Dynamic Power Allocation using Stackelberg Game in a Wireless Sensor Network

Mohit Srinivasan, Ahan Kak, Kaustubh Shivdikar ,Chirag Warty
Intelligent Communications Laboratory, Mumbai, India
E-mail : mohit.s@intelcomlab.com, ahan.kak@intelcomlab.com, kaustubhcs07@gmail.com ,chirag.warty@intelcomlab.com

Abstract—**Wireless sensor networks are characterized by a limited availability of resources such as the power required for data transmission. Cooperative communication enables transmission of data without using too much power. The fading of data is considerably less when the nodes are engaged in a cooperative communication protocol, rather than a competitive game. The quintessential concern for each node is the power it needs to allocate in order to relay the other nodes data. In cooperative communication, the nodes need to transmit not only their own data, but the data of the neighboring nodes too. An efficient solution to this problem can be determined by employing the Stackelberg game. From the determined solutions, improvement in the cooperation among the neighboring nodes can be worked upon. A cooperation region can be established within which the nodes work towards transmitting the data more efficiently. A similar concept can be applied to multi-hop networks and N relay multi-hop networks. Thus, an optimal region of cooperation for a single node, which permits it to achieve maximum cooperation amongst all the other nodes at the same time can be determined. Since we employ a game theoretic approach, we can determine a trade off between quantities such as power allocated and utility of the nodes, which results in maximum optimization of the network. Through this paper, we aim to improve the network utility factor of the wireless sensor network through dynamic power allocation using the Stackelberg game.**

TABLE OF CONTENTS

1. INTRODUCTION

Wireless sensor networks are being used extensively for monitoring real time data and processing the data. One of the main drawbacks of a sensor node is the limited availability of resources such as power for transmission of data. Once the node has drained its power, it cannot function efficiently. Hence, to better sustain a node and to increase its operating life, the focus is now on cooperative communications. Cooperative communications works on the principle of nodes helping each other to transmit their data. Each node acts as a relay to transmit the neighbor's data. In this manner, a single node need not use great amount of power to transmit the data to the destination. Instead, the relaying principle helps in the transmission with less amount of power. Transmission diversity requires multiple antennas at the transmitter. But due to constraints on the design, we sometimes cannot use multiple antennas. This is where cooperative communications comes into the picture. A cooperative network creates a virtual MIMO (Multiple Input Multiple Output) system, thus allowing transmission diversity or cooperation diversity. Cooperative diversity is a technique that combats the slow fading and shadowing effect in wireless communication channel [5]. The author in [1] has analyzed the advantages of using cooperative communication in satellite communication, which justifies the ability of cooperative communication protocols to include a wide range of systems.

Game theory is one of the many tools used to address the issues concerning wireless sensor networks. The application of mathematical analysis to wireless networks has met with limited success, due to the complexity of mobility and traffic models, coupled with the dynamic topology and the unpredictability of link quality that characterize such networks [2]. The ability to model individual and independent decision makers whose actions potentially affect all other decision makers makes game theory particularly attractive to analyze the performance of ad hoc networks [2]. Majority of the wireless systems in modern times are multi agent systems which have the capability to either help in the overall improvement in network efficiency and throughput, or act maliciously and refuse to cooperate. Hence, game theory can be used to analyze the functioning of the network. Some of the important applications of game theory include resource allocation and auctions in wireless sensor networks. Power and bandwidth allocation in such networks can be analyzed using different game strategies. One may also describe cooperation as a zero sum game in terms of power and bandwidth of the mobiles in the network [7]. The premise of cooperation is that certain (admittedly unconventional) allocation strategies for the power and bandwidth of mobiles lead to significant gains in system performance [7]. In the cooperative allocation of resources, each mobile transmits for multiple mobiles [7].

Game theory has been an emerging tool used in wireless sensor networks in recent times. Modern systems involve agents which try to act selfishly or try to maximize their own benefits/utilities. Hence, game theory acts as the best tool to formulate and analyze how a system involving such multi agents works. Stackelberg games and other games have been used for the purpose of power and bandwidth allocation in wireless sensor networks. Power allocation using the Stackelberg game is analyzed in [2] and the authors have explored the situation where the nodes of the model are assumed to be moving. The paper then goes on to prove that when the nodes are closest to each other, they achieve maximum cooperation. The work carried out in [4] assumes that the nodes of the network are selfish and want to maximize their own benefits. It approaches the game strictly from an economic perspective, assuming the source as a buyer and

978-1-4673-7676-1/16/$31.00

the relay nodes as the seller. Work done in [5] focusses on the Karush-Kuhn Tucker (KTT) algorithm for optimal power allocation and best partner choice. The authors of [6] focus on using coalition game theory for the purpose of grouping the nodes, that is, to decide whether a mobile node should join a particular group or not depending on how beneficial the power consumption is.

This paper works towards employing the Stackelberg game for dynamic power allocation in a bidirectional wireless sensor network. The Stackelberg game is a model which consists of a leader and a follower. The leader first performs an action which the follower observes. The follower then performs his action and decides his output. The main challenge as stated earlier is to determine how much power a node needs to allocate in order to transmit the neighboring nodes data. This is a very important issue which needs to be addressed since a single node in a bidirectional network needs to transmit its own data as well as relay the other nodes data. This issue is addressed in this paper. By employing the Stackelberg game, we determine the cooperation region between two nodes. This is the region in which the two nodes cooperate to transmit and relay data. Once this is achieved for a single relay model, a similar concept can be applied to N relay single hop network and N relay multi hop networks. Through this paper, we aim to achieve an improvement in the network utility factor of the wireless sensor network.

This paper performs a unique analysis of nodes which are stationary. The system is a bidirectional cooperative communications network. Using the Stackelberg game, we determine the region where the nodes cooperate, known as the cooperation region. Within this region, we can determine at which points the utilities of the nodes are maximum. We then observe that a certain trade off can be made between parameters of the system such as power allocation and the utility of the nodes. Ultimately, this paper works towards improving the network utility factor of the wireless sensor network.

2. System Model

We consider a simple model, which consists of two nodes involved in a bi-directional cooperative communication. We apply the Stackelberg game to this model and determine the cooperation region. In a similar way, we can apply the same concept to an N node system. In this model, we consider two source nodes. The system is as shown in fig(1). In addition to being source nodes, they also act as relays to transmit the other nodes data. The main issue which is to be addressed is how much power a node needs to allocate in order to transmit the other nodes data. Let the two nodes be denoted by node 2.

The received signals at the destination and node2 are as follows,

$$y_{1,d}(t) = \sqrt{P_{11}G_{1,d}}x_1(t) + n_{1d}(t) \tag{1}$$

$$y_{1,2}(t) = \sqrt{P_{11}G_{1,2}}x_1(t) + n_{12}(t) \tag{2}$$

In the above equations, P_{11} represents the amount of power used by node1 in order to transmit its own data, $G_{1,d}$ represents the path gain for the channel between node1 and the destination, $G_{1,2}$ represents the path gain for the channel between node1 and node2, $x_1(t)$ represents the data transmitted by node1, $n_{1,d}(t)$ represents the noise in the path between node1 and the destination and $n_{1,2}(t)$ represents the noise in the channel between node1 and node2. The noise in the channels can be AWGN noise, Rician noise, etc.

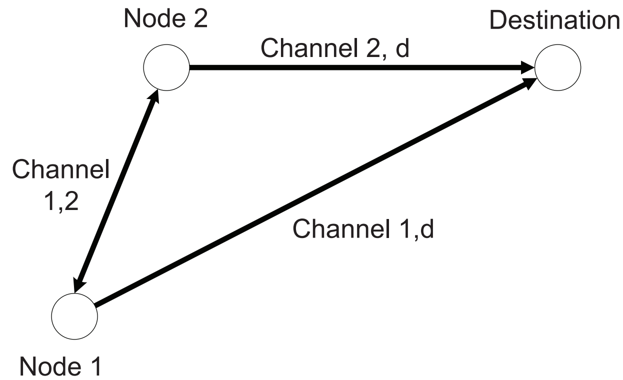


Figure 1. **Two relay bi-directional communication.**

The signal received from the relay node2 at the destination is as follows,

$$y_{2,d}(t) = \sqrt{P_{21}G_{2,d}}x_{21}(t) + n_{2d}(t) \tag{3}$$

In the above equation, P_{21} represents the amount of power used by node2 in order to transmit the data of node1, $G_{2,d}$ represents the path gain for the channel between node2 and the destination, $x_{21}(t)$ represents the data transmitted by node1, $n_{2,d}(t)$ represents the noise in the path between node2 and the destination. The noise in the channels can be AWGN noise, Rician noise, etc.

The signal to noise ratio (SNR) for the direct and relay paths are as given below,

$$SNR_{2d} = \frac{G_{2d}P_{22}}{\sigma^2} \tag{4}$$

$$SNR_{1d} = \frac{G_{1d}P_{11}}{\sigma^2} \tag{5}$$

$$SNR_{12d} = \frac{G_{12}G_{2d}P_{11}P_{12}}{\sigma^2(G_{12}P_{11} + G_{2d}P_{21} + \sigma^2)} \tag{6}$$

$$SNR_{21d} = \frac{G_{21}G_{1d}P_{22}P_{12}}{\sigma^2(G_{21}P_{22} + G_{1d}P_{12} + \sigma^2)} \tag{7}$$

Where, P_{22} represents the power used by node2 in order to transmit its own data and σ^2 represents the noise power.

In order to employ the Stackelberg game, we define the utility function for both the nodes as given below,

$$U_1 = kR_{12d} - (cP_{11} + P_{12}) \tag{8}$$

$$U_2 = kR_{21d} - (cP_{22} + P_{21}) \tag{9}$$

Where, k is the gain per unit of achieved rate at the receiver and c is the constant which determines the extent of cooperation.

For relating P_{12} and P_{21} we define a parameter γ such that,

$$P_{12} = \gamma P_{21} \tag{10}$$

Hence, ultimately, we arrive at the following two equations for the utility of the nodes,

$$U_1 = kR_{12d} - (cP_{11} + \gamma P_{21}) \tag{11}$$

$$U_2 = kR_{21d} - (cP_{22} + P_{21}) \quad (12)$$

Node 1 will tell node 2 to consume P_{21} Watts of power to transmit its data, while node 2 will tell node 1 to consume γ multiples of P_{21} Watts of power to transmit its data. Determining P_{11} and P_{22} is an optimization problem. For node 1 which is assumed to be the follower in the Stackelberg game, determining P_{21} is a game problem. For node 2 which is assumed to be the leader, determining γ is again a game problem.

For the optimization problem, we differentiate equation (7) w.r.t P_{11} and equate it to zero (for maximization of utility). We therefore arrive at the following equation,

$$P_{11} = \frac{w'}{c} - \frac{\sigma^2}{G_{1d}} \quad (13)$$

Similarly, we optimize the utility function of node 2 and equate it to zero to get,

$$P_{22} = \frac{w'}{c} - \frac{\sigma^2}{G_{2d}} \quad (14)$$

where,

$$w' = \frac{kbW}{ln2} \quad (15)$$

where, b is known as the bandwidth factor and W is the transmission bandwidth. We now use the Stackelberg game to determine to maximize the utilities of the two nodes. We consider node 2 to be the follower and node 1 to be the leader.

For the follower side solution, we assume that node 2 provides the value of γ to node 1. The game problem is therefore to choose P_{21} in such a way that it maximizes the utility of the follower that is, node 1. Hence, differentiating the utility of node 1 w.r.t P_{21}, we get,

$$P_{21} = \frac{\gamma A_1 B_1 + \sqrt{(\gamma A_1 B_1)^2 + 4\gamma A_1 B_1 w'(1 + A_1)}}{2\gamma(1 + A_1)} - B_1 \quad (16)$$

where,

$$A_1 = \frac{G_{12}P_{11}}{\sigma^2 + G_{1d}P_{11}} \quad (17)$$

$$B_1 = \frac{\sigma^2 + G_{12}P_{11}}{G_{2d}} \quad (18)$$

This power is the power used by node 2 to transmit the data of node 1. Hence, upto a certain point, the power will remain positive. Beyond that point, the power becomes negative which is not possible. Hence, we denote this point by γ_2. This is the boundary of the cooperation region which we are trying to determine. In order to determine γ_2, we substitute P_{21} = 0 in the above equation. Hence, we get,

$$\gamma_2 = \frac{2K_2}{K_3^2 - 1} \quad (19)$$

where,

$$K_2 = \frac{2w'(1 + A_1)}{A_1 B_1} \quad (20)$$

For the leader side solution, we need to first determine whether R_{21d} is a concave function of γ. By taking the double derivative of P_{12} with respect to γ, we observe that it is negative for all values of γ. Hence, R_{21d} is a concave function of γ. There will be a value of γ at which R_{21d} achieves a local maximum. This is the value of γ_1. Differentiating P_{12} with respect to γ, we get the value of γ_1 as follows,

$$\gamma_1 = \frac{K_2 K_3}{\sqrt{K_3^2 - 1}} - K_2 \quad (21)$$

where,

$$K_3 = \frac{2 + A_1}{A_1} \quad (22)$$

The value of γ_2 will always be more than the value of γ_1. The cooperation region is defined by the following case wise representation,

$$f(x) = \begin{cases} (\gamma_1, \gamma_2) & \text{; Nodes will cooperate} \\ else & \text{; Nodes will not cooperate} \end{cases} \quad (23)$$

This is the region within which the nodes cooperate. The Performance Evaluation Section explains the simulation results and the cooperation region in more detail.

3. Cooperative Communication

Cooperative communications helps single antenna nodes to reap the benefits of a virtual MIMO system. This improves transmission diversity and thus leads to an overall improvement in the throughput and the efficiency of the system. There are three main protocols which are used in cooperative communications, namely Detect and Forward, Amplify and Forward (A.F) and Decode and Forward (D.F).

Amplitude and Forward Scheme

In the A.F scheme, the relay receives a signal from the source and simply amplifies or pumps up the signal and transmits it to the destination. The destination node therefore receives two signals one directly from the source and the other which was amplified by the relay. The destination node compares the signal to noise (SNR) ratio of the two signals and chooses the optimal signal. It has been shown that for the two-user case, this method achieves diversity order of two, which is the best possible outcome at high SNR [7]. In amplify-and-forward it is assumed that the base station knows the interuser channel coefficients to do optimal decoding, so some mechanism of exchanging or estimating this information must be incorporated into any implementation [7]. The AF scheme requires the storage of a large amount of analog data and hence it is not a feasible scheme for TDMA (Time Division Multiple Access) systems. AF also suffers from the noise amplification problem which can degrade the signal quality (since even noise can get amplified), particularly at low SNR values. Another potential challenge is that sampling, amplifying, and retransmitting analog values is technologically nontrivial. Nevertheless, amplify-and-forward is a simple method that lends itself to analysis, and thus has been very useful in furthering our understanding of cooperative communication systems [7].

The equations which govern a two relay system employing the A.F scheme is as follows,

$$y_{1,d}(t) = \sqrt{P_{11}G_{1,d}}x_1(t) + n_{1d}(t) \quad (24)$$

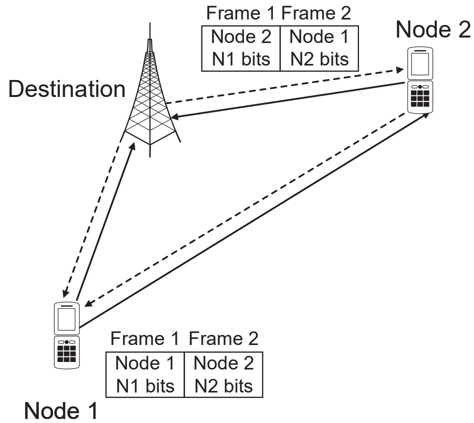


Figure 2. **Coded Cooperation**

The amplification factor which amplifies the the signal received by the relay is given by,

$$\beta = \frac{\sqrt{P}}{\sqrt{PG_{12} + N_0}} \tag{25}$$

where P is the received power from node 1 and N_0 is the variance of the noise in the channel. The signal received at the destination is given by,

$$y_{2,d} = \beta\sqrt{P}G_{12}G_{2d}G_{1d}x(t) + \beta G_{2d}n_{12} + n_{2d} \tag{26}$$

The maximum ratio combiner (MRC) output receives two input signal - y_{1d} and y_{2d}. The output of the MRC is as follows,

$$y = my_{1d} + ny_{2d} \tag{27}$$

where m and n are the combining factors. Thus, this is how the A.F scheme is designed. We employ a similar scheme in the bi-directional model used in this paper.

Decode and Forward Scheme

The decode-and-forward relay protocol is a protocol defined for wireless cooperative communications. In the D.F scheme, the source sends the data in an encoded form to the relay. The relay then decodes this data and again encodes using either the same or a different scheme and transmits it to the destination. The relay does not include any information about the level of reliability of the source-relay link. Hence, this processing of the signal at the relay is also know as a make hard decision. When uncoded modulation is used, this protocol is also know as Detect-and-Forward as the processing of the relay is detection of the signal. There are two types of decode and forward techniques - Fixed Decode and Forward, and Adaptive Decode and Forward. This scheme removes the noise by decoding the received signals and then regenerating and re-encoding the signal to be forwarded to the destination. Sometimes, the relay can incorrectly decode/relay the received message from the source and send this incorrect information to the destination. Hence, the DF scheme suffers from the error propagation problem. In Adaptive Decode and Forward scheme, the relay forwards the signal to the destination only if it is able to decode the signal correctly. The correct decoding can be checked using some error detection check or SNR threshold. A special case is that when the relay detects the signal but does not decode it. In this case the scheme is called detect-and-forward.

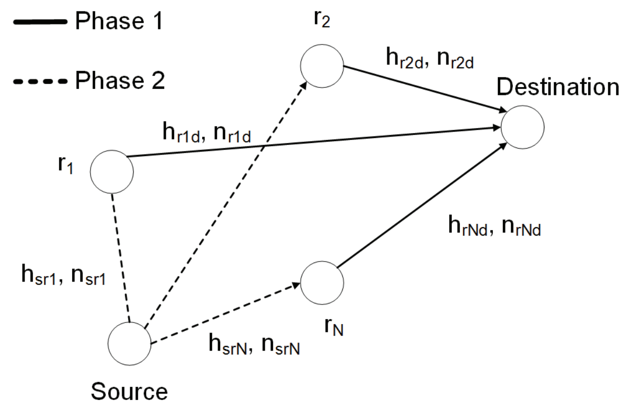


Figure 3. **N Relay A.F scheme.**

Coded Cooperation Scheme

Coded cooperation is a method that integrates cooperation into channel coding [7]. Coded cooperation works by sending different portions of each users code word via two independent fading paths [7]. The basic idea is that each user tries to transmit incremental redundancy to its partner [7]. Whenever that is not possible, the users automatically revert to a non cooperative mode [7]. All this is managed through code design and and there is no feedback between the users. Hence, the efficiency of coded cooperation is high and is more improved. The efficiency of different protocols depends on the quality of the channels and more importantly on the position of the nodes. This paper focusses on the A.F technique owing to its simplicity and ease of implementation.

Multi-Node Amplify and Forward Protocol

The multi-node system model consists of n nodes which forward the data to the destination individually. We consider a source only amplify and forward strategy in which the relays forward the information from the source and the cooperation takes place in two phases. In phase 1, the data is sent from the source node to the destination and the N relays. In phase 2, the relays amplify the received data from the source and transmit it to the destination. By determining the received signals from the relays and the original signal from the source, the destination will determine the best possible signal using maximum receiver combining technique.

The system model for N relay is as shown below, The governing equations for phase 1 of transmission as well as the received signals at the destination and the $i-th$ relay are as follows,

$$y_{s,d} = \sqrt{P_o}h_{s,d}x + n_{s,d} \tag{28}$$

$$y_{s,r_i} = \sqrt{P_o}h_{s,r_i}x + n_{s,r_i} \tag{29}$$

The signal received at the destination from the $i-th$ relay after it has amplified and forwarded the data is as follows,

$$y_{r_i,d} = \frac{\sqrt{P_i}}{\sqrt{P_o h^2_{s,r_i} + N_0}} h_{r_i,d}y_{s,r_i} + n_{r_i,d} \tag{30}$$

The concept of cooperation region and dynamic power allocation can be applied to the above N relay model, thus improving the network utility factor of the system. By using

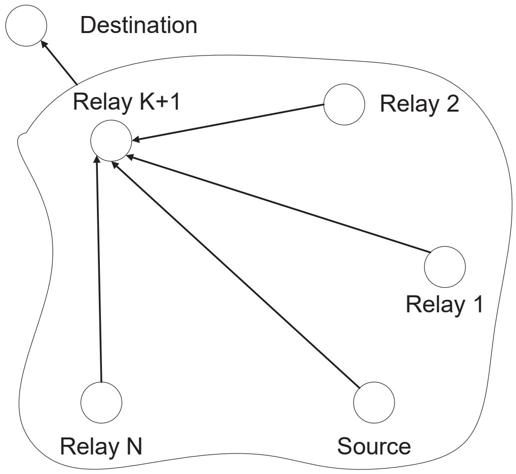


Figure 4. **Multi-node Cooperation. The $(k+1)th$ relay combines information from the source as well as all other relays.**

the same concept as in case of the two relay model, we can determine the cooperation regions between each relays and the source. The source can then determine which relay can cooperate with it the most, and which node will result in maximum utility and least power consumption for the determined cooperation region. Further work can be employed in the domain of N relay multihop networks.

Multi-Node Decode and Forward Protocol

As in the previous case, the link between any two nodes in the network is modeled as a Rayleigh Fading Channel with AWGN. The network model is based on the assumption that the channel coefficients for each link are independent of each other. A fixed DF strategy is not feasible in a multi-node environment, and, thus, a selective DF scheme is employed. Such a scheme works well because the probability of error increases with distance from the source, due to poor SNR. In general, each relay decodes the information after combining the source signal as well as signals from each of the previous relay. Cooperation occurs in $(N+1)$ phases, as opposed to 2 phases for the single relay model. In phase 1, when the source transmits, the expressions for information received by the destination and the $i-th$ relay are

$$y_{sd} = \sqrt{P} t_{\mathrm{sd}} x + n_{sd} \tag{31}$$

$$y_{sr_i} = \sqrt{P} t_{sr_i} + n_{sr_i} \tag{32}$$

The notations used above follow from the single relay model. In phase 2, the first relay, on correct decoding, forwards the information with power P_1 to the destination. The signals from the source and previous relays are combined using MRC at any relay l

$$y_{r_i} = \sqrt{P} t*_{sr_l} y_{sr_l} + \sum_{i=\max(1,l-m)}^{l-1} \sqrt{\widehat{P}_i} t*_{r_i r_l} y_{r_i r_l} \tag{33}$$

Provided, the $l-th$ relay decodes correctly, it transmits with power P_l in Phase $(l+1)$, otherwise it remains idle. Finally, the destination combines all received signals in the $(N+1)$ phase using MRC as follows

$$y_d = \sqrt{P} t*_{sd} y_{sd} + \sum_{i=1}^{N} \sqrt{\widehat{P}_i} t*_{r_i d} y_{r_i d} \tag{34}$$

Table 1. **Utility Table for Prisoners Dilemma**

Action	Cooperate	Defect
Cooperate	(2,2)	(0,3)
Defect	(3,0)	(1,1)

4. Game Theory

Game theory is the branch of mathematics which deals with intelligent agents which are capable of making decisions which are either conflicting with others, or in tandem with the interest of the other agents. This is particularly useful for applications in wireless sensor networks since cooperative communication depends on nodes interacting and cooperating with each other. There are two types of games which can be played- cooperative game and non-cooperative game [8]. As the name suggests, in cooperative games, the players take decisions which depend on the outcomes of the neighboring players. In non-cooperative games, the agents or the players of the games are selfish and have conflicting interests. It is assumed that each player acts without communicating with the other players. John Nashs identification of the Nash equilibrium has perhaps had the biggest impact on game theory [8]. Simply put, in a Nash equilibrium, no player has an incentive to unilaterally deviate from its current strategy [8]. Put another way, if each player plays a best response to the strategies of all other players, we have a Nash equilibrium. One of the features of a Nash equilibrium (NE) is that in general it does not correspond to a socially optimal outcome [8]. That is, for a given game it is possible for all the players to improve their costs (payoffs) by collectively agreeing to choose a strategy different from the NE [8]. A Pareto optimal equilibrium describes a social optimum in the sense that no individual player can improve his payoff (or lower his cost) without making at least one other player worse off [8]. Pareto optimality is not a solution concept, but it can be an important attribute in determining what solution the players should play (or learn to play) [8]. Loosely, a Pareto optimal (also called Pareto efficient) solution is a solution for which there exists no other solution that gives every player in the game a higher payoff (lower cost) [8].

Prisoner's Dilemma

An example of a game problem is the Prisoner's dilemma. It is analyzed as a non-zero sum game. The game is based on an imaginary situation which consists of two people who have committed crimes. The prisoners are given two choices - either to cooperate or defect. If the prisoners cooperate and provide evidence against the other, then they make a gain. If they defect, then they get a punishment. There are multiple cases which are possible. If both the prisoners defect, then the law authorities will not have any evidence against both of them and hence, they won't be charged. The prisoners therefore escape without any punishment. If they both cooperate, then they are let off with a light punishment. If one defects and the other cooperates, then the prisoner who cooperates will get a lesser punishment and the other gets a harsh punishment. The state of the game in which both the prisoners defect is the best strategy for the players, but the

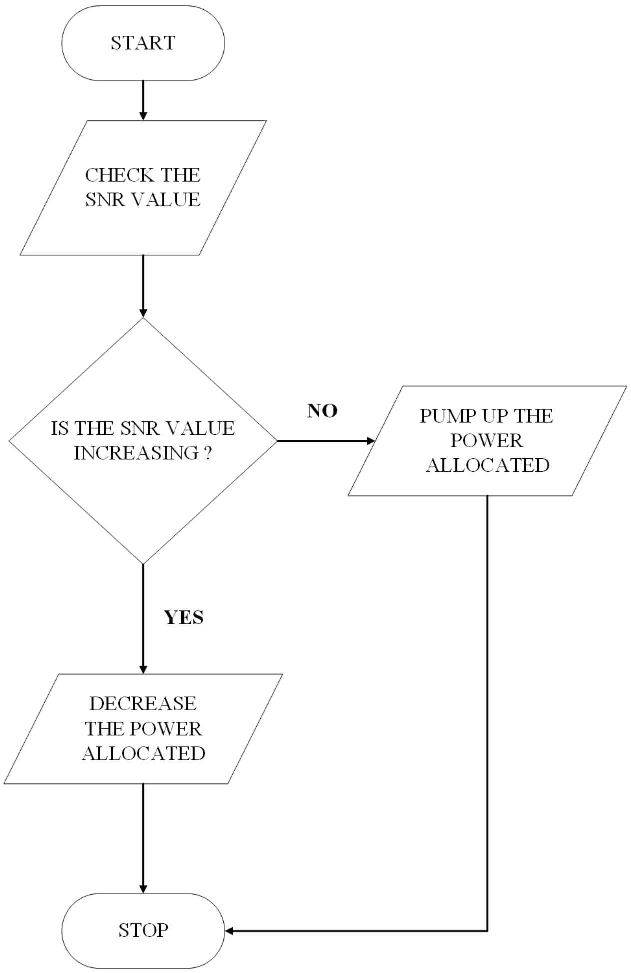


Figure 5. **The Dynamic Power Allocation Algorithm**

prisoners are isolated and hence are not aware of each others strategies. The utility table for the prisoners dilemma is as shown in table 1.

Stackelberg Game

Bandwidth allocation and power allocation are two major areas of application of game theory in sensor networks. A plethora of games can be applied to such networks, common among them being the Stackelberg game. The Stackelberg game is an extensive game which is centered around two agents- the leader and the follower. First, the leader performs his action. The follower then observes the leader and performs his action. Situations can arise where there are multiple leaders or followers. The game used in this paper is the Stackelberg game, which helps in determining the cooperation region between various nodes in a wireless network. Thus, game theory acts as an effective tool in the analysis of resource allocation in wireless sensor networks.

5. Dynamic Power Allocation

Power allocation and bandwidth allocation are two key areas where game theory plays an important role in wireless sensor networks. In wireless communication, the nodes share a single spectrum and hence, bandwidth allocation is important. At the same time, the nodes in a wireless network are characterized by a limited availability of power. Periodic charging of the nodes is not a viable option, especially if the wireless sensor network is situated in mountainous or inaccessible regions. Hence, dynamic power allocation is of quintessential importance.

In this paper, we explore the possibility of a time varying channel. Because the channel is time varying, all the parameters such as the channel gains will keep on varying. Hence, at every instant the SNR values of the channels will vary. If the SNR value is very high, then not much power needs to be used up to transmit the data from the nodes. However, if the SNR value is low, then we need to pump up or amplify the power to increase the signal power. An algorithm based on this concept is employed in this paper. As mentioned earlier, we also address the issue of how much power a node needs to use in order to transmit the neighboring nodes data. We also determine the region of cooperation which facilitates relaying of data between the nodes.

The algorithm is as shown in fig(5). The algorithm checks for the SNR value at each instant of the simulation time. If the SNR value is increasing, then there is no need to allocate much power for the relaying of the data. This is because the signal power is increasing and is more than the noise power. Similarly, if the SNR value decreases, then we need to pump up the power. This is how we dynamically allocate power for the nodes. The results of the algorithm which leads to dynamic power allocation is shown in fig(11).

6. Network Utility Management

Network Utility Management can be defined as the process of managing, monitoring and controlling the important parameters of the wireless sensor network (WSN) such as the power utilized by each node, connectivity between the nodes and environmental obstacles. The main concern, as stated earlier, in a WSN is to minimize the energy consumption by the nodes. Hence, we cannot employ the traditional network management protocols since they only improve the response time and improve information feedback. In addition, WSNs are more prone to abnormal or fault conditions. We need to ensure that we create a system which is perpetual in nature i.e the nodes do not in any way become energy deficient.

The dynamic power allocation algorithm and determination of the cooperation region achieved in this paper will lead to an overall reduction in the power consumed by the nodes to transmit the data. This leads to an improvement in the network utility factor. In this paper, we have used a game theoretic approach for dynamic power allocation. With this approach, we determine an optimum region of cooperation between the nodes which results in maximum utility of the nodes and also results in transmission or relaying of data with the least amount of power. The improvement in the network utility of the nodes can be seen from fig(13). By employing the proposed game theoretic dynamic power allocation algorithm, we have increased the utility of the nodes. Also by achieving a trade off between the power allocated by the nodes to transmit data and the utility functions, important parameters of the network such as energy consumption and life of the network can be carefully managed. Employing a proactive monitoring management system which will determine the cooperation region and at the same time, determine how much power should be allocated dynamically, will maintain the performance of the network. This can be infused with a Reactive Monitoring System and a Fault detection system to maintain and stabilize the parameters of the network such

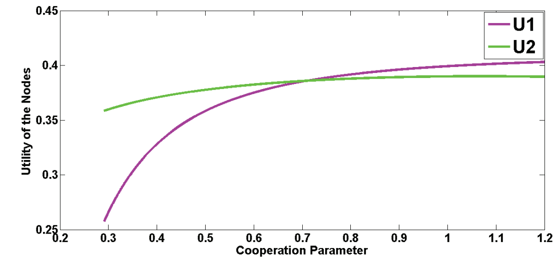


Figure 6. **Utilities of the nodes in the two relay model.**

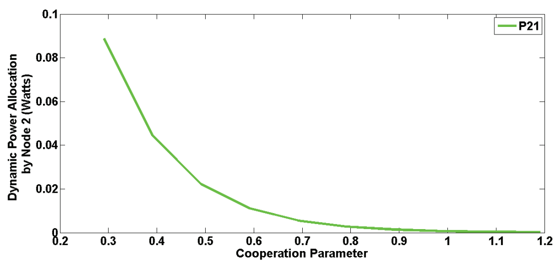


Figure 7. **Power allocation for Node 2**

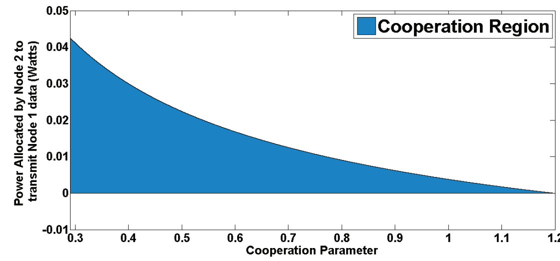


Figure 10. **Region of Cooperation for node 2**

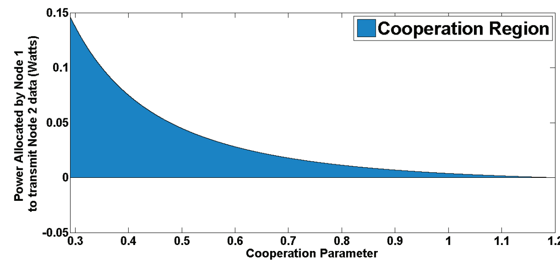


Figure 11. **Region of Cooperation for node 1**

as energy consumption and power allocation. Thus, with the concepts mentioned in this paper, we can obtain an optimization of the network resources and employ an efficient network utility management strategy.

7. Performance Evaluation

We perform the simulation of the above environment in MATLAB, by assuming the following values of the parameters which are taken as constants in the environment of the above system,

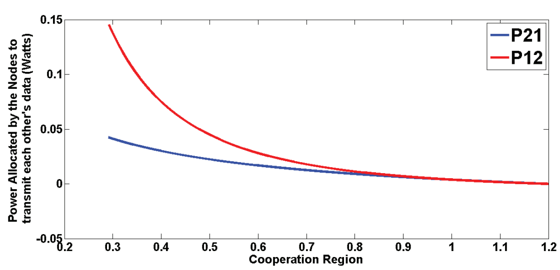


Figure 8. **Region of Cooperation between the nodes of the two relay model**

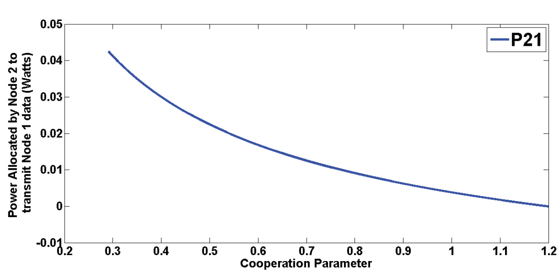


Figure 9. **Power used by node 2 to relay node 1 data**

$G_{1d} = G_{21d} = G_{12} = G_{21} = 1, \sigma^2 = 10^{-8}, c = 1.2, a = 10^{-7}, W = 10^7, b = 0.5$

With the above assumed values, we determine the cooperation region and the power which the nodes utilize to transfer each others data. The cooperation region, as per the above simulation is between (0.2912, 1.2000). This region is highlighted in fig(10) and fig(11). Fig(9) is the curve which indicates the power used by node 2 in order to relay node 1 data. Fig(14) is the curve which represents the power used by node 1 to relay node 2 data. Fig(15) represents the utility function of node 1 while fig(12) represents the utility function of node 2. In fig(8), the blue curve indicates the power used by node 2 to transmit node 1 data i.e P_{21} while the red curve indicates the amount of power used by node 1 to transmit node 2 data i.e P_{12}. As can be observed from fig(6), the utilities of both the nodes are much higher than their initial values at the end of the cooperation region and hence, this would be a preferred region of operation for both the nodes. The purple curve in fig(6) represents the utility of node 1 and the green curve represents the utility of node 2. However, if one observes fig(8), then the power allocated by the two nodes for transmitting the others data is high only in the initial part of the cooperation region. This leads to one of the main conclusions of this paper. It is quintessential to strike a balance between the utility of the nodes and the power they allocate to relay the other node's data. Hence, a trade off must be made between the utility of the nodes and the power allocated by them for relaying data. This can be done by choosing a value of gamma, such that we get near optimal values of utility and power allocation.

Ideally, the nodes should relay the neighboring node's data with the least amount of power. At the same time,the utility of the two nodes should be as high as possible. As we can observe from fig(6) and fig(8), we observe that the power allocated is the least and the utility is maximum at the far end of the cooperation region. Hence, the operation of the nodes of the system for values of γ beyond 0.8 would lead to an improvement in the network utility factor. The same can be observed from fig(13). The utility of node 2 in a

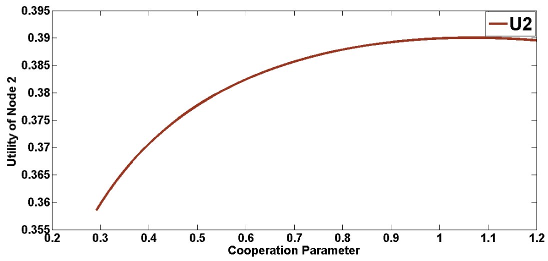


Figure 12. **Utility function of Node 2**

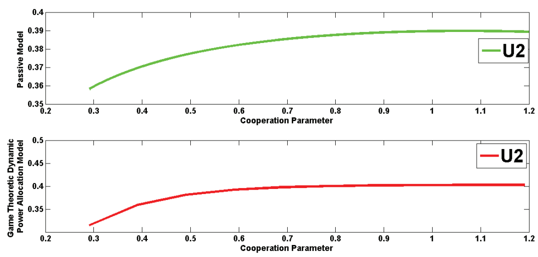


Figure 13. **Improvement in the utility of Node 2 by using Game Theoretic Dynamic Power Allocation**

game theoretic dynamic model is higher than a passive model when it operates in a region beyond $\gamma = 0.8$. For example, at $\gamma = 1$, the utility of node 2 has increased from 0.3899 to 0.4025. This is the main conclusions of this paper. The power allocated by the nodes to transmit each others data at $\gamma = 1$ is nearly the same at $0.0805W$ and $0.0809W$ for node 1 and node 2. For example, the trade off between utility and the power allocated by the nodes can be done by choosing the value of γ beyond 0.8. At this value of γ, the power allocated by the nodes are low and the utilities of both the nodes are also very close to their maximum values and therefore near to the maximum. Thus, the most optimum area in the region of cooperation is the region between γ = 0.8 to γ = 1.2. Thus, an intelligent, logical decision such as the one above needs to be taken by the nodes to ensure that the trade off is done in a fair way to ensure that both the parameters are optimized to an extent to result in an overall improvement in the network utility factor.

In the dynamic power allocation scheme, we employ an algorithm which compares the SNR value of the channel at each instant of time. The flowchart of the algorithm is as shown in fig(5). We have assumed a time varying channel, which means that the parameters of the channel such as gain coefficient keep varying at each instant of time. Under such situations, we perform the simulation of the model from t = 0.1 seconds to t = 1 seconds. The channel coefficients

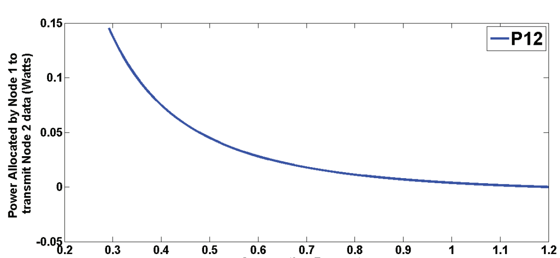


Figure 14. **Power used by node 1 to relay node 2 data**

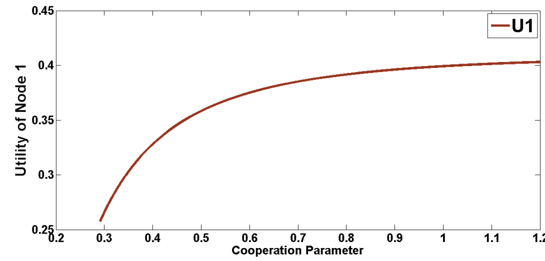


Figure 15. **Utility function of Node 1**

are considered to be the time varying quantities. The other parameters of the system such as bandwidth shared by the nodes, noise power, etc are the same as the previous values and are considered to be static. During this time interval, we observe that the SNR values of the channel increases. Hence, at each instant of time, we need to reduce the power since the signal power is increasing during propagation through the channel. This power allocation result by node 2 is shown in fig(7). We can see that at every instant of time, the power allocated by node 2 to relay node 1 data is reduced by half, since the SNR value of the channels during the time interval is an increasing function. The amount by which the power is reduced or pumped up depends on the user or the controller. We have simply taken a factor of 0.5 to explain the algorithm. From fig(13), we observe that the utility of node 2 has increased after we employ the game theoretic power allocation algorithm. Fig(13) compares the utility of node 2 when it is working in a system which is passive and when it is working in a system which employs a game theoretic dynamic power allocation algorithm. This improves the overall network utility factor of the system.

8. Conclusion

Thus, with the above analysis, we have successfully determined the cooperation region for a two relay model. With the identification of this region, we have identified the amount of power used by each node to transmit the data of its neighboring node. A trade off must be made which will allow both optimal utility of the nodes as well as power allocation by them for relaying the data. This paper also uses a dynamic power allocation algorithm, which appropriately boosts the power allocated by each node depending on the SNR value of the channel. For this analysis, we assumed a time varying channel in which the channel coefficients are varying with time. By comparing the utility of the nodes and the power allocated by them to relay each others data, we observe that a trade off must be made in order to account for good performance both in terms of power allocation and utility. With this trade off, we achieve an overall improvement in the network utility factor.

Further research in this domain can be applied to N relay single hop networks and N relay multi-hop networks. Also, in real life applications, the nodes may be mobile and the destination may also communicate with the nodes. Hence, the complexity of the entire system increases to a great extent. Practical situations will require nodes to cooperate with each and every node in the system, and hence this concept can applied to a large scale wireless sensor network. To summarize, with the dynamic power allocation algorithm and the determination of the 'Cooperation Region' , the network utility factor of a wireless sensor network can be improved.

ACKNOWLEDGMENTS

The authors would like to thank Vinayak Kamble, Vikram Singh, Intelligent Communications Lab and the entire team for their constant support, valuable inputs and encouragement throughout the work carried out during the project.

REFERENCES

[1] Chirag Warty, " Cooperative Communication for Multiple Satellite Network", 2010 IEEE Aerospace Conference, Montana,USA.

[2] Majid Janzamin, Mohammed Reza Pakravan, Hanie Sedghi, A game theoretic approach for power allocation in bidirectional cooperative communications, IEEE WCNC proceedings, 2010.

[3] Allen B. MacKenzie, Luiz A. DaSilva, "Game Theory for Wireless Engineers", 2006.

[4] Beibei Wang, Zhu Han, K.J. Ray Liu, Stackelberg Game for Distributed Resource Allocation over Multiuser Cooperative Communications Networks, IEEE GLOBECOM Proceedings, 2006.

[5] Hadi Goudarzi, Mohamad Reza Pakravan, Optimal Partner Selection and Power Allocation for Amplify and Forward Cooperative Diversity, Personal, Indoor and Mobile Radio Communications, 2008.

[6] Fatemeh Kazemeyni, Einar Broch Johnsen, Olaf Owe1, Ilangko Balasingham, Grouping Nodes in Wireless Sensor Networks using Coalition Game Theory.

[7] Aria Nosratinia, Todd E. Hunter, Cooperative Communications in Wireless Netoworks, IEEE Communications Magazine, October 2004.

[8] Pavel L, "Game Theory for Control of Optical Networks", 2012, XIII, 261 pp.

[9] K. Liu, Cooperative Communications and Networking. Cambridge, UK: Cambridge University Press, 2009.

[10] Beibein Wang, Zhu Han, K.J Ray Liu, "Stackelberg Game for Distributed Resource Allocation over Multiuser Cooperative Communication Networks", IEEE GLOOBECOM 2006.

[11] S. Mehta and K. S. Kwak (2010). Application of Game Theory to Wireless Networks, Convergence and Hybrid Information Technologies, Marius Crisan (Ed.), ISBN: 978-953-307-068-1, InTech, Available from: http://www.intechopen.com/books/convergence-and-hybrid-information-technologies/application-of-gametheory- to-wireless-networks

[12] Yi Zhao, Raviraj Adve, Teng Joon Lim, "Improving Amplify-and-Forward Relay Networks: Optimal Power Allocation versus Selection", IEEE Transactions on Wireless Communications, Vol. 6, No. 8, August 2007

[13] Dejun Yang, Xi Fang, Guoliang Xue, "Game Theory in Cooperative Communication", IEEE Wireless Communications April 2012.

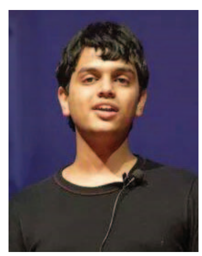
[14] Zhu Han, Dusit Niyato, Walid Saad, Tamer Basar, Are Hjrungnes, "Game Theory in Wireless and Communication Networks", 2012

[15] Winnie Louis Lee, Amitava Datta, Rachel Cardell-Oliver, " Network Management in Wireless Sensor Networks"

BIOGRAPHY

Mohit Srinivasan *is currently pursuing his Bachelor of Technology in Electrical Engineering from Veermata Jijabai Technological Institute (V.J.T.I), Mumbai, India. He received a scholarship from the Maharashtra Government for being in the top one percent of outstanding students in the state, and has also received several scholarships in his board exams. He was a project trainee at the Department of Robotics and Remote Handling at Bhabha Atomic Research Centre (B.A.R.C), Mumbai, India. He is currently working as a research fellow at Intelligent Communications Lab, Mumbai. His current research interests include cooperative communications, game theory, control systems, robotics, Linear Control Theory, heterogeneous networks, microgrids.*

Ahan Kak *is pursuing his Bachelor of technology in Electrical Engineering from Veermata Jijabai Technological Institute (VJTI), Mumbai, India. He is currently working at the Intelligent Communication Lab as a research fellow, and has interned at Ericsson and Larsen and Toubro in the past. He is a recipient of the Sir Ratan Tata Trust Scholarship for excellence in education for the years 2014 and 2015. His current research interests include cooperative communication, cooperative relaying, game theory and LTE-A networks.*



Kaustubh Shivdikar *is currently research fellow from the MIT Media Lab India Initiative, Kaustubh Shivdikar specializes in the field of Artificial Neural Nets and Deep Learning Algorithms. Pursuing Electrical Engineering from Veermata Jijabai Technological Institute (VJTI), he currently conducts research at the internship program by Intelligent Communications Lab on Wireless Sensor Networks. He has worked on multiple projects ranging from Magic Pillow in the field of AR to E-Bag consisting of analog circuits and power modules. Winner of the AngelHack Hackathon he is also the youngest speaker from his college to present his project at TEDx BITS Hyderabad.*

Chirag Warty *is currently the CEO of Quantspire. He is also the chief scientist at Intelligent Communication Labs. He manages extensive network of research teams in US, Italy and India. He received his Bachelor of Science in Electrical Engineering from University of Mississippi, USA, Masters of Engineering from University of IllinoisChicago, USA. His other alma maters include Stanford, Cornell, Univ. of Illinois Urbana Champagne (UIUC), UCLA, UC Berkeley, UC San Diego, USC. He also has several academic accolades in communications and signal processing from several IEEE societies. He is a visiting faculty for University of Mumbai, VJTI, and SNDT university for management, IT and engineering programs. He currently manages several projects and is responsible for* *technology related global strategic decisions. His research interest include Software Defined Networking (SDN), 4G/5G wireless technologies and Cyber Physical Systems, Big data in Mobile Cloud Computing, Physical Layer Security. He has organized several panels and hosted forums on various technical subjects. He is a well published author with several international publications and is a well renowned speaker for future technologies. He holds several key and executive positions on IEEE societies. He is currently the guest editor for Elsievers Special Issue on Big Data Inspired Data Sensing, Processing and Networking Technologies. He serves on the editorial boards of both IEEE and non-IEEE ventures. He has also served as chair, co-chair (general or TPC) and international advisor in various IEEE conferences around the globe.*