the finite value* υ *of the zero-sum two-person game* $\Gamma = \langle X, Y, P\rangle$ *to exist, it is necessary and sufficient that, for any* $\in > 0$, *there be* $\in -$ *optimal strategies* $x_\in, y_\in$ *for the players I and II, respectively, in which case*

$\lim_{\in \to 0} P(x_\in, y_\in) = \upsilon$ --------------- (3.7).

Proof

Case (i) first to prove the Necessary condition:

Suppose the game Γ has the finite value υ . For any $\in >0$ we choose strategy $x_{\in}$ from the condition

$$\sup_{x\in X} P(x, y_{\in}) - \frac{\in}{2} \leq \upsilon \quad \text{----------- (3.8)}$$

And strategy $x_{\in}$ from the condition

$$\inf_{y\in Y} P(x_{\in}, y) + \frac{\in}{2} \geq \upsilon \quad \text{-------------------- (3.9)}$$

We know that $\underline{\upsilon} = \max_{x\in X} \inf_{y\in Y} P(x, y)$, $\bar{\upsilon} = \min_{y\in Y} \sup_{x\in X} P(x, y)$

From equation (8) & (9) we obtain the inequality

$$P(x, y_{\in}) - \frac{\in}{2} \leq \upsilon \leq P(x_{\in}, y) + \frac{\in}{2} \quad \text{---------------- (3.10)}$$ for all strategies x, y .

Consequently, $\left|P(x_{\in}, y_{\in}) - \upsilon\right| \leq \frac{\in}{2}$ ----------------- (3.11)

The relations $P(x, y_{\in}) - \in \leq P(x_{\in}, y_{\in}) \leq P(x_{\in}, y) + \in$, $\lim_{\in\to 0} P(x_{\in}, y_{\in}) = \upsilon$ follows from

$$\sup_{x\in X} P(x, y_{\in}) - \frac{\in}{2} \leq \upsilon \text{ and } \inf_{y\in Y} P(x_{\in}, y) + \frac{\in}{2} \geq \upsilon \; .$$

$$\sup_{x\in X} P(x, y_{\in}) - \frac{\in}{2} \leq \upsilon \leq \inf_{y\in Y} P(x_{\in}, y) + \frac{\in}{2}$$

Case (ii) Next to prove the sufficient condition:

If the inequalities $P(x, y_{\in}) - \in \leq P(x_{\in}, y_{\in}) \leq P(x_{\in}, y) + \in$ hold for any number $\in > 0$, then

$$\bar{\upsilon} = \inf_{y\in Y} \sup_{x\in X} P(x, y) \leq \sup_{x\in X} P(x, y_{\in}) \leq P(x_{\in}, y_{\in}) + \in \leq \inf_{y\in Y} P(x, y) + 2\in \leq \sup_{x\in X} \inf_{y\in y} P(x, y) + 2\in = \underline{\upsilon} + 2\in$$ ----------- (3.12)

Hence it follows that $\bar{\upsilon} \leq \underline{\upsilon}$, the inverse inequality holds true. Thus, it remains to prove that the value of the game Γ is finite.

Let us take such sequence $\{\in_n\}$ that $\lim_{n\to\infty} \in_n = 0$.

Let $\in_k \; \{\in_n\} \; \in_{k+m} \in \{\in_n\}$, where m any fixed natural number is. We have

$$P(x_{\in_{k+m}}, y_{\in_k}) + \in_{k+m} \geq P(x_{\in_{k+m}}, y_{\in_{k+m}}) \geq P(x_{\in k}, y_{\in_{k+m}}) - \in_{k+m} ,$$

$$P(x_{\in_k}, y_{\in_{k+m}}) + \in_k \geq P(x_{\in_k}, y_{\in_k}) \geq P(x_{\in_{k+m}}, y_{\in_k}) - \in_k \; .$$

Thus $\left|P(x_{\in_k}, y_{\in_k}) - P(x_{\in_{k+m}}, y_{\in_{k+m}})\right| \leq \in_k + \in_{k+m} = \delta_{km}$.

Since $\lim_{k \to \infty} \delta_{km} = 0$ for any fixed value of m, then there exists a finite limit $\lim_{\in \to 0} P(x_{\in}, y_{\in})$. From the relationship equation (10) we obtain the inequality

$\left| P(x_{\in}, y_{\in}) - \upsilon \right| \leq \in$; Hence $\upsilon = \lim_{\in \to 0} P(x_{\in}, y_{\in})$.

This completes the proof of the theorem.

IV. LIFETIME EXTENSION ALGORITHM

In this section, we propose a infinite zero-sum game theory life time extension algorithm. In order to implement the algorithm, the node *i* receives the sum of interference power from sink node to the destination node **[6].** The lifetime sensor node maintained according to the equation $\max_{x \in X} \inf_{y \in Y} P(x, y) = \min_{y \in Y} \sup_{x \in X} P(x, y) = \upsilon$ and $\lim_{\in \to 0} P(x_{\in}, y_{\in}) = \upsilon$

The latency at the source node L_S is given by,

$$L_S = \frac{T_{sleep}}{2} + T_1 + T_2 + T_{data} \quad \text{-------------------- (4.1)}$$

The latency at the intermediate node is same as that of source node, which is given in equation (13).

The end-to-end latency for multi-hop L_m transmission is given by, $L_m = \sum_{i=1}^{N} L_i$ -------------------- (4.2).

V. SIMULATION RESULTS AND DISCUSSION

The proposed algorithm has been simulated and validated through simulation. The sensor nodes are deployed randomly in a 100x100 meters square and sink node deploy at the point of (50, 50), the maximum transmitting radius of each node is 80 m; other simulation parameters are displayed in Table1. In this section, we first discuss utility factor and pricing factor's influences on transmitting power, and then evaluate the algorithm with other existing algorithm. Figure1. Shows that the average delivery delay with increasing transmission rate.

Table 1. Simulation Parameters

Parameters	Value
Number of Nodes	50-100
Network Area	100 X 100
Sensing Range	16m
Initial Energy of sensor node	2KJ

Sending and Receiving Slot	50msec
Transmission Range	250meter
Packet Size	64 Bytes
Energy threshold E_{th}	0.001mjoules
Channel Frequency	2.4GHz
Receiving power	36mW
Power consumption in sleep mode	0.36J
Type of mode	Mica 2
Radio Bandwidth	76kbps

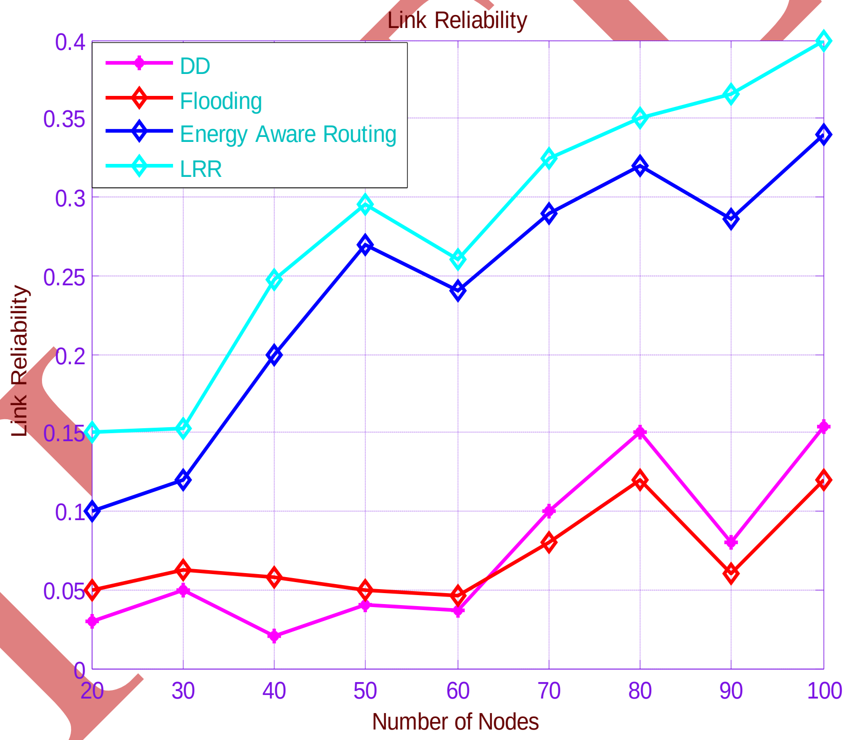

Figure 1: Average Delivery Rate with various Transmission Rate

The average delay means the average delay between the instant the source sends a packet and moment the destination receives this packet. When the transmission rate is 1 packet per second, we can see that the average delivery delay of DD, Flooding, and Energy Aware is lower than the proposed LRR protocol.

In the proposed protocol, when the packets reach at destination, the relay or intermediate nodes have a lower multiple strategies. In the forwarding node selection game, the probability that a great amount of packets are forwarded by the same node is relatively low. Thus, the average delivery delay of our protocol does not significantly increase with an increase in transmission rate. The following table 2 shows the network life time of nodes in the respective routing protocols.

Routing Protocols	Nodes Alive		Number of Nodes	
	100 Rounds	700 Rounds	20 Nodes	100 Nodes
LRR (Proposed)	100	45	0.15	0.4
Flooding	59	18	0.05	0.07
DD	42	5	0.035	0.15
Energy Aware	68	20	0.1	0.34

VI. CONCLUSION

In this paper, we introduce a zero-sum game theory for maintaining a sensor network lifetime. In this network connectivity of nodes forward to any packets to its neighbor nodes. Zero-sum game theory improves the network lifetime. Direct diffusion (DD) protocol, after 400 rounds, about 25% of nodes alive. In proposed link reliability routing (LRR) protocol, after 550 rounds Network lifetime is increasing about 70%. Path reliability for direct diffusion (DD) protocol is random. Path reliability for proposed link reliability routing (LRR) protocol, increases Number of nodes increases to above 70 nodes, the path reliability is more than 0.3. This shows that our proposed model and algorithm increases the network lifetime. Also, we will be optimizing the algorithm to find the maximum usefulness function of all nodes that cooperate in path.

REFERENCES

[1] F.Akyldiz, W.Su, Y. Subramanian, Sankaras and E. Cayirci, "Wireless sensor networks: a survey" Computer Networks,
[2] Vol.38, Pp. 393-422, 2002.
[3] "Theory of Games and Economic Behavior"-Von Neumann and Morgenstern-1953.
[4] "Game theory in Wireless sensor networks" – Pedro O.S.Vazdemelo, Cesar Fernandes, Raquel A.F, Mini Antonio

[5] A.F.Loureiro.

[6] A. Agah, S. K. Das, and K. B.Basu, "Preventing DoS attack in sensor and actor networks: A game theoretic approach",

[7] IEEE Int'l. Conf. On Communications (ICC), Seoul, Korea, May 2005, pp. 3218-3222.

[8] S. Buchegger and J. Le Boudec, "Performance Analysis of the CONFIDANT Protocol," Proc. Third ACM Int'l

[9] Symp. Mobile AdHoc Networking & Computing, pp. 226-236, 2002.

[10] L. Buttyan and J.P. Hubaux, "Nuggets: A Virtual Currency to Stimulate Cooperation in Self organized Mobile

[11] Ad- Hoc Networks, "Technical Report DSC/2001/001, Swiss Fed. Inst. Of Technology, Jan. 2001.

[12] 7.W. Wang, M. Chatterjee, and K. Kwiat, "Enforcing Cooperation in Ad Hoc Networks with Unreliable Channel,"

[13] Proc. Fifth IEEE Int' Conf. Mobile Ad-Hoc and Sensor Systems (MASS), pp. 456-462, 2008.

[14] V. Srinivasan, P. Nuggehalli, C. Chiasserini, and R. Rao,"Cooperation in Wireless Ad Hoc Networks," Proc.

[15] IEEEINFOCOM, vol. 2, pp. 808-817, Apr. 2003.

[16] Chang, C.Y.; Shih, K.P.; Lee, S.C.; Chang, S.W. RGP: Active route guiding protocol for wireless sensor networks with

[17] Obstacles. In Proceedings of IEEE MASS, Vancouver, Canada, October 2006; pp. 367-376.

[18] K. Sanzgiri, B. Dahill, B.N. L E.M. Royer, "A Secure Rohoc Networks", In Proc. of on Network Protocols (IC2002,

[19] pp. 78-87. Levine, C. Shields, and using Protocol for Ad 10th IEEE Int'l. Conf.CNP'02), IEEE Press.