# GAME THEORETIC APPROACHES FOR CHANNEL SELECTION, POWER CONTROL AND ROUTING IN WIRELESS SENSOR NETWORKS

by

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# ABSTRACT

NATWAR RAMPRASAD DARAK. Game theoretic approaches for channel selection, power control and routing in wireless sensor networks. (Under the direction of DR. ASIS NASIPURI)

This work proposes a game theoretic framework for managing the radio resources of wireless sensor nodes in Wireless Sensor Networks (WSNs). We consider data collecting sensor networks that are typical of environmental monitoring applications, which employ asynchronous duty-cycling for energy conservation. Overhearing is a big cause of energy loss in this type of network and hence, controlling the amount of overhearing can improve the lifetime of such networks. We propose two approaches for reducing overhearing: multi-channel operation, and joint power control and route adaptation. These approaches require nodes to take autonomous decisions with the global objective of improving the network lifetime, and involve high computational complexity. We prove that each decision can be associated with a utility function, and by undertaking game theoretic approach we can reduce the complexity of the problems, thereby both the approaches can be implemented as multi-player games. The first approach – multi-channel operation with receiver based channel selection – is proposed as a coalition game, with the aim of reducing the effect of overhearing and interference in the network. The second approach – joint power control and routing – is formulated as a potential game, with the objective function of maximizing the lifetime of the network. Computer simulated results are presented for both the approaches.

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# CHAPTER 1: INTRODUCTION

A WSN consists of low cost and low power devices with capabilities of sensing physical or environmental conditions, computing and communicating to perform predefined tasks. A typical WSN may comprise of several hundred or even thousands of wireless sensor nodes, where each node is equipped with several components: a *radio transceiver*, a *micro-controller* and usually is powered by an on-board *battery*, along with a few *sensors*. WSNs are becoming increasingly popular because of the ease of deployment, programmability and the distributed processing capabilities of individual nodes. Through on-board micro-controllers, sensors can be programmed to accomplish complex tasks rather than just data sensing tasks. The wireless transceiver and networking protocols enable the formation of an autonomous multi-hop wireless network using the sensor nodes and communicate the sensed and processed data to a centralized node called *sink*, which is typical of data gathering sensor network. Sensor nodes can support various sensing platforms such as temperature, pressure, ambient light, vibrations, to name a few. These sensor nodes operate autonomously and cooperate together to monitor the environment and to communicate the observed data. WSNs can be deployed in a simple *star network* or the nodes can configure themselves in an advanced *multi-hop mesh network*. WSNs can be applied in many industrial and consumer applications such as industrial process monitoring and control, health care applications to monitor the health of elderly and disabled patients, etc. Sensor nodes can even sense and forecast natural disasters.

Sensor nodes have typically a very short communication range of the order of few tens of meters. They also have very low power processors and limited storage facilities. However, WSNs can still be programmed to perform powerful distributed sensing and processing operations by intelligently utilizing the inherent multihop communication capabilities and their potential for distributed processing.

Recent research in WSNs is focused to meet the above constraints by introducing new designs, creating or improving the current communication protocols, building new applications and designing new algorithms.

## 1.1. Energy Constraint in WSNs

One of the biggest challenges in WSNs is overcoming the limitations of their limited energy resources. Since the nodes have limited energy storage, conserving the energy is of critical importance in WSNs. Typically, nodes are deployed in remote inaccessible locations and in large numbers that can not be accessed every day for either changing or charging the batteries. Consequently, every node must make the best use of the available resources while managing all the tasks it has to perform. The major functions every node performs in multi-hop networking are sensing/monitoring, multi-sensor collaboration, time-synchronization, localization, etc. These tasks must make frugal usage of energy for achieving the maximum lifetime. If battery of any node in the network is depleted, in a multi-hop network, there are high chances of network breakdown, as the data-flow in the network will be affected. Thus, research has focused on mechanisms to improve the lifetime of the nodes by conserving energy consumption in each task of the node, specifically the communication protocols. One widely cited model of energy consumption is presented in [1], which is extensively used as a guide for simulations and the design of low power consumption communication protocol. A lot of research is involved towards developing low-power routing techniques and energy efficient hardware architectures [2, 3, 4].

A viable approach for addressing the energy problem is to harvest energy from the environment such as solar, vibrations, thermal, etc., which is possible by using an energy harvesting device (e.g., solar cell). This device converts different forms of ambient energy into electrical energy that can be supplied to and used by a sensor node. This may potentially provide unlimited energy, resulting into apparently unlimited lifetime of the node. Variety of framework and approach has been proposed to harvest and manage the harvested power from the environment [5, 6]. In [7], Kansal et al. discusses various mechanisms to manage the power in energy harvested sensor networks.

Although harvesting energy from the environment may solve the issue of energy depletion, WSNs powered by environmental energy face many design challenges for energy management. Firstly, the harvested energy must be stored in on-board rechargeable batteries for continuous operation, which typically have a limited number of charge-discharge cycles. Hence, charging and discharging must be conserved. Secondly, the energy harvested at the nodes experience a substantial variation over space and time, due to natural and uncontrollable differences of ambient environmental energy availability. For instance, solar energy heavily depends on the time of the day, solar irradiance patterns, weather, as well as location-specific shading factors. Furthermore, harvesting energy has a limit on the maximum rate at which it can be used. Consequently, it is critical, for the sensor nodes powered by the environmental energy to *adapt the energy consumption depending in its current energy resources* as determined by the state of charge of its rechargeable batteries.

## 1.2. Motivation

Energy consumption in WSNs occur in three domains: data sensing, processing and communications. However, radio activities such as packet transmissions, receptions, and idle listening consume more energy as compared to any of the other activities of a wireless sensor node. Therefore, approaches for lifetime optimization are mainly focused on controlling such radio activities. An effective mechanism to reduce the energy consumption by the radio is asynchronous duty-cycling between active and sleep modes, called *low power listening* (LPL), has been extensively applied in WSNs. Though LPL is a popular technique to reduce energy losses due to idle listening, it does not eliminate the effect of *overhearing* – a phenomenon of sensor node receiving the packets that are intended for different node – which is particularly significant because of the requirement of long preambles in the transmitted packets in these type of asynchronous networks. Several approaches have been proposed to reduce this overhearing effect by appropriate modifications of the LPL format, such as interruption of reception of unnecessary packets based on the information transmitted in the preamble [8], adaptive duty-cycling [9], [10], and others. However, these techniques do not completely eliminate the energy wastage from overhearing in asynchronous networks, which can be significant loss in large scale and high density WSNs. The traditional approach for reducing overhearing is synchronized scheduling of sleep and wake patterns. However, that requires the nodes to be time-synchronized, which is usually difficult to achieve in large scale networks.

Experiments conducted by Nasipuri et al. estimate the current consumed by MICAz motes in various events as [11]:

$$I = \frac{I_{Bt}T_{Bt}}{T_B} + M.I_{Dt}T_{Dt} + N.\frac{I_{Br}T_{Br}}{T_B} + O.I_{Dr}T_{Dr} + F.I_{Dt}T_{Dt} + \frac{I_s T_s}{T_D} + N_P.I_P T_P \tag{1.1}$$

which is the sum of the average currents drawn by a sensor node during various event. $I_x$ and $T_x$ represent the current drawn by the event $x$ and duration of the event $x$, respectively; $Bt/Br$ represent the transmission/reception of beacons, $Dt/Dr$ are the data transmit/receive events, and processing and sensing events are denoted by $P$ and $S$, respectively. $O$ and $F$, respectively, represents overhearing and forwarding rates, and $N$ is the number of neighbors. $M$ is the rate of transmission of data and if there are no retransmissions, then $M = \frac{1}{T_D}$, with $T_D$ representing the data interval. $T_B$ represents the beacon interval. $N_P$ represents the number of times a node wakes per second to check for the idle channel, and was set to $8$.

With this, the remaining lifetime of node can be estimated as:

$$\mathcal{L} = \frac{B}{I} \tag{1.2}$$

where, $B$ is the current state of charge (SOC) of the node.

As can be noted from equation (1.1), the current consumption in a node increases with the increase in $N$, i.e., with the number of neighbors of the node. Also, the fact that increase in $N$, results in increase in $O$ – amount of overheard traffic – implies that, the more the number of neighbors, more is the amount of overhearing, and thus, more is the current consumption. Hence, increase in the amount of overhearing leads to a decreased node lifetime.

Table 1.1: Measurements of current drawn by various events of MICAz node. [11]

| **Event** | **Current (mA)** | **Duration (ms)** |
|---|---|---|
| RU transmit/receive ($Bt/Br$) | 20 | 140 |
| Data transmit/receive ($Dt/Dr$) | 20 | 140 |
| Processing ($P$) | 8 | 3 |
| Sensing ($S$): | | |
| –Amb. temp. | 7.5 | 112 |
| –Vibration/sound | 9.5 | 7000 |

The table above shows the amount of current consumed by various events of a MICAz node and the duration of each event. These values were used in calculating the current consumption in the simulations.

Therefore, we direct our focus to reduce the effect of overhearing, to ensure energy efficiency to prolong the lifetime of the network. The following few mechanisms can help to reduce the overhearing in the node:

- multi-channel WSNs: the nodes can choose to operate on multiple orthogonal channels so as to avoid the overhearing from the neighboring nodes,
- power control: nodes can reduce their transmission power such that it can avoid the overhearing to the neighboring nodes, as the communication range of transmitting nodes will be reduced, and
- routing: in order to reduce the amount of overhearing, the nodes select routes to avoid the neighborhood of a particular node, thus reducing the overhearing traffic to the node.

Applying the above mechanisms involve, complex computations and heavy overhead of data traffic to be communicated to take an action, thus adding to the amount of current consumption. Actions can mean selecting a channel from multiple available channels, selecting an optimum power level, or selecting a route, i.e., selecting a new parent. Also, these approaches require the nodes to take autonomous decisions, which involves high computational complexity.

Each action can be associated with a certain amount of “profit” to each node (or to the network), and is often times achieved at some “cost” or “loss”. When faced with multiple choices to choose from, each choice can be assigned an *utility value*, that each node will be focused to maximize, specially maximize the profit and reduce the loss. Nodes can learn to adapt their behavior by gaining the knowledge about the utility value. Since all the nodes will seek to optimize their utility, it makes sense to program the profit as the global objective, which can be decrease in the amount of overhearing, or the improvement in the network lifetime. So these decisions can mean the nodes cooperating together to achieve this global objective. In this respect, game-theoretical concepts of profit and loss determining the utility value can be used as a design guide for the above mechanisms of reducing the overhearing, where the distributed actions are taken in the network. Thus, ideas and fundamental concepts of game theory can be used to solve these problems, which can thus be posed as multi-player games. Game-theoretic framework reduces the complexity of these problems, by adopting a simple iterative approach.

Game-theoretic approaches to radio resource allocation have recently attracted much attention and is the adopted framework for this work. We have shown that game theory can be used as a unifying framework to study radio resource management in wireless networks. The focus is on infrastructure networks where nodes transmit to a common concentration point called sink or base-station (tree topology). The trade-offs between the quality of link (ETX) and energy efficiency is also discussed.

In the next chapter, we discuss some important concepts of game theory, which we will later use to solve the energy issue in the WSNs. The selection of channels in multi-channel WSNs is presented as a *coalitional game* in Chapter 3, while we combine power control and routing and present it as a *potential game* in Chapter 4. In the proposed coalitional game, the nodes take actions in a distributed fashion, and the joint power control and routing is presented using both the centralized and the distributed approaches.

# CHAPTER 2: INTRODUCTION TO GAME-THEORY

Game theory is a study of strategic decision-making. It provides a set of mathematical tools to study the interactions among rational players. A game in everyday sense – "competitive activity in which players contest with each other according to a set of rules", in the words of a dictionary. An alternative term that can be used to define game theory is "interactive decision making".

Game theory has impacted a large number of fields such as engineering, political science, economics, and even psychology [12]. A list of some of the applications in which game theory is applied: firms competing for business, political candidates contending for votes, the study of people's behavior towards money, animals fighting over prey, to name a few. Recently, a significant rise in the research activities using game theory for analyzing communication networks is observed. And the main reason behind this growth is the need of autonomous, distributed networks with the capability of taking rational strategic decisions; and the need to effectively represent competitive or collaborative scenarios between network entities using low complexity distributed algorithms [13].

The science of game theory is based on modeling quantitative models, which can be unrealistically simple in many respects, but this simplicity can make competitive and collaborative aspect of the game easier to understand, when compared with extensive and complicated real-life scenarios. Of course, we wish to add enough of the ingredients to obtain these non-trivial insights while modeling the game; but not so many which may result into a rather simplistic view of these scenarios.

## 2.1. The Theory of Rational Choice

Majority of the models of game theory are assumed to based on the theory of rational choice. In short, the decision-maker always chooses the best action based on his preferences, among all the available choices it is confronted with. Rationality of the decision-maker resides on the consistency of his decisions when faced with different sets of actions; with no qualitative restriction over his preferences.

### 2.1.1. Actions

In a real life scenario, a decision-maker is always confronted with a set of actions, let's say set $A$, and to these set of actions, he has a preference order. We assume that he always has to choose a single element from a subset of $A$, based on his preferences. At any given time, the decision-maker is aware of about this subset of available choices, and this subset is not influenced by his preferences.

### 2.1.2. Preferences and Payoff Functions

The decision-maker when presented with any pair of actions, we assume that he knows his preferred action among the two, or regards both the actions equally likely, which is the case when the decision-maker is "indifferent" to both the actions. And we assume that the decision-maker is consistent with his preferences, implying that if an action $a$ is preferred over the action $b$, and the action $b$ is preferred over the action $c$; then he will always prefer action $a$ over action $c$. These preferences of the decision-maker though depend on the outcome he would likely receive.

How can we describe these preferences? One way is to specify, for each possible pair of actions, the action the decision-maker prefers, or to note that he is indifferent between the two. Alternatively, the preferences can be associated with a number for each action, in such a way that the preferred actions are the ones corresponding to the higher numbers. This value associated with each action is the *payoff function* representing the action. Formally, if an action $a$ in subset $A$ is preferred over the action $b$ in $A$ by a decision-maker $S_i$, we can represent the payoff function $\phi$ as,

$$\phi_i(a) > \phi_i(b) \tag{2.1}$$

In economics, payoff function is often called as *utility* function. We will use this terms interchangeably throughout this text.

The preferences presented here only convey *ordinal* information. The payoff values associated with every action may tell us about the preferences of the decision-maker, for example, he may prefer action $a$ over action $b$, and action $b$ over action $c$, but the payoff values do not tell us "how much" he prefers action $a$ over action $b$, or whether action $b$ is more preferred over action $c$, as compared to action $a$ over action $b$. In short, only the ordinal information is conveyed by the utility function.

### 2.1.3. The Theory of Rational Choice

Stated simply: according to the theory of rational choice, in any given situation, a decision-maker will always choose the best action from the available set $A$ based on his preferences over $A$. With the possibility, that there may be several equally preferred best actions, we can define,

Definition 2.1. *(The theory of rational choice)[14]: The action chosen by a decision-maker is always at least as good, according to his preferences, as every other available action.*

## 2.2. Interacting Decision-Makers

The model discussed in the previous section discusses only the scenario where a decision-maker has to choose an action from a set $A$, and he cares only about this action. But the real-life scenarios are quite different as compared with this situation. The action of any decision-maker is based on the variables, sometimes which are beyond his control. These variables may be at times be the decisions of other decision-makers, making the decision-making process altogether more interesting and challenging. We model these situations as *games*, and study of such situations make up the rest of the chapter.

Consider a situation where you are negotiating a purchase. You care about the price, which depends on both your and the seller's behavior. What price should you offer? Or consider, the situation where firms are competing for business. The variables that each firm can control is its price, while the prices of other firms is beyond control. However, each firm cares about not only his price, but also about the prices of other firms, because these prices affect its sales. How should a firm then decide its price?

Thus, one more component of game theoretic model comes into the picture: *players*.

### 2.2.1. Players

The members competing (or cooperating) together in a game are called players. Buyer and seller, different firms, are the players in participating in the above games. In the majority of the situations, actions of one player do affect the actions of other players and hence, modeling this component in the game is equally important.

## 2.3. Strategic Games

We can define a *Strategic game* as a model of interacting decision-makers (or players). This model is unaffected by time, i.e., the actions chosen by all the players in a game is "simultaneous", and the players are unaware of the choices of other players. Of course, each player chooses his action depending upon his preferences for each action. For this reason, strategic games are usually referred as "simultaneous-move games". The fact that time is absent from the model means, the player at no time is allowed to change his actions by analyzing the actions of other players. The actions chosen are once and for all. However, the games discussed in this work employs an iterative approach, allowing players to choose a new action, from the available set, every round. We can completely determine the outcome of a game by the actions of all the players which is called action profile.

More precisely, a strategic game is defined as:

Definition 2.2. *(Strategic game with ordinal preferences) A strategic game $\mathcal{G} = \langle \mathcal{N}, A, \phi \rangle$ consists of*

- *a set of players, $\mathcal{N} = \{S_1, S_2, \ldots, S_n\}$,*
- *a set of actions for each player, $a = (a_1, a_2 \ldots, a_n) \in A$ is the action profile, and $A = A_1 \times A_2 \times \ldots \times A_n$ is the cartesian product of the action available to each player; $A_i$ representing the actions available to player $S_i$,*
- *utility function assigns a utility value to every action $a \in A$ for every player $S_i$, and can be given as $\phi = (\phi_1, \phi_2, \ldots, \phi_n)$*

## 2.4. Nash Equilibrium

What actions will be chosen by the players in a strategic game? According to the theory of rational choice (Section 2.1), each player chooses the best action from the available set. The best action, in a game, generally depends on the actions of other players. So while choosing an action, the player must consider the choices that other players can make. Thus, the two components of solution theory are:

- Each player chooses his action based on the output predicted by the model of rational choice, given his belief about the choices of other players' actions.
- The player's belief about the choices of other players' actions is correct.

Thus, combining the two components in the definition, which can be stated as:

Definition 2.3. *(Nash Equilibrium) An action profile $a^*$ is a Nash equilibrium if, for every player $S_i$ and every action of $a_i$ of player $S_i$, $a_i^*$, according to the player $S_i$'s preferences, is at least as good as the action profile $(a_i, a_{-i}^*)$ in which player $S_i$ chooses $a_i$ while every other player $S_j$ sticks with $a_j^*$, represented as $a_{-i}^*$. Equivalently, for every $S_i$,*

$$\phi_i(a_i^*, a_{-i}^*) \geq \phi_i(a_i, a_{-i}^*) \quad \forall a_i \in A_i, \tag{2.2}$$

*where $\phi_i$ is the payoff function representing the player $S_i$'s preferences.*

In words, an action profile is a Nash equilibrium if every player maximizes its utility given that other players choose their action according this action profile. Every player is best-responding to the behavior of other players, and no player is willing to deviate from this profile.

Also, the definition neither implies that a strategic game must have a Nash equilibrium, nor it states that it has only one. In the case of multiple Nash equilibria, every state is stable, though may be different. Moreover, each stable state is equally likely.

## 2.5. Best Response Functions

In the cases where each player has to choose from a small set of actions, we can find Nash equilibrium by examining each action profile in turn and check whether the equilibrium condition is satisfied or not. In more complex games, it is often better to work with the ”best response functions” of the players.

Consider a player, say $S_i$. Every different action chosen by $S_i$ will yield him a different payoff. The best actions are one which will yield him the highest payoff.

The set of best actions of player $S_i$, when the actions of other players is $a_{-i}$ is denoted as $B_i(a_{-i})$.

Precisely,

$$B_i(a_{-i}) = \{a_i \text{ in } A_i : \phi_i(a_i, a_{-i}) \geq \phi_i(a_i', a_{-i}) \text{ for all } a_i' \text{ in } A_i\} : \tag{2.3}$$

any action $B_i(a_{-i})$ for player $S_i$ is at least as good as every other action, when other players' actions are given by $(a_{-i})$. $B_i$ is called the *best response function* of player $S_i$.

### 2.5.1. Nash Equilibrium Redefined Using Best Response Functions

A Nash equilibrium is an action profile with the property that no player can gain a higher payoff by changing his action, when other players are sticking to the same action profile. We can thus, alternatively define a Nash equilibrium to be an action profile for which each player's actions is a best response to the other players' actions. Thus, we have the following result.

Proposition 2.1. *The action profile $a^*$ is a Nash equilibrium of a strategic game if and only if every player's action is a best response to the other players' actions [14]:*

$$a_i^* \text{ is in } B_i(a_{-i}^*) \text{ for every player } S_i. \tag{2.4}$$

## 2.6. Cooperative and Non-Cooperative Games

In general, *non-cooperative*[15] and *cooperative*[12] game theory are the two branches of game theory. These two branches differ from each other depending on how the interdependence among the players is modeled. Non-cooperative theory deals with a detailed model of all the moves available to the players. Non-cooperative games has several celebrated solution concepts including *Nash Equilibrium* [15]. Non-cooperative games are applied in various mainstream communication networks such as distributed resource allocation [16], congestion control [17], power control [18], and sharing of spectrum in cognitive radio.

In contrast with non-cooperative game theory, cooperative theory usually is not concerned with these details, and mainly describes the outcomes resulting when the players choose to cooperate forming coalitions. Cooperative games describe the formation of groups among the players to strengthen their positions in the game [12]. Solutions of the cooperative games are described using core and Shapley values [13]. Recently, cooperation has emerged as a new networking paradigm which has a dramatic effect of improving the performance from the physical layer [19] up to the networking layer [16]. However, implementing cooperation in large-scale networks is not an easy task. Adequate modeling, efficiency, complexity, and fairness are few of the challenges faced by cooperating networks.

We further discuss cooperative game as a coalitional game and non-cooperative game as a potential game, and will use these concepts to formulate games in Wireless Sensor Networks.

### 2.6.1. Coalitional Games

A model of interacting decision-makers focusing on the behaviors of the groups of players is called a *coalitional game*. It associates a set of actions not only with individual players of the game, but also with every group of players participating in the game. And the group of players coming together to cooperate are called *coalitions*.

Definition 2.4. *(Coalitional game) A coalitional game $\mathcal{G} = \langle \mathcal{N}, C, v \rangle$ consists of*

- *a set of players, $\mathcal{N}$,*
- *a set of coalitions, $C = \{C_1, C_2, \ldots, C_m\}$, and*
- *a value $v$ assigned to each coalition.*

### 2.6.2. Potential Games

If the incentives of all the players in the game can be expressed in one global function, then the game is called a *potential game*. In potential games, the incentives are mapped into a global function called the *potential function*.

Definition 2.5. *(Potential game) A game $\zeta$ is a potential game (ordinal and exact) if there exists a function $\Phi : A \to R$ such that $\Phi(a_i, a_{-i})$ gives the information about $u_i(a_i, a_{-i})$ for each player $S_i$, where player $S_i$ is choosing action $a_i$ and other players selecting strategy profile $a_{-i}$ .*

A potential function is a real-valued function on the strategy space (action-profile) that matches deviation to a change of the potential value. Depending on the matching, a game can be an ordinal potential game or an exact potential game. In exact potential game, the difference in payoffs of a player when changing unilaterally its strategy has the same value as the difference in values of the potential function. Whereas, in an ordinal potential game, only signs of the differences have to be the same.

Definition 2.6. *(Ordinal potential game) A function $\Phi : A \rightarrow R$ is an ordinal potential for game $\zeta$ if for every player $i$ and for every $a_{-i} \in A_{-i}$:*

$$u_i(x, a_{-i}) - u_i(z, a_{-i}) > 0 \textit{ iff } \Phi(x, a_{-i}) - \Phi(z, a_{-i}) > 0, \forall x, z \in A_i \tag{2.5}$$

In other words, if player $i$ acquires a better (or worse) payoff by unilaterally deviating from one strategy to another, the potential function will also increase (or decrease) with this deviation.

Definition 2.7. *(Exact potential game) A function $\Phi : A \rightarrow R$ is an exact potential function for game $\zeta$ if for every player $i$ and for every $a_{-i} \in A_{-i}$:*

$$u_i(x, a_{-i}) - u_i(z, a_{-i}) = \Phi_i(x, a_{-i}) - \Phi(z, a_{-i}), \forall x, z \in A_i \tag{2.6}$$

In other words, a strategic game is called an exact potential game if there exists a potential function which reflects the exact change in the utility received by every unilaterally deviating player.

Next chapter deals with multi-channel allocation game based on the coalitional game. Chapter 4 discusses joint power control and routing game as a potential game.

# CHAPTER 3: CHANNEL SELECTION IN MULTI-CHANNEL WSNs

In this work, we address the energy conservation problem in WSNs by reducing overhearing using multi-channel transmissions. Wireless sensor node platforms such as those equipped with IEEE 802.15.4 compliant radios are equipped with radio interfaces that can operate on multiple orthogonal channels, primarily for interference considerations. Here, we consider the benefit of multi-channel operation for reducing unwanted overhearing. The main idea is to reduce the number of neighbors operating on the same channel, thereby reducing the amount of overhearing. Moreover, appropriate channel selection can enable the nodes to *balance their energy consumption* so as to maximize the *lifetime of the network*, i.e. the time until the first node depletes its battery. The key design challenge for implementing such multi-channel WSNs is the high computational complexity of solving the channel selection problem. To address this challenge, we formulate the channel assignment as a coalition game, which leads to an iterative solution that converges within a small number of iterations or rounds.

Single channel networks with heavy traffic suffer a large number of collisions and interference. Thus, the benefits of using multiple channels are:

- increase in network capacity,
- reception and transmission of data can be accomplished in parallel, and
- low interference and fewer collisions.

A considerable number of multi-channel protocols for wireless networks is already proposed [20, 21, 22]. But most of them assume that the transceivers can operate on multiple frequencies simultaneously. Wireless sensor nodes are usually equipped with single radio interfaces to conserve costs, and cannot operate on multiple channels simultaneously. Recently, some multi-channel protocols for dynamically assigning channels in WSNs have been proposed [23] and [24]. In [25], a game theoretical approach for allocating multiple channels to the nodes is presented, while game theory is used for accessing multi-access MAC channel in [19] and [26]. While the main focus of these efforts are to address interference issues for performance improvement, our work is focused on maximizing the lifetime of the network.

Following are the assumptions undertaken in this work.

- All the sensor nodes are equipped with a single half-duplex transceiver.
- Every node can select any of the available frequency channels at any given time.
- All the nodes have an omni-directional transmit and receive antenna with the same gain over all the frequencies it operates on.

In the next section, we present a simple case study to start off with, then we present the related concepts of coalitional game, followed by the framework and proposed algorithm. We present results showing the improvement in network lifetime and the immediate redistribution of nodes in each channel to reach balanced allocation using computer simulations.

## 3.1. Case Study

At first, a simple example is presented to show the effectiveness of game theory for the channel selection problem. Here, we consider a network of $n$ sensor nodes where each node can hear all other nodes. We assume $m$ channels in the network, which each node can select individually. The aim of this example is to redistribute $n$ nodes in $m$ channels, so as to balance the number of nodes in each channel, which leads to a network with minimal interference and overhearing.

Initially, each node selects a channel randomly from the available set of channels. Sensors participate in the game in an iterative manner to reach a balanced allocation. In each step, sensor may decide whether to select a new channel or to stay in the same channel. Here, no centralized control is exercised, i.e., each node has an autonomy to select any of the available channels based on the information it gathers from the environment.

The components of the game are: the player set $\mathcal{N} = \{S_1, S_2, \ldots, S_n\}$; the set of channels $C = \{C_1, C_2, \ldots, C_m\}$, where $n \gg m$; and value $v$ assigned to each channel. Let $v_{max}$ be the maximum value any channel can attain. As the preferred outcome of the game is a balanced allocation which has sensors evenly distributed among channels, we can define $v_{max} = \lceil \frac{\mathcal{N}}{C} \rceil$. There may exist $|C|-1$ coalitions with value $v(C_k) < v_{max}$, but still the assignment of nodes in channels is balanced as the payoffs that each player receives is maximum (as will be seen later). Value of a coalition can be defined as,

$$v(C_k) = \begin{cases} |C_k| & \text{if } |C_k| \leq v_{max} \\ 1 & \text{if } |C_k| > v_{max} \end{cases} \tag{3.1}$$

Allocation of payoffs among the members will define the stability of the underlying assignment of sensors to channels. Thus, the goal is to find a balanced allocation where, $\sum_{\forall S_i \in \mathcal{N}} \phi_i = |\mathcal{N}|$. We assume that the value of coalitions is independent of the actions taken by the sensors that are not part of the coalition, i.e., $v(C_k)$ is not influenced by the actions of the members which are not part of $C_k$. In other words, $v_{max}$ is the maximum value in a stable situation that $C_k$ can guarantee independently of the behavior of the other channels. The value of the coalition is distributed evenly among its members. Therefore, the payoff of each $S_i \in C_k$ in multi-channel selection game is,

$$\phi_i = \begin{cases} 1 & \text{if } v(C_k) = |C_k| \\ \dfrac{1}{|C_k|} & \text{if } v(C_k) = 1 \end{cases} \tag{3.2}$$

The maximum payoff received by any node is $\phi_{max} = 1$, which is the case when $|C_k| \leq v_{max}$. All the nodes play the game to gain this maximum payoff, and the nodes receiving $\phi_{max}$ do not participate in the game for that round, as they do not have any incentive to deviate. The channel with $|C_k| = v_{max}$ is called the *balanced* channel and the payoff received by each node in this channel is $\phi_{max}$. Thus, the nodes of this channel will remain inactive henceforth. The channel having $|C_k| < v_{max}$ are the *underloaded* channels and can accommodate more nodes in the next round. But the nodes currently part of these channels are inactive for this round as the payoffs received by these nodes is $\phi_{max}$. All the sensors with payoff less than $\phi_{max}$ are active, as they are a part of the *overloaded* channel having $|C_k| > v_{max}$. These nodes can receive a higher payoff value by switching to one of the underloaded channels, and hence are active. The active nodes select channels probabilistically in each round; resulting into new distribution of nodes after every round. We set the probability of selecting any underloaded channel based on the number of vacancies available in the channel as follows:

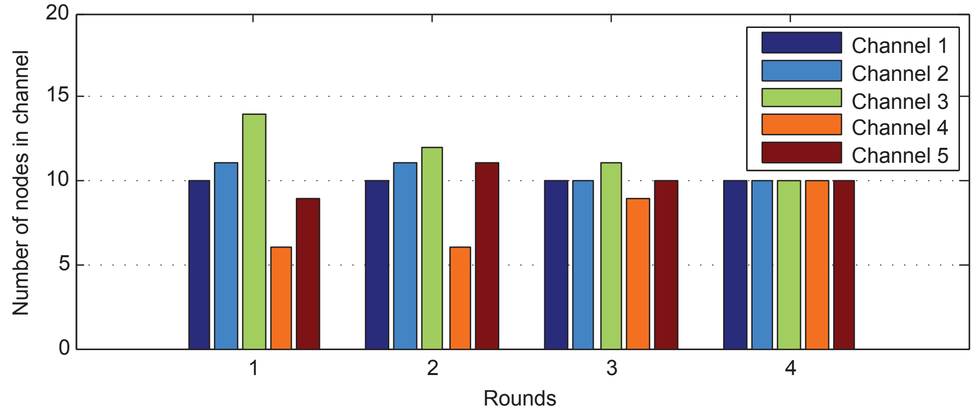
$$pc_j^i = \frac{v_{max} - |C_j|}{Tvac} \tag{3.3}$$

where, $pc_j^i$ is the probability of node $S_i$ selecting channel $C_j$; $|C_j|$ denotes the number of nodes in channel $C_j$; thereby, $v_{max} - |C_j|$ represent the number of vacancies in channel $C_j$; and, $Tvac$ is the total number of vacancies in the network, i.e., sum of vacancies in each channel. Therefore, probability of selecting a channel is defined as the ratio of the number of vacancies in the channel to that of total vacancies in the network. As can be seen, the probability of selecting channel with $|C_j| = v_{max}$ is $0$, implying that the balanced channel is not a part of the game anymore. Also, the probability of active nodes, already member of overloaded channels, selecting a different overloaded channel is negative, implying that the active nodes will only select underloaded channels. One more constraint implemented is, instead of all the nodes from overloaded channel participating in the game, a few nodes are selected to take the action. These nodes are selected probabilistically, with probability depending on the number of nodes in the overloaded channel, of which the active node is a member. The probability can be expressed as,

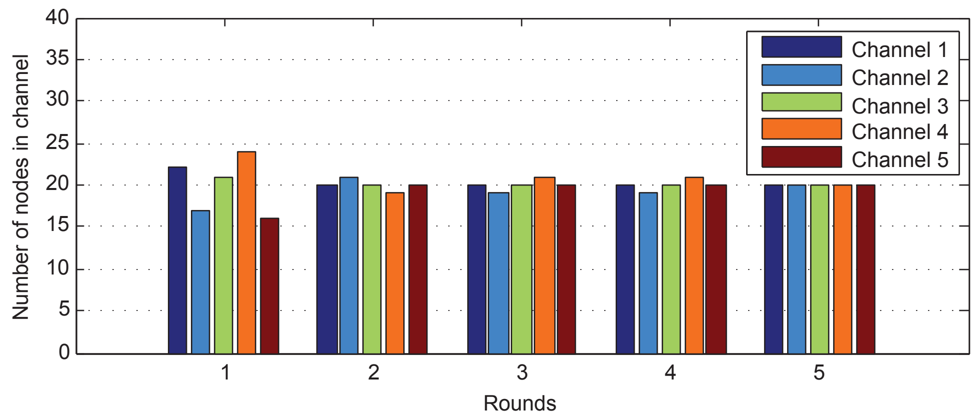
$$p_i = \frac{|C_k| - v_{max}}{|C_k|} \tag{3.4}$$

where, $p_i$ is the probability of node $S_i$, currently member of the overloaded channel $C_k$. $|C_k| - v_{max}$ is the number of nodes needed to switch from $C_k$ so that the channel has $v_{max}$ sensor nodes, giving each node a payoff equal to $\phi_{max}$.

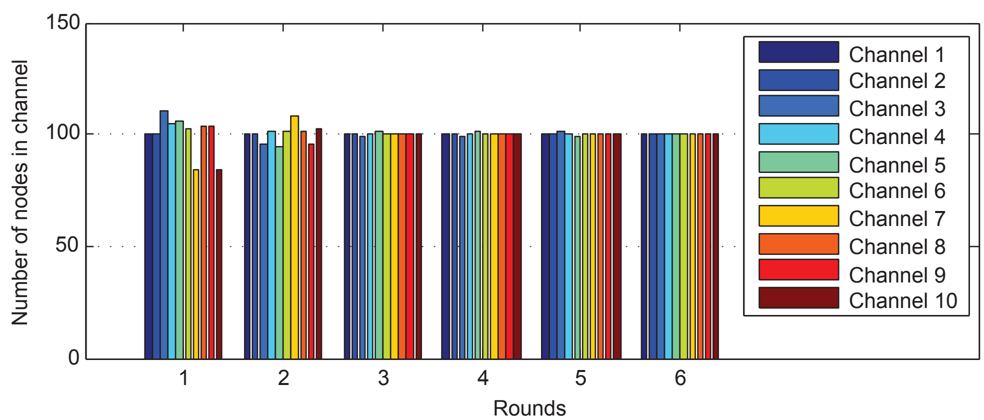
The redistribution game repeats in an iterative manner till the payoff of each node reaches $\phi_{max}$. In this stable state, as already stated, there may exist $|C| - 1$ coalitions with $|C_k| < v_{max}$, i.e., there will be few underbalanced channels. But since all the nodes have received payoff equal to$\phi_{max}$, no node is willing to change its state. Thus, the balanced state may result into a few channels with $v(C_k) < v_{max}$.




(a)




(b)




(c)

Figure 3.1: Redistribution of nodes in channels after every step of simulation. Figure (a) shows the situation with 50 nodes and 5 channels, Figure (b) with 100 nodes and 5 channels, and Figure (c) with 1000 nodes in 10 channels

The outcome of this game is known beforehand – each channel should have equal number of nodes, which should be equal to $v_{max}$. This expected result is reached with less than $10$ rounds, even with $1000$ nodes, as can be seen from Figure 3.1. Things to note are: few nodes from the overloaded channels switch to underloaded channels; balanced channels are unaltered; while the number of nodes in the underloaded channels increase after every round as the active nodes select these channels. The results obtained motivated to further explore a more viable problem, discussed in the next section – a receiver based channel selection in multi-channel WSNs, where each node can gather only its neighborhood information, as opposed to the above example, where each node has the knowledge about the entire network.

## 3.2. Receiver Based Channel Selection in Multi-Channel WSNs

We next consider a realistic scenario involving a data gathering WSN where all sensor nodes obtain periodic sensor readings and transmit them to a sink using least-cost routes. This implies that the WSN has a tree topology. Transmissions are omnidirectional, and consequently, a node can overhear all transmissions that occur within its radio range, even when they are intended for other destinations. We denote the WSN by $\mathcal{G} = (\mathcal{N}, E)$, where $\mathcal{N}$ is the set of sensor nodes and $E$ represents the set of edges among them. There is an edge $(i, j) \in E$, if sensor $i$ can send data to sensor $j$ (parent). We assume that the available frequency band is split into orthogonal channels using Frequency Division Multiple Access (FDMA) [27] and the set of channels obtained are denoted by $C = \{C_1, C_2, \ldots, C_m\}$. For the proposed multi-channel operation, each sensor node is assigned a specific receive channel, which is the channel in which it can receive. Nodes remain tuned to their respective receive channels by default, and temporarily switch to that of the receiver channel of their parent for transmission. In [28], authors have demonstrated that channel switching can be performed relatively quickly so that it does not interrupt the communication in the network. Therefore, the channel allocation is a function $f : \mathcal{N} \mapsto C$, such that the interference is minimized.

Since overhearing is a dominating factor in energy consumption, the energy consumption of a node is high if it has a large number of co-channel nodes in its neighborhood. Therefore, optimum allocation of channels among the sensors plays an important role to reduce the energy consumption in the underlying network. We assume that initially sensors are using the same channel for communication to form a tree rooted at the sink. To reach balanced state, all the sensors participate in channel selection iteratively by noting its neighbors. In each iteration, sensors take some action resulting into channel allocation successively to a desired one. Here, action refers to either the node decides to stay in the same channel or select some other channel for reception. There is no centralized control and the sensors are unaware of the actions taken by other nodes of the network, specially the actions of their neighbors, making the problem even more interesting. It is desirable that the channel allocation process takes place in a distributed manner, where the players have an autonomy of the decision as to whether or not to join a channel.

The proposed framework yields a balanced multi-channel tree with minimal interference and overhearing, resulting into a much improved lifetime of the network. In a balanced multi-channel allocation, no node is willing to switch to a different channel. The game is further discussed as a coalitional game.

### 3.2.1. Coalition Formation Framework

In this subsection, we discuss coalition formation game theory in the context of our problem. Coalitional game theory mainly deals with the formation of groups, i.e., coalitions, that allow each player to strengthen their positions in a given game. In fact, for maximum gains, players may prefer to cooperate with a select set of players to form coalitions that are closed to cooperation from players outside the group. We use the framework of coalitional game theory to determine the *stable* coalition structure, i.e., a set of coalitions whose members do not have incentives to break away. The channel allocation game consists of: a player set, the set of receivers participating in the game; a set of orthogonal channels forming different coalitions; and a value assigned to each coalition. The outcome of this game should be an optimal allocation of channels to the sensor nodes, with the goal of forming balanced coalition structure (defined later in this section) such that possible gains are fairly distributed among the nodes.

Definition 3.1. *(Coalition Formation Game) A coalition formation game can be defined as a triplet $\mathcal{G} = \langle \mathcal{N}, C, v \rangle$ in characteristic function form, where $\mathcal{N} = \{S_1, S_2, \ldots, S_n\}$ is a fixed set of players; $C = \{C_1, C_2, \ldots, C_m\}$ shows the partitions available for $\mathcal{N}$; and $v$ is a characteristic function (or partition function).*

Definition 3.2. *(Characteristic Function Form) A coalition game in characteristic function form consists of a finite set $\mathcal{N}$ and a real valued function $v : 2^{\mathcal{N}} \rightarrow \mathcal{R}$ defined on the set of all coalitions, satisfying the following conditions:*

*(a)* $v(\emptyset) = 0$ *and,*

*(b)* $v(C_k \bigcup C_l) \geq v(C_k) + v(C_l)$*, for every two disjoint coalitions* $C_k$ *and* $C_l$ *superaddi-*

*tivity holds.*

In many environments, there are significant externalities from coalition formation where the effectiveness of one coalition may be affected by the formation of other distinct coalitions. In such cases, coalition formation can be modeled as a partition function game (PFG). In characteristic function games, any coalition $C_i \subseteq \mathcal{N}$ generates a value $v(C_i)$ and this value is independent of what other players – not in $C_i$ – do.

Proposition 3.1. *The proposed multi-channel allocation game is a coalition formation game in a characteristic function form.*

*Proof.* In the proposed multi-channel allocation game, the performance of any coalition is independent from co-existing coalitions in the system. Characteristic function game representation is sufficient to model the coalition formation, as the sensor nodes (players) do not interact with each other while pursuing their actions. Each node probabilistically determines its action in each step. $\square$

Definition 3.3. *(Coalition Structure) A coalition structure is simply a partition of the players into disjoint coalitions. Formally, $C = \{C_1, C_2, \ldots, C_m\}$ is a coalition structure over a set of players $\mathcal{N}$ if $\bigcup\limits_{i=1}^{m} C_i = \mathcal{N}$ and $C_k \bigcap C_l = \emptyset$ for all $k \neq l$. The set $\varphi$ denotes all possible coalition structure on $\mathcal{N}$.*

Mainly, the coalition value , $v(C) = \sum\limits_{\forall C_i \in C} v(C_i)$ is interpreted as the worth or the value of the coalition. In other words, it represents the amount available to be distributed among the players in $\mathcal{N}$, if the coalition forms. The payoff distribution $\phi = \{\phi_1, \phi_2, \ldots, \phi_n\}$ describes how the worth of the coalition is shared among the players. Given a game $\langle \mathcal{N}, C, v \rangle$, the optimal coalition structure $C^* \in \varphi$ is the partition that maximizes the global welfare, i.e., for any other $C \in \varphi$, we have $v(C) \leq v(C^*)$.

In the channel selection game, the outcome will be a balanced assignment of channels among the participating set of sensors $\mathcal{N}$. Here, the goal is to build $|C|$ coalitions denoted by the coalition structure $C$, such that each player gets the maximum possible payoff. The payoff that each $S_i \in C_k$ receives in multi-channel allocation game is,

$$\phi_i = \frac{1}{|C_k^i|} \tag{3.5}$$

where, $|C_k^i|$ represents the number of co-channel neighbors of node $S_i$, including $S_i$.

Definition 3.4. *(Balanced coalition structure) A balanced coalition structure $C$ of a given multi-channel game $\mathcal{G}$ is one where any node $S_i \in C_k, \forall C_k \in C$, cannot increase its payoff $\phi_i$ by changing its strategy unilaterally, i.e., all nodes have minimum co-channel neighbors.*

The value of any coalition $C_k \in C$ of the game $\mathcal{G} = \langle \mathcal{N}, v, C \rangle$ in which $|\mathcal{N}| = n$ and $|C| = m$ with $n \gg m$, is given by,

$$v(C_k) = \sum_{\forall S_i \in C_k} \phi_i \tag{3.6}$$

The maximum payoff that a player may receive in the multi-channel game is $\phi_{max} = 1$ (from equation 3.5), which is the case when a player forms an individual coalition. However, there is a restriction on the number of coalitions that can be formed in the game which is equal to $|C|$. As a result, the balanced coalition structure does not guarantee that all the nodes in the network will receive maximum payoff $\phi_{max}$, considering $|\mathcal{N}| \gg |C|$; but since the number of co-channel neighbors of each node are minimum, there is no incentive for any node to deviate. A player (node) can select probabilistically any coalition (channel) in each round and once it receives the maximum payoff, it may not participate for this round.

In a multi-channel allocation game, a coalition $C_k$ is said to be a *winning* coalition if $\forall S_i \in C_k, \phi_i = \phi_{max}$ and a *losing* coalition if $\phi_i < \phi_{max}$. However, the balanced allocation may contain the winning coalitions along with the losing coalitions due to the fact that all the sensor nodes have achieved the maximum possible utility.

An outcome for a given game is an imputation taken from a payoff distribution for all the players in the game. This outcome should represent a kind of agreement amongst players, which has to be *stable* with respect to the possibility that the subsets of players may have incentives to deviate from it, by forming coalitions on their own. In the multi-channel allocation game, our goal is to find an allocation vector for all players, from which no smaller coalition of players have an incentive to deviate. In many situations, the value of a coalition depends on the actions taken by the players which are not a member of that coalition. Nevertheless, the interpretation of a coalition formation game in the multi-channel allocation is that it models a situation in which the actions of the players – not part of the coalition $C_k$ – do not influence $v(C_k)$.

### 3.2.2. Coalition Formation Algorithm

As discussed earlier, the proposed channel selection in multi-channel WSNs is formulated as a coalition formation game with the player set of receiver sensor nodes $\mathcal{N}$ and the outcome being an allocation of the sensors among the available set of orthogonal channels $C = \{C_1, C_2, \ldots, C_m\}$. The objective is to produce a balanced allocation. In [29], merge and split rules are discussed which are very useful to devise algorithms to dynamically form coalitions among the players. This approach can be applied in a distributed manner and thus is suitable for sensor network games.

Definition 3.5. *(Collection) A collection is any family* $C = \{C_1, C_2, \ldots, C_m\}$ *of mutually disjoint coalitions; and* $|C| = m$ *is called its size. The collection* $C$ *is also called a partition of* $\mathcal{N}$ *and* $\bigcup_{i=1}^{m} = \mathcal{N}$.

In the context of multi-channel allocation game, the probabilities that a player joins or leaves any coalition are determined from the received utility in the previous step and the knowledge it gathers about the environment. In each round, players individually decide to join or stay in a channel. When a player decides to join a new coalition, it will split up from its current coalition and then merge to the new coalition.

– *Join (split and merge)*: A player $S_i$ will join any other coalition $C_j$, if it can improve its payoff by switching to $C_j$.

– *Stay*: A player $S_i$ will stay in a coalition $C_k$, if it has minimum co-channel neighbors, thus having no incentive to switch.

To obtain the balanced allocation of channels for sensors, a distributed algorithm based on the mechanisms discussed above is presented in Algorithm 3.1. Initially routes are setup using Collection Tree Protocol (*CTP*) [30]. All the nodes in the network are active, and participate in an iterative manner to select one of the receiver channels. During transmission, the transmitter channel of a node is temporarily switched to the receiver channel of its parent. Initially, we assume all sensors are using the same default channel, say $C_1$. The algorithm is based on the learning mechanism in which the sensors gradually learn the benefit of joining a new coalition or staying in the same coalition. This involves interaction between an active decision-making sensor and its neighborhood, within which the sensor seeks to achieve a goal despite the uncertainty about the environment. Every sensor takes its decision based upon its knowledge about the environment ($updateKnowledge()$), in order

Algorithm 3.1**:** Coalition formation algorithm of multi-channel selection game.

```
/* Input: Set of sensors N = {S_1, S_2, ..., S_n} and set of orthogonal channels
C = {C_1, C_2, ..., C_m} */
/* Output: Balanced allocation profile C* */
/*Collection tree protocol */
CTP;
step = 0;
/* Initialize φ */
for ∀S_i ∈ N_A do
    φ_i ← 0;
end
/* Initialize value of each coalition in the coalition structure */
for ∀C_i ∈ C do
    v(C_i) ← 0;
end
/* Initialize the balanced allocation profile */
C* ← {∅};
while (True) do
    step++;
    N_A ← N;
    for ∀S_i ∈ N_A do
        /* Environment learning */
        updateKnowledge();
        φ_i ← updatePayoff(S_i);
        /* C^i_min is the channel with minimum neighbors of S_i */
        if S_i ∈ C^i_min then
            N_A ← N_A \ {S_i};
        end
    end
    for ∀C_i ∈ C do
        updateCoalitionValue(C_i);
    end
    if |N_A| == ∅ then
        /* C* is the balanced allocation profile */
        return C* ;
    end
    /* Decision making using merge and split rules */
    for ∀S_i ∈ N_A do
        p_i = 1 − φ_i;
        split(C_k, S_i, p_i);
        pc^i_j = 1 − (|C^i_j| / Σ_{∀C_j ∈ C} |C^i_j|);
        merge(C_j, S_i, pc^i_j);
    end
end
```

to maximize its payoff. The required knowledge here is the number of neighbors receiving in each channel of the network. Every node $S_i \in \mathcal{N}$ calculates its payoff – using the gathered neighborhood information, as discussed earlier in equation (3.5). If a node $S_i \in \mathcal{N}$ belongs to a coalition $C^i_{min}$, which has minimum number of co-channel neighbors of $S_i$, it will not participate in the game for that round, i.e., becomes inactive player and stays in the same channel (coalition); while all other nodes will still actively participate in the game. The value of each allocation is updated using equation (3.6) ($updateCoalitionValue(C_i)$). An active node $S_i \in C_k$ decides to split from its current channel to merge with some other channel with probability $p_i$, and consequently decides to stay in the same channel with probability $(1 - p_i)$, where

$$p_i = 1 - \phi_i \tag{3.7}$$

As can be seen, if $\phi_i = \phi_{max} = 1$ – the case when the node has no co-channel neighbor – $p_i = 0$ , i.e., the node is unwilling to move to any other coalition and is inactive. An active node $S_i$ selects any other channel probabilistically, which is given as,

$$pc^i_j = 1 - \frac{|C^i_j|}{\sum\limits_{\forall C_j \in C} |C^i_j|}, \tag{3.8}$$

where, $pc^i_j$ is the probability of node $S_i$ to select channel $C_j$, $|C^i_j|$ is the number of neighbors of $S_i$ listening in channel $C_j$. The probability of selecting any channel thus, depends on the number of neighbors receiving in the channel, i.e., higher the number of neighbors in a channel, lower is the probability of selecting the channel. This implies that every node is willing to switch to channels with minimum number of neighbors, so as to receive a higher payoff. If there are no active nodes willing to switch to other channels, the assigned channel allocation is a balanced coalition structure $C^*$, and the game terminates. But if there are one or more active nodes, the game proceeds further to the next round. In the next round, all the nodes again check their neighborhood and decide whether to participate in that round or stay inactive, and this continuous participation of the nodes is repeated until there are no active nodes in the network. The sample space is $|C|^{|\mathcal{N}|}$ outcomes. We are interested in the balanced allocation and the required number of steps to reach equilibrium, as well as the improvement in the network lifetime.

Average current consumed by all the nodes is calculated by periodic assessment of forwarded and overhead traffic (refer equation (1.1)). By using the average current consumption and knowing the state of charge (SOC) of batteries, each node is able to estimate its remaining lifetime (refer equation (1.2)). The node with the minimum lifetime is called the *critical node* ($CN$). The lifetime of the $CN$, also known as the *network lifetime*, is plotted, along with the average lifetime of the network after every step.

### 3.2.3. Results

The underlying simulation environment can be defined as: $100$ nodes distributed uniformly in $70 \times 70m$ area, with each node sending data packets periodically to the sink at a rate of $2$ packets every $5$ minutes, and route update packets are broadcasted after every minute. We evaluate the performance at an instant where the SOC of the batteries follow a uniform distribution in $(3750, 5000)mAH$. The maximum transmit power level of the MICAz sensor node is assumed; with the receiver threshold for successful reception of packets in the absence of interference being assumed to be $-90dBm$. A log-normal channel model is assumed with a path loss exponent of $3$, shadowing standard deviation of $3dB$, and the path loss of $-55dBm$ at $1m$. All simulations are performed with the same set of parameters.

The routes are initially setup using *CTP* and all the nodes transmit their data packets in the default channel. The nodes then participate in the multi-channel selection game with the motive of reducing the overhearing and interference, which results into improvement in the lifetime of the network.

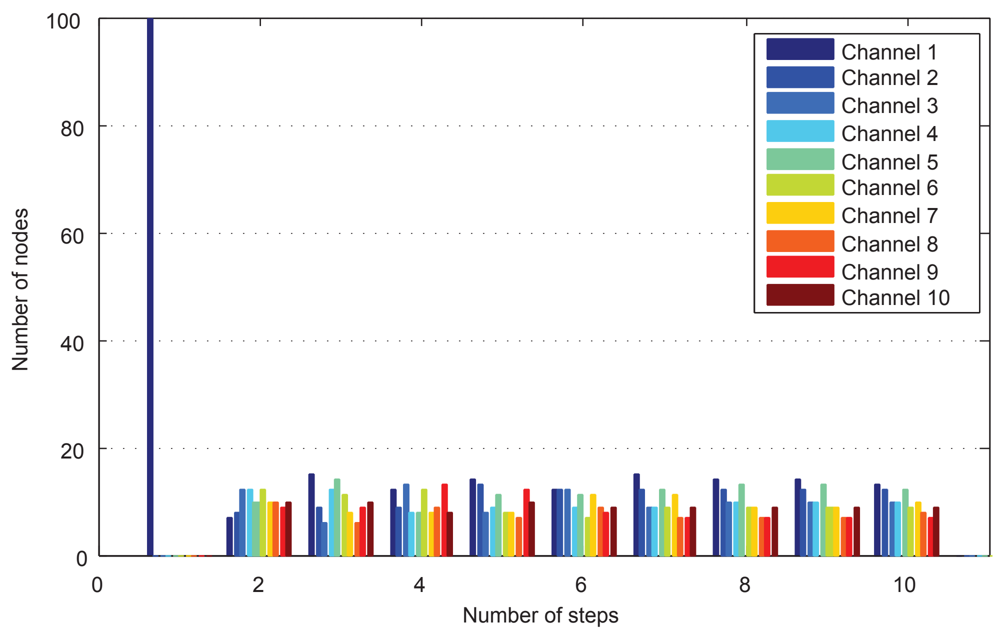



Figure 3.2: Nodes in each channel after every step of simulation of multi-channel selection game.

Figure 3.2 depicts the redistribution of nodes in each channel (coalition) with each step, till it reaches to equilibrium, for one of the simulations' run. We assume $10$ orthogonal channels for this simulation. As can be seen, even after reaching equilibrium, the number of nodes receiving in each channel is unequal; but since all the nodes are receiving in the channel with minimum co-channel neighbors, they do not have any incentive to switch to any other channel, thereby remain part of the same channel. Redistribution of nodes is performed in an iterative decentralized manner, with no centralized force acting to decide the action of any node. The information needed by each node to decide its action is just the receiver channel of each of its neighbors. From this information, each node can calculate its utility value as well as the probabilities of selecting different channels, and decide upon its action – whether to switch or to stay in the same channel. The number of iterations required to reach equilibrium is $8 - 10$, which is very less as compared to the number of nodes in the network and the action space of each node.

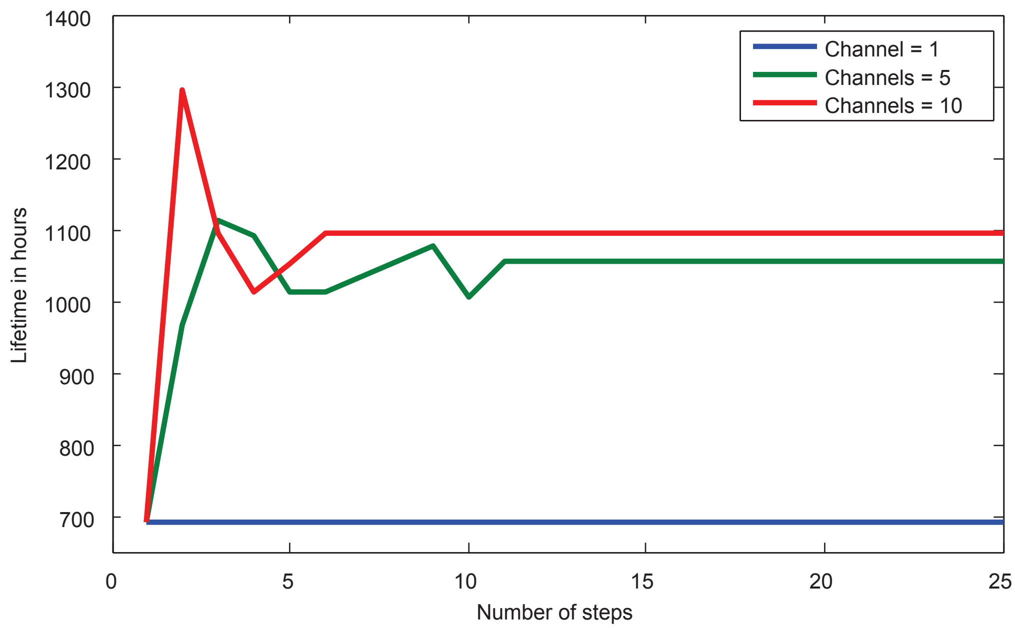



Figure 3.3: Network lifetime comparison with different number of channels.

Figure 3.3 and 3.4 explains the improvement in the network lifetime and average lifetime of the network, respectively, with different number of channels in the network. The presented results are averaged over $10$ independent simulations. The peak observed at step $2$ explains that the nodes moving out from the default channel $C_1$, and selecting other

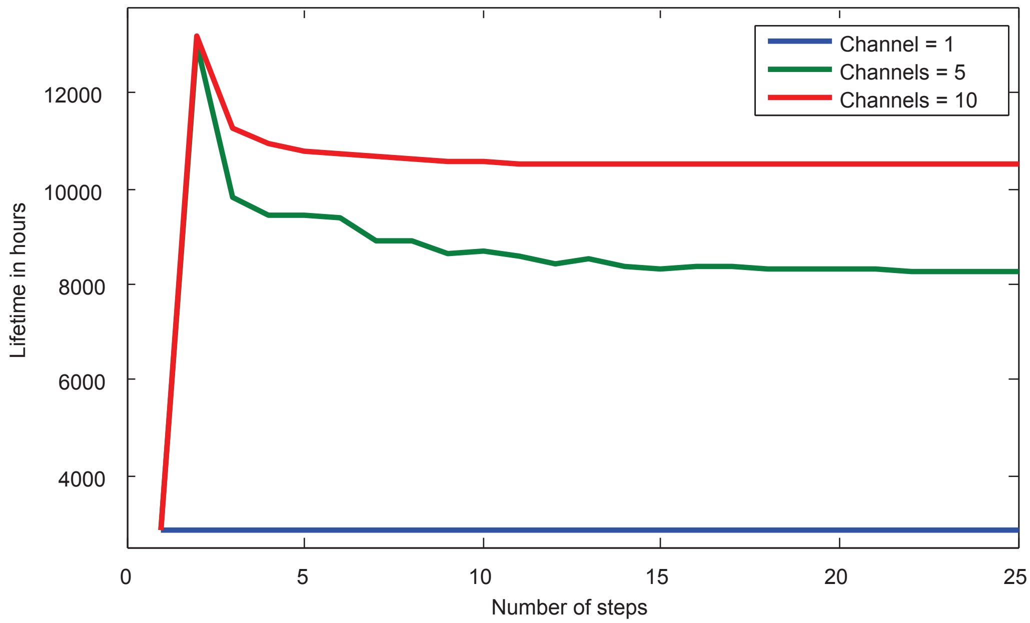



Figure 3.4: Average lifetime of the network with different number of channels.

channels resulting into lower overhearing losses. As expected, increase in the number of channels result into decrease in overhearing losses thus, improved lifetime. The scheme with $1$ channel is just the *CTP* implementation. Improvement in the network lifetime with $5$ channels as compared with $1$ channel being used is $53\%$, while with $10$ channels the improvement is around $60\%$. The average lifetime of the network, however, triples with $5$ channels and almost quadruples with $10$ channels, as compared against only $1$ channel in the network. One more thing to notice is the number of steps required to reach equilibrium with $5$ channels is around $20$, while with $10$ channels the system reaches equilibrium in less than $10$ channel. Energy losses due to the small amount of data traffic to be exchanged between the neighboring nodes can be neglected as compared to the achieved improvement in the lifetime of the network.

In conclusion, multi-channel receiver based channel selection helps in reducing the losses due to overhearing, with the result being an improved network lifetime. Also, game theoretical framework reduces the complexity of the problem, by providing an iterative solution, to reach the balanced assignment of channels. In the next chapter, we propose joint power control and parent adaptation problem as a potential game, with the same motto of reducing the overhearing losses in the network.

# CHAPTER 4: JOINT POWER CONTROL AND ROUTE ADAPTATION IN WSNs

We next present another approach for handling the overhearing issue in the WSNs using power control and routing for the improvement of the network lifetime. As before, we assume WSNs with data collection traffic that is typical of environmental monitoring applications where all sensor nodes transmit periodic sensor readings to a centralized sink node. As we have seen in Section 1.2, overhearing is the main source of energy consumption in such data collecting networks, which can be controlled by adapting the transmit power levels, along with the route selections. Hence, the goal is to determine assignments of optimal transmit power levels for all the sensor nodes to maintain acceptable quality of routes to the sink and also maximize the lifetime of the network by controlling the overhearing in the nodes.

Transmission power control has been extensively researched in the wireless community [31, 32], with the objective of reducing transmit power to conserve energy and reduce interference. In [33, 34], authors propose power control schemes using feedback control to set the tranmsit power to minimum threshold level to achieve a required link quality. In [35], a joint power control and quality aware routing scheme for rechargable WSNs is proposed to meet the energy requirements by dynamically contolling the transmission powers and route selection. Game theoretic framework to solve the power control problem and controlling the topology in distributed WSNs is presented in [36, 37]. Their objective is to obtain an optimal power level selection and high frame success rate, i.e., reliability of data transmission to gain the highest of the utililites, while our main objective is to reduce the overhearing effect in order to maximize the network lifetime.

Joint power control and routing can be an effective technique to control overhearing thus, controlling the energy consumption [38]. However, it requires *cooperative control* under a given set of energy constraints, which is difficult to achieve in a large dense network. Here, game theory is used to address the problem which does not require any cooperation between the nodes and the computational complexity of the problem is reduced by undertaking an iterative approach. The main highlights of this chapter are as follows. First, we prove that the proposed power control and route adaptation problem can be posed as an exact potential game, when the potential function is defined as a combination of the network lifetime (lowest lifetime of any node in the network) and the end-to-end link quality. Secondly, we evaluate the improvement in the lifetime of the network that can be achieved with the help of the game theoretic framework, using global information and hence, can be implemented only in a centralized fashion. Results from such complex computations are important to estimate the "best case" results. Finally, we develop two versions of more applicable distributed implementations of the power control and routing algorithm.

## 4.1. Preliminaries

As already seen in equation (1.2), remaining lifetime of any node, $S_i$, is inversly dependent on the amount of current $I_i$ consumed by the node, for a given distribution of battery estimate $B_i$. So the main objective here is to determine the strategies that will conserve $I_i$ to maximize the network lifetime, i.e, $\min \mathcal{L}_i$. This is done iteratively using methods that manages current consumption by node with the minimum $\mathcal{L}_i$, i.e, the *critical*

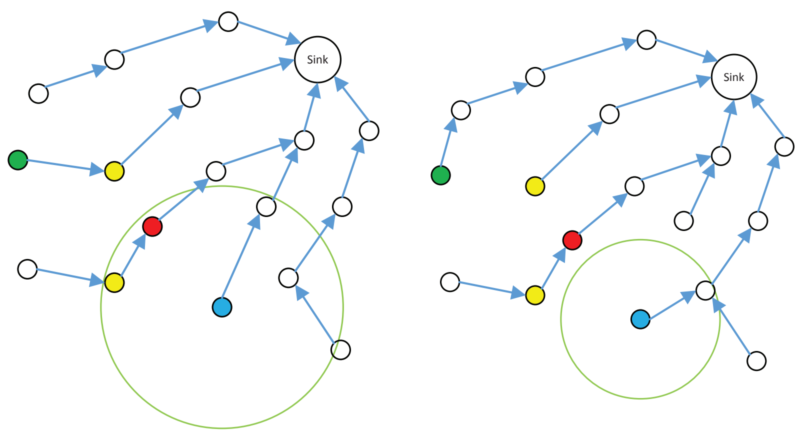



Figure 4.1: Example to demonstrate the reduction of overhearing in a critical node (in red) from (a) to (b) by reducing the transmit power level of a neighbor (in blue), and route adaptation of a child of another neighbor (in green).

*node* of the network.

The principle of the joint power control and route adaptation for controlling the current consumption is illustrated in Figure 4.1. Here, the critical node is marked in red. The average current consumption by the critical node is reduced, from (a) to (b), due to two effects, both resulting into the reduction of overhearing. Firstly, one of its neighbors (marked in blue) adapts power level to a lower level, having a lower transmission range, by choosing a different parent, which completely *eliminates* the overhearing caused by its traffic to the critical node. Notice the cost incurred in doing so is switching to a longer route. Secondly, while none of its other neighbors (marked in yellow) could perform the same act; the child of one of these neighbors (marked in green) switches to a different, albeit a longer route, to avoid the forwarding traffic to the neighbor of the critical node. By adapting this strategy, the neighbors and the children nodes, reduces the amount of overhearing caused – the dominating factor in the current consumption – to the critical node. This results into a lower average current consumption by the critical node, and hence an improved lifetime of the network.

To implement the joint power control and route adaptation, the main challenge is to determine an optimal policy for selecting power levels and routes in the network for each node, given a random distribution of battery levels for each node. The task is computationally challenging even with the global information. In the next section, this problem is posed as a multi-player potential game.

## 4.2. Game Theoretic Formulation of Power Control and Routing

Consider a wireless sensor network of $n$ sensors. Since the lifetime of the network is defined by the lowest lifetime the nodes, we set to improve only the lifetime of the critical node. Our approach, as explained earlier, uses two phases: first phase, *eliminates* the overhearing caused to the critical node by its neighbors, by reducing the transmit power level of neighbors (i.e., shortening the transmission range by selecting a new parent). Since this result into change of topology of the network, power control is associated with the route selection as well. And second phase: *reduces* the overhearing caused by controlling the amount of forwarding traffic carried by the neighbors of the critical node. This is achieved by selectively diverting the routes of children of the neighbors of the critical node to regions that exclude the neighborhood of the critical node. These phases are exclusively used in the decentralized implementation, while centralized scheme employs these phases internally. Thus, the problem is posed as a joint power control and route selection for improving the lifetime of the critical node.

We use game theory to address this problem, which is justified due to the following reasons:

- First, the sensors make decisions spontaneously and independently, thus competing with each other. The objectives of every sensor node may conflict as each node selfishly tries to maximize its own payoff.

- Secondly, the action of one sensor node may influence the actions of other nodes. Nodes, though, may co-operate to maximize a global objective.

We formulate the proposed approach of power control and routing as a strategic game, which is later proved to be an *exact potential game*. Consequently, it has a best response NE, which is the desired solution for the problem. As seen in Section 2.3, a strategic game has the following three elements:

- a set of *players* $S = \{S_1, S_2, \ldots, S_n\}$, which is a group of nodes in a given sensor network,

- a set of *actions* $A_i = \{a_1, a_2, \ldots, a_m\}$ available to each player $S_i \in S$ and an action is a pair: parent and power level; the action set of all the players is called as a strategy profile, and

- the *payoffs* $\{\phi_1, \phi_2, \ldots, \phi_n\}$ resulted from the strategy profile.

A node can choose different actions to maximize its own utility value. The optimal outcome of a game is one where no player has an incentive to deviate from it's chosen strategy after considering others' choices. An NE is reached when no player gains by unilaterally changing its own strategy. And the necessary condition to reach NE is thus, each player gaining the maximum utility.

### 4.2.1. Joint Power Control and Routing as a Potential Game

As explained in Section 2.6.2, a potential game exists if the incentives of all the players can be expressed with one global function called the potential function. A family of potential games were introduced by Monderer and Shapley [39]. These games received increasing attention recently in the field of wireless networks [40, 41] and [42]. The best response NE can be found by locating the local optima of the potential function [43].

We define the utility function of node $S_i$ corresponding to the action $a_j$ in the proposed game as:

$$u_i(a_j) = W_l \times f(\mathcal{L}_c) + W_{ETX} \times g(pathETX_i) \tag{4.1}$$

where, $u_i(a_j)$ is the utility of sensor $S_i \in S$ for action $a_j$, and is the weighted sum of the network lifetime and the route quality factors: $f(\mathcal{L}_c)$ = normalized improvement of the critical node lifetime due to $a_j$, and $g(pathETX_i) = \dfrac{1}{pathETX_i}$, where $pathETX_i$ is the path ETX of sensor $S_i$ as used in the collection tree protocol (***CTP***) [30]. $W_l$ and $W_{ETX}$ are the corresponding weights.

Similarly, the potential function of the proposed game is defined as:

$$\Phi(a) = W_l \times f'(\mathcal{L}_c) + W_{ETX} \times \sum_{\forall S_i \in S} g(pathETX_i) \tag{4.2}$$

where, $\Phi(a)$ represents the potential function of the network, and $a = \{a_1, a_2, \ldots, a_n\}$ represent the action profile of all the nodes; $f'(\mathcal{L}_c)$ = normalized lifetime of the critical node. Then the system-centric objective is to find the optimal parent selection profile $a_{opt}$ such that the system throughput is maximized. Formally,

$$a_{opt} = \arg\max \Phi(a) \tag{4.3}$$

Theorem 4.1. *The joint power route adaptation game is a finite exact potential game with potential function* $\Phi$ *and it has at least one best response Nash equilibrium.*

*Proof.* We need to prove that $\Phi$ is an exact potential function in parent assignment game which satisfies equation (2.6). Assuming that a player $S_i \in S$ changes its parent to $k'$ from $k$, (i.e., action changes to $a'_i$ from $a_i$) while others are using the strategy profile $a_{-i}$, the difference of utility function can be expressed as:

$$\begin{aligned} u_i(a'_i, a_{-i}) - u_i(a_i, a_{-i}) = W_l \times (f(\mathcal{L'}_c) - f(\mathcal{L}_c)) + \\ W_{ETX} \times (g(pathETX'_i) - g(pathETX_i)) \end{aligned} \tag{4.4}$$

Now, consider the potential function (equation (4.2)), which can be expressed as:

$$\begin{aligned} \Phi(a'_i, a_{-i}) = W_l \times f'(\mathcal{L'}_c) + W_{ETX} \times g(pathETX_i) + \\ W_{ETX} \times \sum_{\forall S_l \in S, S_l \neq S_i} g(pathETX'_l) \end{aligned} \tag{4.5}$$

The difference in potential function is then:

$$\begin{aligned} \Phi(a'_i, a_{-i}) - \Phi(a_i, a_{-i}) = W_l \times (f'(\mathcal{L'}_c) - f'(\mathcal{L}_c)) + \\ W_{ETX} \times (g(pathETX'_i) - g(pathETX_i)) + \\ W_{ETX} \times \sum_{\forall S_l \in S, S_l \neq S_i} (g(pathETX'_l) - g(pathETX_l)) \end{aligned} \tag{4.6}$$

Let,

$$d_{ETX} = W_{ETX} \times \sum_{\forall S_l \in S, S_l \neq S_i} (g(pathETX'_l) - g(pathETX_l)) \tag{4.7}$$

Now, using equations (4.4), (4.6), and (4.7), we get:

$$\Phi(a'_i, a_{-i}) - \Phi(a_i, a_{-i}) = u_i(a'_i, a_{-i}) - u_i(a_i, a_{-i}) + d_{ETX} \tag{4.8}$$

If we restrict only one node can change its parent at a time then, $d_{ETX} = 0$ in equation (4.8). Thus, $\Phi$ becomes an exact potential function.

Clearly, any exact potential game is an ordinal potential game (if $d_{ETX} \neq 0$) but not the other way around. Here, each node selects its best response and is defined as:

$$B_i(a_{-i}) = \arg \max_{\forall a_i \in A_i} u_i(a_i, a_{-i}) \tag{4.9}$$

Best response dynamics is an update rule where at each time instant, a player chooses its best response to other players' current strategy profile.

In any finite potential game, best response dynamics always converge to a Nash equilibrium [43, 44]. The global maximum of an ordinal potential function is a best response Nash equilibrium. To understand this, let $a^* = (a_1^*, a_2^*, ..., a_n^*)$ corresponds to the global maximum. Then, for any $S_i \in S$, we have, by definition,

$$\Phi(a_i^*, a_{-i}^*) - \Phi(a_i, a_{-i}^*) \geq 0, \ \forall a_i \in A_i \tag{4.10}$$

But since $\Phi$ is a potential function, for all $S_i \in S$,

$$\begin{aligned} u_i(a_i^*, a_{-i}^*) - u_i(a_i, a_{-i}^*) \geq 0 \text{ iff} \\ \Phi(a_i^*, a_{-i}^*) - \Phi(a_i, a_{-i}^*) \geq 0, \ \forall a_i \in A_i \end{aligned} \tag{4.11}$$

Therefore, in best response dynamics:

$$u_i(a_i^*, a_{-i}^*) - u_i(a_i, a_{-i}^*) \geq 0, \ \forall S_i \in S \text{ and } \forall a_i \in A_i \tag{4.12}$$

Hence, $a^*$ is a best response Nash equilibrium. However, there may also be other best response Nash equilibria corresponding to local maxima.

□

### 4.2.2. Centralized Algorithm

Note that implementing this scheme would require all nodes to have global knowledge of node parameters, or any centralized force that will provide all the nodes this information, which will lead to heavy communication cost and is unrealistic in practice. Our objective of this game theoretic formulation is two fold. Firstly, it provides the best case results using an iterative computative framework, which otherwise requires heavy computations. We call this centralized approach. Secondly, it provides framework for designing a decentralized, albeit suboptimal scheme, which is described in the next section.

The best response dynamics based approach for joint power control and routing is presented in Algorithm 4.1. At the beginning, the routing tree is established using *CTP* ($CTP(G)$). *CTP* uses expected number of transmissions (ETX) as its routing metric. A root has an ETX of $0$. The ETX of a node is the path ETX of its parent to the root plus the ETX of its link to its parent. Each node, using *CTP*, chooses the neighbor with the lowest ETX value as its parent. Once the initial routes are setup, according to our algorithm, every node in the network calculates its utility value ($getUtility(S_i)$), as defined by equation (4.1), which is the function of network lifetime and path ETX. The incentive of the nodes to change their strategy (i.e., power control or route adaptation) is expressed by the potential function defined by equation (4.2). Potential value is calculated ($Potential(G)$) to capture the global effect. Each node calculates the utility vector for a set of probable parents ($utilityVector(S_i, \vec{P_i})$), which is later used to select best response. Every node

Algorithm 4.1**:** Centralized algorithm for lifetime improvement

/* Input: Topology $G = (S, E)$; Initial parent and power assignment */
/* Output: optimal parent (power) assignment i.e., feasible and better or no worse than any other feasible solution */
$step \leftarrow 0$;
/* Collection tree protocol in G */
$CTP(G)$;
**for** $\forall S_i \in S$ **do**
    $u_i^{cur} \leftarrow getUtility(S_i)$;
**end**
/* Calculating potential function to get the social effect */
$\Phi_{cur} \leftarrow Potential(G)$;
**while** *(*$True$*)* **do**
    $step + +$;
    **for** $\forall S_i \in S$ **do**
        /* Build the utility vector of $S_i$ for parent vector $\vec{P_i}$ */
        $\vec{u_i} \leftarrow utilityVector(S_i, \vec{P_i})$;
    **end**
    /* Sink select $l$ nodes out of $k$ nodes to take action */
    $S' \leftarrow selectActiveNodes(l, k)$;
    **for** $\forall S_i \in S'$ **do**
        $u_i^{prv} \leftarrow u_i^{cur}$;
        /* Select best response */
        $a_i^* \leftarrow bestResponse(\vec{u_i})$;
        /* Feasible and optimal power level assignments */
        $selectParent(S_i, \vec{u_i}, a_i^*)$;
        $u_i^{cur} \leftarrow getUtility(S_i)$;
    **end**
    $\Phi_{prv} \leftarrow \Phi_{cur}$;
    $\Phi_{cur} \leftarrow Potential(G)$;
    $count = 0$;
    **for** $\forall S_i \in S$ **do**
        **if** *(*$u_i^{cur}$ *==* $u_i^{prv}$*) and (*$\Phi_{cur} \geq \Phi_{prv}$*)* **then**
            $count + +$;
            $u_i^{prv} \leftarrow u_i^{cur}$;
        **end**
    **end**
    **if** *(*$count == |S|$*)* **then**
        /* It is an NE point as no sensor can improve its payoff by deviating unilaterally */
        $exit$;
    **end**
**end**

is assumed to be equipped with the global information about the lifetime of the critical node and is also assumed to be aware of the effect of selection of different parents in the network – to calculate the utility vector. A profile of power adaptation and new parent selection ($selectParent(S_i, \vec{u_i}, a_i^*)$) strategies results in a profile of expected utility or payoffs. Nodes with zero utility vector do not participate in the game in that round. Let at any given round, there are $k$ nodes with non-zero utility vector. We consider that a subset $l$ out of these $k$ nodes take action to improve the critical node lifetime, so as to avoid instability. This selection is achieved by using a probability $p$ for each node which decide its participation in that round, where $p = \dfrac{L_a - L_c}{\alpha \times k \times L_a}$; $L_a$ is the average lifetime of the network[1], $L_c$ is the lifetime of the critical node in the network, and $\alpha$ is an adjustment factor.

In the next round, each node's strategy is based on the best response dynamics of this selected subset of $l$ nodes ($bestResponse(\vec{u_i})$). This approach maximizes each nodes payoff with respect to its strategy. The potential value is also calculated by the sink to see the improvement in the network. At the end of each round, each node calculates its new payoff and explores the chances of any further improvement. Stability of the system is ensured by the ability of the network to reach equilibrium. In the proposed scheme, a sensor node selects a parent (and adjusts its transmission power level) so as to maximize its own utility value by playing its best strategy. Best response Nash equilibrium is the stable state, as each node is assumed to be playing his best response, where the game reaches an equilibrium state, if there is no such node which can improve its utility. If the game reaches NE, then change of any nodes' profile disturbs the equilibrium state. Thus, there is no further advantage of changing the strategy. However, the selfish behavior by sensors may lead to an inefficient result, which can be improved by exercising a dictatorial control over every nodes' actions. On the other hand, imposing such control may be costly or infeasible

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[1] $L_a$ is the ratio of sum of lifetimes of all the nodes to the total number of nodes, and should not be confused with the lifetime of the network, which is the critical node lifetime.

(due to oscillation in the states) with large networks. Therefore, it is significant to find the conditions under which decentralized optimization by sensors is guaranteed to provide a near-optimal outcome.

### 4.2.3. Decentralized Algorithm

The centralized mechanism, discussed in the previous sub-section (Section 4.2.2), is not a viable option to implement in order to reduce the overhearing caused in the network because of the two reasons:

- huge amount of overhead requirement, and
- high complexity computations.

In this section, we propose two distributed implementations for joint power control and routing: the *DPCR-H* and the *DPCR-L*, which utilize the game theoretic formulation presented above in Section 4.2.1. While both schemes require a much lower amount of global network information as compared to the centralized scheme, the *DPCR-L* requires a single instance of network-wide flood and the *DPCR-H* requires multiple instances of flooding, both initiated by the sink, and hence, the *DPCR-H* has a relatively higher communication overhead.

Initially routes are setup using *CTP*. All nodes transmit their health metric (estimated remaining lifetime $\mathcal{L}_i$) to the sink ($sendHealthMetric()$). The sink then selects $k$ nodes with the lowest lifetimes forming a critical node set $CN = \{CN_1, CN_2, \ldots, CN_k\}$, and broadcasts this information to all the nodes ($informCriticalNodes()$).

Let $N_i^c \subseteq S$ be the set of nodes that cause overhearing to any node $CN_i \in CN$. Then all $AN_j^i \in N_i^c, i = 1, \ldots, k$, are active nodes in the first phase of the game, i.e., all the nodes causing overhearing to any member of the set $CN$ are the active nodes. Here, $AN_j^i$

**Algorithm 4.2: Decentralized approach for sub-optimal solution**

/* Input: Topology $G = (S, E)$; Initial parent and power assignment */
/* Output: optimal parent (power) assignment i.e., feasible and better or no worse than any other feasible solution */
$step \leftarrow 0$;
/* Collection Tree Protocol in G */
$CTP(G)$;
**for** $\forall S_i \in S$ **do**
    $u_i^{prv} \leftarrow getUtility(S_i)$;
**end**
**while** *($True$)* **do**
    $step++$;
    **for** $\forall S_i \in S$ **do**
        /* Each node sending its health metric to sink */
        $sendHealthMetric()$;
    **end**
    /* Sink selects $k$ critical nodes in the network */
    $CN \leftarrow findCriticalNodes()$;
    /* Sink informs critical nodes in the network */
    $informCriticalNodes()$;
    **for** $\forall S_i \in CN$ *is a critical node* **do**
        /* Critical node sending alerts in its neighborhood, say $N_i^c$ */
        $S_i.sendAlert()$;
    **end**
    **for** $\forall AN_j^i \in N_i^c$ **do**
        **if** $AN_j^i$ *can improve its utility by selecting a new parent* **then**
            $AN_j^i.selectParent()$;
        **end**
        **if** $AN_j^i$ *cannot avoid overhearing to* $CN_i$ **then**
            /* Children will select new parent without power control */
            $AN_j^i.childrenSelectNewPath()$;
        **end**
        $u_i^{cur} \leftarrow getUtility(S_i)$;
    **end**
    $\Phi \leftarrow Potential(G)$;
    $count = 0$;
    **for** $\forall S_i \in S$ **do**
        **if** *($u_i^{cur} == u_i^{prv}$)* **then**
            $count++$;
            $u_i^{prv} \leftarrow u_i^{cur}$;
        **end**
    **end**
    **if** *($count == |S|$)* **then**
        /* It is an NE point as no sensor can improve its payoff by deviating unilaterally */
        return $A^*$;
    **end**
**end**

is nothing but a node $S_j$ causing overhearing to the critical node $CN_i$. Every active node calculates its utility value for all probable actions. Action here is again, to select a parent and the corresponding power level. Utility value for $AN_j^i$ for an action $a_l$, i.e. selecting a parent $S_l$ along with an appropriate power level, is given by

$$u_j(a_l) = \frac{W_l'}{\sum\limits_{\forall CN_i \in \text{ route of } S_l} W_{OH}^i * OH(CN_i)} + \frac{W_{ETX}'}{pathETX(S_j)} \tag{4.13}$$

Note that $u_j()$ also represents a weighted sum of lifetime and route quality factors (similar to equation (4.1)), where the lifetime factor is defined to be inversely related to a weighted sum of overhearing caused to all the critical nodes ($OH(CN_i)$, $i = 1, \ldots, k$) en-route sink, and is called the *path Overhearing*, while the route quality metric is described by the path ETX, as usual. Hence, the decentralized implementation is a finite potential game as well, when the potential function can be defined as the weighted sum of network lifetime and path ETX (same as equation (4.2)). Potential function is again calculated to capture the global effect ($Potential(G)$). Each node here, requests its parent to send its path ETX value and the path Overhearing value to calculate its utility vector. Since overhearing caused to different members of $CN$ will affect the network lifetime differently, we use a weighting factor, to calculate the path Overhearing. For each $CN_i \in CN$, $W_{OH}^i = \dfrac{\mathcal{L}_c}{\mathcal{L}_i}$, where $\mathcal{L}_c$ is the critical node lifetime and $\mathcal{L}_i$ is the lifetime of $CN_i$. This ensures that the overhearing caused to the nodes with lower lifetime are given higher weights and thus, are assumed to have greater effect on the network. After calculating the utilities, the active nodes select their best responses ($AN_j^i.selectParent()$). If this response succeeds in avoiding overhearing caused by $AN_j^i$ to $CN_i$, then no further action is taken for $AN_j^i$ and the game proceeds with other nodes in the active set. Otherwise, it introduces a second phase of the game, similar to one explained in Figure 4.1 – if the neighboring node of the critical node cannot avoid overhearing caused to the critical node by selecting a new parent, its children try to divert their data traffic through a new route which excludes the neighborhood of the critical node, thus reducing the overhearing caused to the critical node. In this phase, a small fraction of child nodes of $AN_j^i$ are chosen as active nodes, where each of these new active nodes try to divert their traffic by playing the same above game – calculate the utility vector for all its probable parents and choose the best response to maximize their utility values, but without any power control ($AN_j^i.childrenSelectNewPath()$). Here, children calculate their utility values for all probable actions using the same above equation (4.13). A fraction of children of $AN_j^i$ are chosen randomly with probability $p_i = \dfrac{L_a - L_i}{L_a}$, where $L_a$, as mentioned earlier, is the average lifetime of the network, and $L_i$ is the lifetime of the critical node $CN_i$. This probabilistic selection of child nodes removes the possibility of oscillations, which can be caused when too many children switch routes. This phase is completed when all active nodes of this phase complete their actions, after which the game proceeds with the remaining active nodes of the first phase.

In the following round, the *DPCR-H* requires the sink to evaluate and broadcast a new set of critical nodes $CN$, whereas the *DPCR-L* uses the same set of $CN$. The process terminates when nodes are unable to improve their utility any further, i.e., when best response Nash equilibrium is reached.

## 4.3. Results

The performance of the proposed *DPCR* schemes is compared to *CTP* and the centralized scheme, using computer simulated results. We evaluate the network lifetime, which is the lowest lifetime among all the nodes in the network, and the average end-to-end

ETX for all the nodes, along with the potential value of the network, as obtained in every step of the process. Simulation environment is same as used in the multi-channel game, except for the number of nodes in the network, and the underlying network area. In our simulations, we consider a network of $40$ sensor nodes that are uniformly distributed over a $50 \times 50m$ area. All nodes are assumed to transmit periodic data packets generated at a rate of $2$ packets every $5$ minutes, and route update packets are sent after every minute. We evaluate the performance of the joint power control and routing schemes at an instant where the state of charge (SOC) of the batteries are randomly distributed following an uniform distribution in $(3750, 5000)mAH$. The transmit power levels are chosen based on the parameters of the MICAz sensor node, and the receiver threshold for successful packet reception in the absence of any interference is assumed to be $-90dBm$. A log-normal channel model is assumed with a reference path loss of $-55dBm$ at $1m$, a path loss exponent of $3$, and a shadowing standard deviation of $3dB$. Results presented below are obtained from the simulations using the same set of parameters.

Figure 4.2 represents the improvement in the network lifetime using the ***DPCR-H*** scheme, with varying number of nodes in the critical node set, averaged over $5$ independent sets of simulations. As expected, with increasing number of nodes in the set $CN$, more information about the network is available to nodes, and hence better action set to choose from, thereby resulting into higher lifetimes. Improvement in the network lifetime, with respect to the lifetime from ***CTP***, when $k = 10$ is around $24\%$, while the improvement when $k = 1$ is around $12\%$. All the results next presented are with $k = 10$ for both the ***DPCR-H*** and the ***DPCR-L***.

Figure 4.3 depicts the improvements of the critical node lifetime at each step for all the proposed algorithms form one of the simulation runs. The results indicate more than $50\%$ improvement in the critical node lifetime in the first few steps of the algorithm, for the centralized scheme (Figure (a)), while the improvement with the *DPCR-H* and the *DPCR-L* is about $35\%$ (Figure (b) and Figure (c), respectively). The game stabilizes in approximately $5$ rounds. This indicates that the iterative approach is viable for lifetime improvement within a reasonably small number of iterations.

The lifetime of the network averaged from $10$ simulations after every step are plotted in Figure 4.4 for all schemes: the centralized, the *DPCR-H*, and the *DPCR-L*, and is compared with *CTP*. It can be observed that a $35\%$ improvement over the lifetime with *CTP* is achievable using the centralized scheme, which is much better as compared to the sub-optimal decentralized schemes. The improvement using the proposed *DPCR-H* is about $25\%$ and that using the *DPCR-L* is $15\%$. It is reasonable to expect better performance

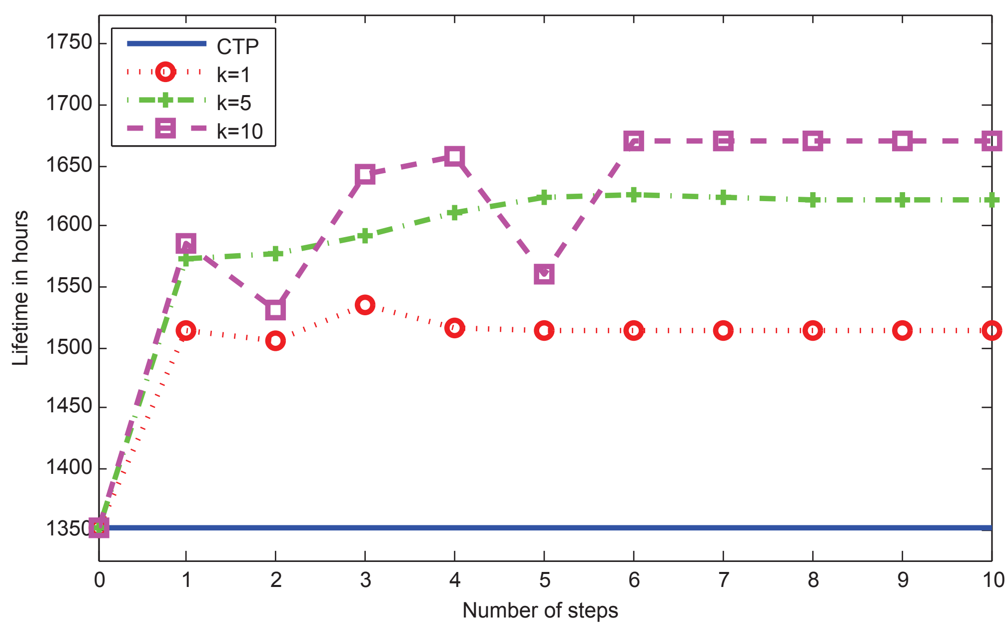
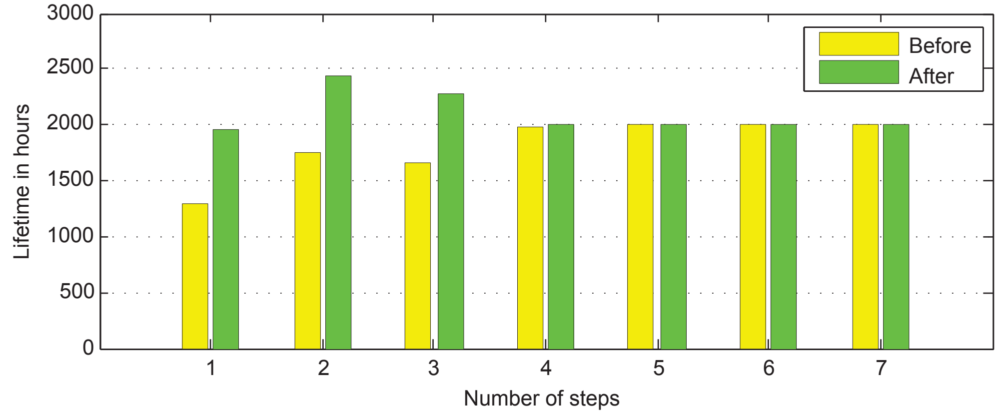
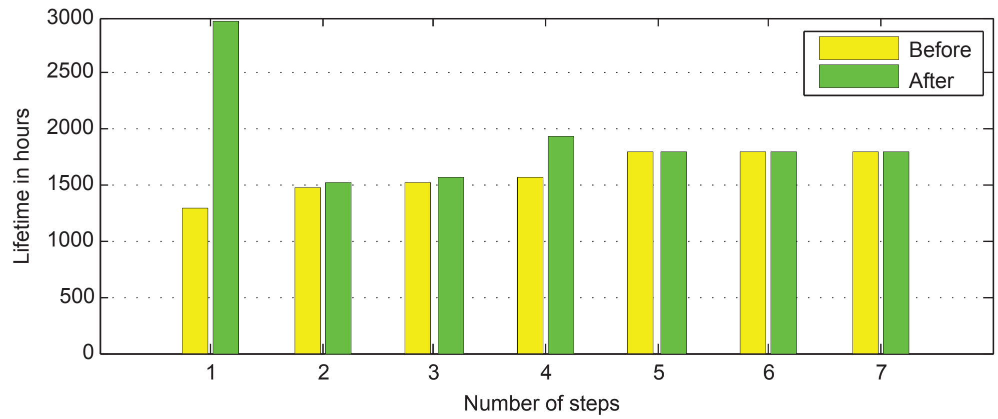


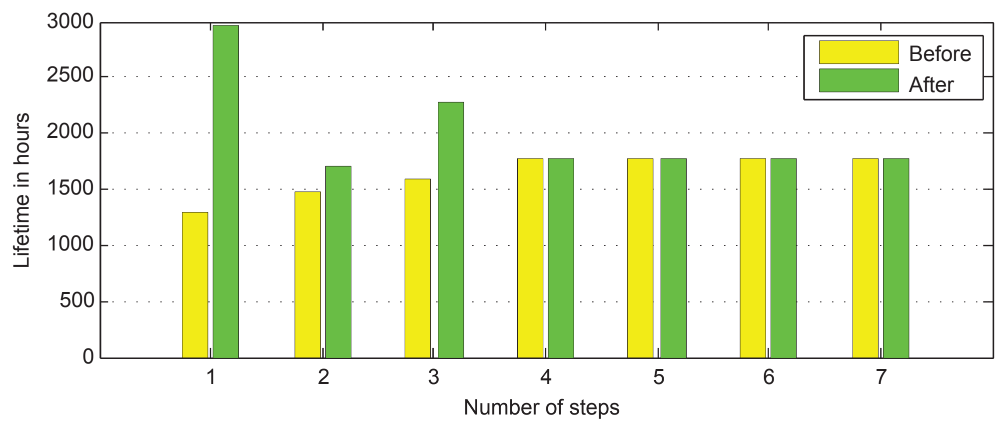

Figure 4.2: Average improvement in the network lifetime using the *DPCR-H* scheme with different number of nodes in the critical node set.




(a)




(b)




(c)

Figure 4.3: Lifetime of the critical node in the network obtained before and after completion of the actions in each round from simulations. Figure (a) shows the centralized scheme, while Figure (b) and (c) are the simulation results for the *DPCR-H* and the *DPCR-L*, respectively.

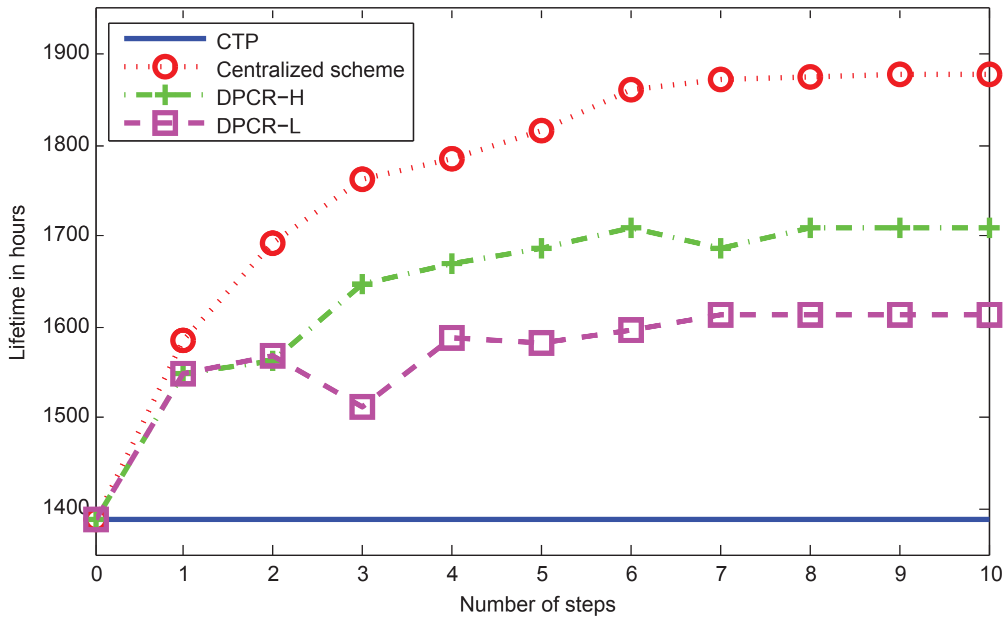



Figure 4.4: Average network lifetime obtained in different steps of the power control and route selections schemes.

with the *DPCR-H* as compared to the *DPCR-L*, since the actions are based on the round-by-round updated list. However, it must be noted that even with one time broadcast of the critical node set information, it is possible to achieve $15\%$ improvement of the network lifetime.

The improvement in the lifetime of the network is achieved at the cost of some reduction of route quality. This is because *CTP* always chooses routes which have best end-to-end performance based on ETX values, whereas the proposed power control and routing scheme apply a combination of ETX and network lifetime criteria for power control as well as route selections. The effect on the end-to-end delivery performance using the proposed schemes is presented in Figure 4.5 which is the average path ETX values, again averaged over the same $10$ simulations. The results indicate a slightly higher values of the average ETX using the *DPCR-H* and the *DPCR-L* in comparison to the centralized scheme.

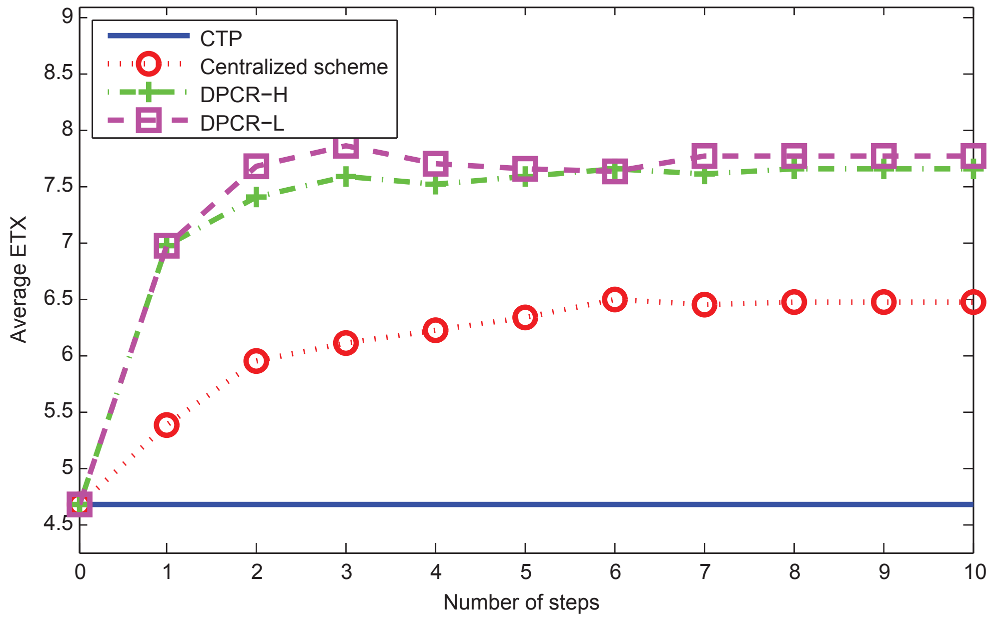



Figure 4.5: Average path ETX values obtained in different steps of the power control and route selections schemes.

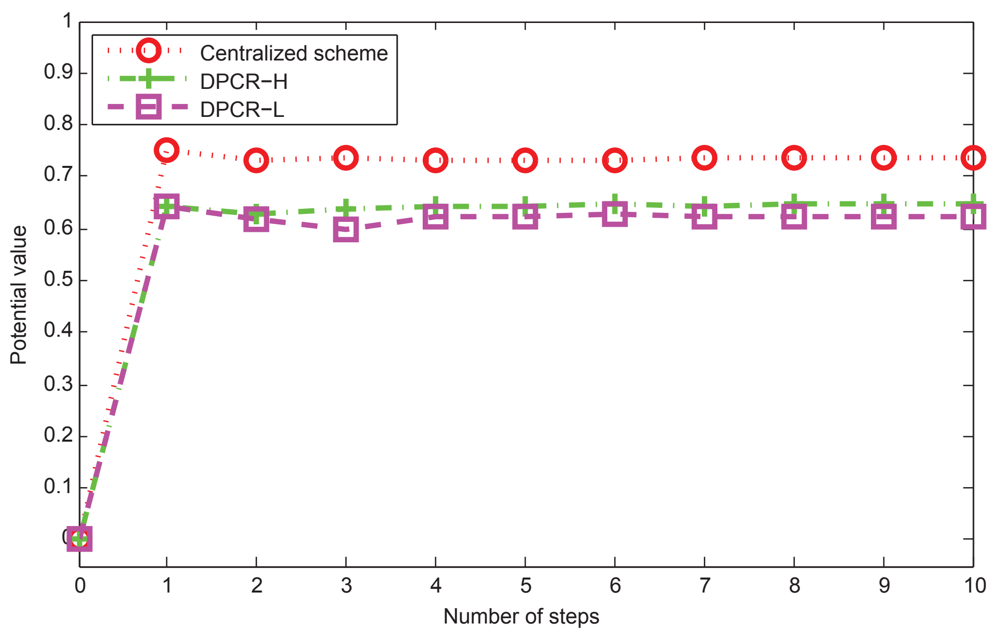



Figure 4.6: Average potential values obtained in different steps of the power control and route selections schemes.

However, the difference is not significant. The values for the *DPCR-H* and the *DPCR-L* are though, comparable.

As the game proposed is a potential game, potential value of the network is plotted in Figure 4.6 (averaged over the same $10$ simulations). From the figure, it can be seen that the potential value of the network increases after every step, before the network reaches the equilibrium state. Also, the potential value is highest when using the centralized scheme; and the *DPCR-H* and the *DPCR-L* have comparable values.

To conclude, we have shown that an iterative game-theoretic approach can result into an improved network lifetime, and the computational complexity is greatly reduced using this framework.

# CHAPTER 5: CONCLUSION

The objective of this work is to develop mechanisms for controlling the amount of overhearing and interference in the WSNs, so as to control the current consumption by the nodes to balance their remaining lifetimes, thus contributing towards an improved network lifetime. We explore two different approaches for achieving this objective. In the first approach, we consider that the nodes operate in multiple non-overlapping channels to reduce overhearing, where we address the problem of optimum channel selection to extend the network lifetime. In the second approach, we consider power control and routing to control the overhearing. Generally, this kind of processes involves high computational complexity. We present game theoretic formulations of these approaches, which lend iterative solutions that converge within a finite time and greatly reduces the computational complexity. We present computer simulated results for both the above games.

We proposed a coalitional game for the receiver based multi-channel selection, where the nodes are assigned one of the available orthogonal channels. Transmission of data by any node is performed by switching to the receiver channel of the parent. Cost incurred with this approach to reach equilibrium is the number of steps required, and the gain is presented as an improvement in the network lifetime, thus confirming the reduction of the overhearing and interference effect.

We show that the joint power control and routing problem can be modeled as an exact potential game having a Nash Equilibrium. The corresponding framework is used to develop a “god-aided” centralized solution that is expected to give the best case results on lifetime improvement. Finally, we proposed two versions of a distributed (albeit sub-optimal) scheme, which only requires the knowledge of the list of the critical nodes in the network. In the *DPCR-L*, this is achieved by a single broadcast from the sink while, in the *DPCR-H*, multiple broadcasts from the sink are required. Again, the cost is presented as the route quality in the network while the gain is the still the improvement in the network lifetime. Results are presented for the centralized scheme, the *DPCR-H*, and the *DPCR-L* are compared with *CTP*.

# CHAPTER 6: FUTURE WORK

The two proposed methods (channel selection, and joint power control and routing) can be further combined to get much more improved result. These two approaches can be combined in two ways, based on the order of application of the proposed methods.

- First, we can initially set up routes using *CTP*, and assign receiver channels to the nodes using the proposed coalitional framework. Now without changing these receiver channels, joint power control and routing mechanism can be used to redefine power level and new parent to each node in the network, so as to minimize the amount of overhearing caused to the critical node in the network.

- Second, after setting up routes using *CTP*, power control and routing mechanism can be applied and after obtaining a new topology of the network, receiver channels can be assigned to reduce further overhearing.

The first approach can prove to be a little more effective as power control mechanism exclusively deals with the improvement of the critical node lifetime, while multi-channel selection does not consider any such node. So, after allocating channels to the receiver nodes, the first approach can still be focused to improve the critical node lifetime. In contrast, the second approach which deals with improving the critical node lifetime first, and then work towards reducing the overall effect of overhearing in the network, by allocating receiver channels to the nodes, may not give the results as comparable to the first approach.

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